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Language Skills and Employability: The Case of Ukrainian Refugees in the Czech Republic

Bachelor's Thesis

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Declaration of Authorship

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Prague, July 31, 2024

Daniela Javurkova

Abstract

This thesis investigates the relationship between the Czech language proficiency of Ukrainian refugees who arrived in the Czech Republic after the onset of the Russian invasion of Ukraine in February 2022 and their chances of finding employment. The study utilizes a correspondence experiment, where curricula vitae of fictitious applicants are submitted in response to online job postings. The applicants are categorized into three groups: Ukrainian refugees with poor Czech language skills, Ukrainian refugees with a good command of the language, and native Czech citizens. The results indicate no significant differences in callback probabilities among Ukrainian refugees with varying levels of Czech proficiency, suggesting that, in this particular context, improved knowledge of the host country's language may not necessarily enhance refugees' labor market prospects.

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Abstrakt

Tato práce zkoumá vztah mezi úrovní znalosti českého jazyka ukrajinských uprchlíků, kteří přišli do České republiky po začátku ruské invaze na Ukrajinu v únoru 2022, a jejich šancí najít si zaměstnání. Studie je koncipována jako korespondenční experiment, v rámci něhož jsou životopisy fiktivních uchazečů zasílány v reakci na nabídky práce zveřejněné na internetu. Analýza odpovědí náborářů nenaznačuje významné rozdíly v pravděpodobnosti obdržení pozitivního signálu ze strany náboráře (zejména pozvání na pohovor) při porovnání ukrajinských uprchlíků s různou úrovní znalosti češtiny. Z tohoto zjištění lze vyvodit, že v tomto konkrétním kontextu nemusí pokročilejší znalost jazyka hostitelské země nutně zlepšovat vyhlídky uprchlíků na trhu práce daného státu.

Klasifikace JEL	J24, J61
Klíčová slova	jazykové dovednosti, zaměstnatelnost, uprchlíci, korespondenční experiment
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Acronyms

AI Artificial Intelligence

CEFR Common European Framework of Reference for Languages

CV Curriculum Vitae

CZ Czech

EN English

ESOL English as a Second Language

FT Full-time

HR Human Resources

ISCO International Standard Classification of Occupations

LPM Linear Probability Model

NUTS Nomenclature of Territorial Units for Statistics

OLS Ordinary Least Squares

PT Part-time

SFI Swedish for Immigrants

UA Ukrainian

UK United Kingdom

USA United States of America

Chapter 1

Introduction

Intuitively, it would be expected that the knowledge of the local language plays a vital role in immigrants' and refugees' integration into the host country's labor market. The extent and consequences of language barriers have been studied by numerous authors, focusing on various countries and employing various approaches - both experimental and non-experimental. However, the existing literature has not produced consistent findings regarding the relationship between immigrants' or refugees' language skills and their employment outcomes. Our research seeks to explore the previously unexamined link between proficiency in the Czech language and the probability of success in job application processes. Specifically, we focus on the case of Ukrainian refugees who arrived in the Czech Republic following the start of the Russian military invasion of Ukraine in February 2022.

Our research involves conducting a correspondence experiment, based on sending curricula vitae (CVs) of fictitious candidates as responses to job offers posted on popular Czech job application portals. The fictitious candidates are divided into three groups: treatment group A consists of Ukrainian refugees with poor Czech language skills, treatment group B comprises Ukrainian refugees with a good command of Czech, and the control group consists of native Czech citizens. For each selected job offer, two manipulated CVs are sent, each of them corresponding to a different group.

In the subsequent analysis of the employers' responses, our primary focus is on examining the differences in callback probabilities (i.e., the likelihood of receiving a positive signal from the employer, such as an interview invitation) between treatment groups A and B. In this context, the research question can be formalized by the following hypotheses (or two versions of Hypothesis 1):

Hypothesis 1a: Czech language proficiency of Ukrainian applicants has no impact on callback probability.

Hypothesis 1b: Better Czech language proficiency of Ukrainian applicants increases the callback probability.

The hypotheses are assessed using standard statistical methods and econometric analyses, including linear probability models, logit models, and probit models. In summarizing the results of these analyses, we do not find sufficient evidence to reject Hypothesis 1a in favor of its two-sided alternative or in favor of Hypothesis 1b. This suggests that Czech language proficiency may not have a significant impact on increasing the Ukrainian refugees' chances of success in job application processes.

Further, the interpretation of results could be narrowed down to provide insights into the phenomenon of Ukrainians currently working in positions for which they are overqualified. This interpretation is made possible by two specific features of the experimental design. Firstly, the Ukrainian candidates' CVs are constructed to indicate that they are presently employed in a job that requires lower skills than the one they would have in their home country under normal circumstances, given their education and experience. Secondly, the selection of suitable job postings primarily focuses on positions that align with their qualifications and educational background (excluding language proficiency). Given the conclusions regarding our hypotheses, our research presents suggestive evidence that improved language skills may not necessarily address the issue of "overqualification".

The remainder of the thesis is structured as follows:

- Chapter 2 briefly summarises the situation of Ukrainian citizens in the Czech labor market,
- Chapter 3 offers an overview of relevant literature related to the language proficiency of refugees/immigrants and their labor market outcomes,
- Chapter 4 discusses correspondence experiments in general and subsequently provides a detailed description of the experimental design used,
- Chapter 5 introduces the key features of the dataset obtained from the experiment,
- Chapter 6 primarily presents the results of the statistical and econometric analysis,

- Chapter 7 elaborates on these results,
- and finally, Chapter 8 concludes the thesis.

Chapter 2

Context: Ukrainian Citizens in the Czech Labor Market

Even prior to the beginning of the Russian invasion of Ukraine on February 24, 2022, and a subsequent influx of Ukrainian refugees into the Czech Republic, the Ukrainian minority was one of the largest minority groups in the country. According to the 2021 Census, over 90,000 residents identified themselves as Ukrainian nationals.[1] However, in spite of certain similarities between Czechs and Ukrainians as Slavic nations, discriminatory practices against individuals of Ukrainian origin have been noted in the Czech labor market. Pasichnyk (2023) examined this issue through a correspondence experiment, which involved sending job applications of fictitious candidates as responses to suitable job advertisements. The study revealed that job seekers with Ukrainian backgrounds face discriminatory hiring practices, resulting in a 72.7% decrease in callback probability compared to native Czech applicants, despite having been educated in the Czech Republic and possessing excellent knowledge of the local language.

The Russian military invasion of Ukraine caused millions of Ukrainians to flee their country. Globally, over 6.5 million Ukrainian refugees have been recorded (as of July 2024), with the majority of them seeking asylum in other European countries. Measured by the number of applications for asylum, temporary protection, or similar schemes, Poland, Germany, and the Czech Republic have been the most frequent destination countries for refugees.[2] Focusing

[1]Data downloaded from `https://scitani.gov.cz/narodnost`, accessed on July 28, 2024.

[2]Data retrieved from `https://data.unhcr.org/en/situations/ukraine`, accessed on July 28, 2024.

on the case of the Czech Republic, as of April 30, 2022, over 310,000 refugees were granted temporary protection, with women of productive age and children forming the majority. As of July 21, 2024, this number exceeded 360,000.[1] Moreover, since the commencement of the invasion, multiple laws and regulations (collectively referred to as "Lex Ukrajina") aimed at providing help to the refugees, have been introduced to the Czech legal system.

The "Hlas Ukrajinců" survey series, primarily organized by the non-profit organization PAQ, monitors the integration progress of Ukrainian refugees in the Czech Republic in various domains, including labor market integration. The latest report[2] documents relatively high levels of employment among Ukrainian refugees; as of November, 78% of economically active respondents were employed. However, it was highlighted that a large portion of refugees were working at positions much less qualified compared to their jobs in Ukraine. An improvement in Czech language proficiency is widely believed to be a possible solution to this issue. While 47% of adult respondents claimed to communicate in Czech comfortably in daily situations, 35% stated that they can only construct and understand simple sentences.[3] The remaining respondents reported having practically no knowledge of the local language. Further, it was suggested that many refugees opt for self-study rather than enrolling in language courses, with lack of time due to work commitments and financial constraints being the primary reasons for not attending language courses.

Aside from language skills, discrimination may present another barrier to labor market integration. A correspondence experiment focused on discrimination against Ukrainian refugees was conducted by Roy (2023), who contacted prospective employers about potential vacancies under various fictitious identities - including Ukrainian refugees and native Czech job seekers. A surprising pattern emerged: in the earlier stages of the experiment (i.e., in the initial months of the invasion), there was a preference for refugee applicants over native applicants. However, this effect diminished in time and the opposite pattern, i.e., preference for native workers, was observed later. This study may therefore provide suggestive evidence that Ukrainian refugees may face discrimination in the Czech labor market

[1] Data downloaded from `https://www.mvcr.cz/clanek/statistika-v-souvislosti-s-valkou-na-ukrajine-archiv.aspx`, accessed on July 28, 2024.

[2] Referring to the report published in February 2024, downloaded from `https://www.paqresearch.cz/post/dva-roky-pote/` on July 28, 2024.

[3] Please note that the percentages stated in this paragraph do not necessarily pertain to the same samples.

Chapter 3

Literature Review

Proficiency in the predominant language of a host country is widely considered crucial for the successful integration of immigrants and refugees into the local labor market. This notion is also supported by the economic theory of human capital (see, e.g., Becker 2009). According to Chiswick (2008), "Language skills satisfy the three requirements for human capital, that it is productive, costly to produce, and embodied in the person" (p. 4). Research on the adaptation of immigrants has mainly focused on the issue of the imperfect international transferability of human capital, which is especially obvious in the context of language skills (Chiswick & Miller 2009).

Specifically, the extent and consequences of linguistic barriers have been the subject of numerous studies in different countries, employing various methodological approaches. However, the findings regarding the effect of host language proficiency on labor market outcomes - which can be viewed in the form of, e.g., incidence of employment, success in a job application process, or income levels - are mixed. This chapter aims to provide an overview of some of the investigations into this issue, beginning with observational and quasi-experimental studies and subsequently delving into experimental research.

However, before presenting specific studies, it is important to outline the primary challenges that researchers encounter when examining this topic. Yao & van Ours (2015) highlight the following sources of biases: endogeneity of language skills[1], errors in measuring language proficiency, and reverse causality (i.e., work experience causing the improvement of language skills). In this

[1]The issue of endogeneity arises primarily when language skills are correlated with other personal characteristics, such as intelligence, which intuitively makes it easier for individuals to learn a foreign language. Consequently, assessing whether an immigrant's success in the labor market is predominantly influenced by their language skills *per se*, or by unobserved characteristics, presents a significant challenge.

chapter, we also aim to discuss whether (and how) these issues are addressed in the studies presented.

3.1 Non-Experimental and Quasi-Experimental Studies on Language and Labor Market Outcomes

3.1.1 Efficiency of Language Training Programs

Multiple authors evaluated the efficiency of local policies represented by specialized language training provided by governments to assist in the integration of immigrants/refugees into the labor market of the host country. While the reliance on participation in language courses serves as a means to minimize measurement error, a "selection issue" may arise when applying such an approach. That is because, under normal circumstances, it is not randomly determined which immigrants attend a language course and which do not. Instead, the decision of whether or not to attend a course may be correlated with an immigrant's motivation levels or intelligence, leading to an endogeneity issue. To mitigate the potential bias, multiple authors rely on quasi-experimental methods to ensure the randomness of language course participation.

A quasi-experimental study by Delander *et al.* (2005) examined a pilot scheme for unemployed Swedish immigrants with insufficient command of the host country's language. Their findings suggest that participants engaged in the pilot program subsequently experienced accelerated transitions from unemployment to employment. A quasi-experiment (or a "local randomized experiment", as the authors specify) by Lochmann *et al.* (2019) concentrated on the contributions of training provided to immigrants by the French Ministry of Interior. A pivotal aspect of this policy is that only individuals who score below a specific threshold on an initial exam are eligible for the training, and the allocated hours of training also differ. By utilizing the discontinuity between test scores and variables of interest due to the eligibility rule (specifically employing a "regression discontinuity design"), the authors identified a positive effect of hours spent in French classes on immigrants' labor force participation. They further noted that this impact was even more pronounced for individuals with higher levels of education.

Heller & Mumma (2023) aimed to assess the efficiency of a public adult

ESOL (English as a Second Language) program in Massachusetts. In this study, the potential endogeneity bias is minimized by using randomized enrollment lotteries. Their results indicate that the corresponding courses led to an increase in immigrants' average yearly earnings by over 50 percent as well as a rise in voter participation. The authors also proposed subsidizing the expansion of such programs, as the future tax revenue of the participation exceeds the initial investment into the immigrant's language education, also because the demand for the program largely exceeds the supply.

In contrast with the three above-mentioned papers, some studies did not confirm the beneficial effect of language training on labor market outcomes. One such example is a study by Hayfron (2001), relying on data collected through a questionnaire among third-world immigrant men in Norway. The authors found a positive impact of a government-sponsored language training program on the individuals' Norwegian fluency. However, no significant effect of language proficiency on income was revealed.

Lastly, there were two Danish reforms which, according to the relevant literature, yielded different outcomes. Foged *et al.* (2022) investigated the consequences of a 1999 reform that introduced a more intensive mandatory language program for refugees admitted after a specific date.[1] Similarly to Lochmann *et al.* (2019), they also utilized the "regression discontinuity design" - in this case, based on the threshold date which divided refugees into those eligible for new training and those with the original limited one. The investigation revealed an increase in both employment rates and earnings of the refugees who completed the reformed training. Furthermore, the authors emphasized that the economic benefits of the training are substantially larger than its costs. Subsequently, Foged *et al.* (2023) concentrated on the impact of this reform on the children of the refugees affected. Evidence of beneficial intergenerational spillover effects was found, implying that the children of refugees treated by the reform were more likely to finish their lower secondary education and less likely to commit juvenile crime.

While the 1999 Danish was proven to be effective, the same cannot be concluded about an updated mandatory integration program, introduced in response to the arrival of mostly Syrian refugees in Denmark in 2015. Despite the fact that the program, including language classes and work internships, was

[1]One of the major changes introduced by the reform was a longer duration of language training, with an additional 430 hours that could be taken over 3 years, as opposed to 1.5 years before the reform.

meant to accelerate the refugees' Danish learning, Lønsmann (2020) concluded that it led to decapitalization and marginalization of the affected refugees instead.[1]

3.1.2 Impact of Language Proficiency Alone

There have also been numerous studies that concentrate on the impact of language proficiency *per se*, without considering specialized training. In these cases, two sources of a potential bias are crucial: endogeneity of language skills and measurement error. When considering the latter, a vital question arises regarding the optimal definition of one's fluency level - i.e., whether it is appropriate to rely on self-reported data, results of standardized tests, or different measures. This methodological factor is a point of differentiation among relevant research papers, as will be described in what follows.

Self-reporting

Multiple researchers have used self-reported indicators of immigrants' language skills, with a focus on immigrants residing in various countries - e.g., Germany (Dustmann & Van Soest 2002, or Aldashev *et al.* 2009), the United Kingdom (Dustmann & Fabbri 2003), Ukraine and Estonia (Lindemann & Kogan 2013), the Netherlands (Yao & van Ours 2015), Australia (Tam & Page 2016), Spain (Budría *et al.* 2018, or Miyar-Busto *et al.* 2020), and Italy (Pieroni *et al.* 2022). However, their approaches differ in whether (and how) they attempt to alleviate potential measurement errors.

In certain studies, the potential measurement error has not been dealt with. This is the case of, e.g., Lindemann & Kogan (2013), who investigated the influence of language proficiency on the labor market success of young Russian immigrants in Ukraine and Estonia. Specifically, they concentrated on the difference between the chances of finding any first job in the country and a high-status one. They revealed different patterns for each country - while in Estonia, the linguistic barrier was estimated to be significant, especially for high-status jobs, the barrier in Ukraine seemed to be almost negligible, even for high-status jobs. Another example might be Miyar-Busto *et al.* (2020), who concluded that poor command of Spanish limits the immigrants' access to employment.

[1] This conclusion was made based on fieldwork analysis, including, e.g., participant observation in classes or interviews with the participants.

In contrast, multiple authors took steps to mitigate measurement errors by including an instrumental variable (IV) estimator. For instance, Yao & van Ours (2015), Tam & Page (2016), and Budría *et al.* (2018) used an instrumental variable consisting of the interaction of an immigrant's age at arrival and a dummy variable representing not being born in a country speaking the same language as the host country (or not speaking the host country's language during childhood).[1] Tam & Page (2016) concluded that a better command of English contributed to increases in income as well as immigrants' weekly hours of work. Budría *et al.* (2018) reported that a good command of Spanish decreased the likelihood of immigrants' unemployment. In contrast, research by Yao & van Ours (2015) brought evidence that the effect of language-related problems might vary by gender. Specifically, female immigrants who experienced language difficulties earned substantially lower wages compared to female immigrants with similar personal traits but without language problems. However, no such pattern was found for male immigrants.

An instrumental variable was also utilized by Dustmann & Fabbri (2003). In this case, data from two different surveys was considered - one with self-reported language questions and the other with interviewer-assessed language questions - employing the information about the interview language as an instrument for measurement error. Furthermore, they aimed to mitigate the issue of endogenous choice of language acquisition by employing a matching estimator. The intuition is described as follows: "The matching approach is based on the idea that the observable characteristics are sufficient to explain any relationship the choice of learning the language has on the outcome if non-proficient in English." The results showed that a good command of English is linked with higher employment probabilities and higher earnings.

Further, Pieroni *et al.* (2022) utilized an instrumental variable consisting of an interaction between the immigrant's age at arrival and an index-measured linguistic distance between Italian and the immigrant's mother tongue, intending to reflect the different amount of effort or training to acquire language knowledge. They showed that improved knowledge of Italian positively affected the immigrants' likelihood of employment as well as hourly wages.

[1]Aside from dealing with the measurement error, this approach allows the authors to address the issue of endogeneity.

Dustmann & Van Soest (2002) aimed to address the potential measurement error (which they further divided into unsystematic and time-persistent) as well as unobserved heterogeneity. Using panel data spanning over 10 years, they tried to minimize biases by including variables with information about immigrants' partners and households, as well as leads and lags of self-reported information on fluency as instruments for real fluency. The main conclusion of their article is that simple OLS estimates using self-reported data might substantially underestimate the true values of coefficients representing the effect of language skills on income.

Lastly, Aldashev *et al.* (2009) used a proxy variable for self-reported fluency level, represented by reported language usage in a household. i.e., whether it was German only, mother tongue only, or a combination of both. They confirmed a positive influence of German knowledge on participation and employment probabilities.

Test and Interviews

A potentially more objective method for assessing fluency levels is by third parties. However, it is important to note that this approach still carries a risk of measurement error. This possibility was highlighted, e.g., by Carlsson *et al.* (2023), who emphasized that this problem may arise when the stakes are low while taking such tests.

Cohen-Goldner & Eckstein (2008) focused on immigrants to Israel from the former Soviet Union and utilized survey data with interview-assessed language skills. Their dynamic choice model led to the conclusion that knowledge of Hebrew had a positive impact on both blue-collar and white-collar job opportunities. Further, Himmler & Jäckle (2017) relied on data from a German adult literacy test, including interviews, with both native and immigrant participants. The results indicated that "the migrant-native employment and wage gaps disappear completely and become insignificant when literacy levels are taken into account - that is, the differences in the labor market outcomes are fully explained by the literacy gap" (p. 622). Schmaus (2019) used test-based language information from the German "National Educational Panel Study" to separate the impact of language-related productivity increases from the effect of language-based discrimination. The results revealed group-specific returns to improved command of German, with strongly disliked immigrant groups benefiting more significantly from language skill improvement.

Alternative Approaches

Rooth & Saarela (2007) adopted an alternative non-experimental approach to measure the returns of language knowledge on a level close to the one of natives. Two groups of Finnish immigrants in Sweden were compared: one group whose mother tongue was Swedish and another group whose mother tongue was Finnish, known for being linguistically distant from Swedish. The authors estimated a lower limit for the expected returns associated with possessing perfect language skills, acknowledging that some native Finnish speakers might also be fluent in Swedish. Despite this, they concluded that having the same mother tongue as natives had a significant influence on employment probabilities and income levels. The authors suggest that this effect should be attributed to the language skills *per se*, highlighting that they consider alternative explanations (such as cultural behavior) unlikely.

Mergener & Maier (2018) applied a quasi-experimental procedure, by conducting a "factorial survey experiment" (also called a "vignette study"). In an online survey, German HR professionals were asked to assess the chances of recruitment success of fictitious immigrants with systematically different personal attributes and under various labor market conditions. Fluency in German was evaluated as the feature having the strongest positive influence on potential success.

3.2 Experimental Studies on Language and Labor Market Outcomes

Despite being less frequent, there have also been experimental investigations into the relationship between the language skills of immigrants/refugees and their labor market outcomes. The primary advantage of experimental approaches lies in minimizing the endogeneity of immigrants' language skills.

3.2.1 Natural Experiment and Discrete Choice Experiment

A "natural experiment", such as the one investigated by Auer (2017), represents a relatively unique approach. The random placement of asylum seekers into Swiss cantons with different official languages allowed for analyzing the consequences of a match (or a mismatch) of the cantons' official language with refugees' individual skills while dealing with the endogeneity of language proficiency. Furthermore, given the fact that immigrants' fluency was assessed by job center caseworkers during counseling sessions, the method should bear a lower risk of measurement error compared to self-reporting. The analysis showed that a "language match" increased the likelihood of finding a job, but participating in dedicated courses could counteract the repercussions on employment in the event of a "language mismatch."

Theys *et al.* (2020) conducted a "discrete choice experiment" to investigate the impact of ethnic preferences and language skills on the recruitment of domestic workers. In a questionnaire to households in the Brussels urban region, the respondents were asked to choose between different profiles of fictitious housekeepers. The results exhibited a significant preference for housekeepers who spoke the household's home language. Additionally, there was a preference for communication in an alternative language over having no shared language at all. Despite this, discriminatory behavior among respondents was still observed.

3.2.2 Correspondence Experiments

The remainder of the chapter is devoted to "correspondence experiments", a method that was also used in our research and is one of the approaches used to deal with the endogeneity of language skills. In the context of this topic, this method always involves sending manipulated job applications indicating different levels of language proficiency as responses to real job advertisements, and a subsequent analysis of callback rates. Carlsson *et al.* (2023) consider this method more powerful than observational studies as it allows researchers to overcome some of the usual shortcomings of such studies, including omitted variable bias, measurement error, and reverse causality. For a discussion about methodological aspects of correspondence experiments, please refer to Subsection 4.1.1.

Oreopoulos (2011) sought to understand why skilled immigrants in Canada experience difficulties in the job market. During 2008 and 2009, he carried out an experiment in which he sent out four distinct manipulated resumes in response to each of over 3,000 chosen job openings. The resumes varied based on the applicant's education, experience, and name - either English/Canadian or foreign. The results revealed significant discrimination against candidates with foreign-sounding names across various fields, and that explicit information about fluency in English, French, and mother tongue failed to offset the negative effect. Contrary to the empirical evidence, a follow-up survey with some recruiters suggested that concerns about language proficiency may be driving this relationship.

Despite being primarily focused on ethnicity-based discrimination, an experiment by Edo *et al.* (2017) also revealed interesting findings regarding language-related signals. All of the fictitious applicants were French citizens, educated in France, but differing in ethnic backgrounds. To minimize potential concerns about insufficient language skills of candidates with non-French-sounding names, half of the resumes included signals reflecting such skills, such as mentioning French tutoring or experience in writing for an inter-college newspaper. Between September 2011 and February 2012, manipulated job applications were sent out for over 500 accounting positions, with six different experimental resumes submitted in response to each selected vacancy. The subsequent analysis showed an asymmetrical impact of language-related signals. While the inclusion of such signals significantly decreased discriminatory behavior against women with non-French-sounding names, the same could not be concluded for men.

A correspondence experiment by Ek *et al.* (2021) examined Syrian refugees in Sweden. The design (which served as a source of inspiration for our research in many aspects) entailed the creation of eight fictitious identities of 23-year-old refugees with high-school education from their home country. The applicants were distinguished based on gender, work experience in Sweden (differentiating between experience in a low-skilled job and only being registered at the employment service), and a signal regarding language knowledge (completion of a Swedish for Immigrants (SFI) program, which includes language training, versus no information about such courses). During 2019, over 2,000 experimental applications (one per job opening, randomly assigned to one of the eight fictitious identities) in the form of resumes and short cover letters were submitted as responses to low-skilled job openings published on the Swedish Public Employment Service's portal. In the following analysis, the impact of SFI completion, previous work experience as well as their interaction were assessed as insignificant, implying that participation in language training does not substantially influence callback probabilities. The only consistently significant variable was the one signalizing gender, with females being approximately 3.8 percentage points more likely than males to receive a callback.

Lastly, another Swedish study on a similar topic was conducted by Carlsson *et al.* (2023). The scope of their research was rather wide - through a content analysis of approximately six million job postings published on the website of the Swedish Public Employment Service between 2007 and 2019, they estimated that there had been more than a threefold increase in the requirements for literacy skills - with the proportion of job offers requiring literacy skills rising from 10 percent in 2007 to 35 percent in 2019. However, the main part of their investigation was a correspondence experiment with over 3,000 manipulated resumes sent out between February 2020 and March 2021, one per each chosen employer. Unlike the one by Ek *et al.* (2021), this experiment concentrated on immigrants from Germany, Poland, Romania, and the UK to mitigate potential ethnic-based discrimination. The study covered various job types, with approximately 74 percent of the addressed vacancies corresponding to low- to medium-skilled jobs. Further, a unique approach was adopted to signal the applicants' fluency in Swedish. A professional linguist manipulated the linguistic quality of the resumes to imitate four distinct levels by including realistic second-language features. The validity of this approach was also tested in a survey among employers, confirming that recruiters were able to evaluate the differences between the Swedish level of the candidates based on the materials provided. The analysis showed that a better command of Swedish increased callback rates across virtually all job types. Specifically, "improving language skills increases the callback rate linearly, and moving from a low level to a level similar to that of natives almost doubles the callback rate from 8 to 15 percent" (p. 24). Lastly, the study aimed to determine the driving force behind the positive implications of better language skills. The authors hypothesized two possibilities: that improved language knowledge directly increases work productivity, or that they act as a proxy for other unobserved characteristics of immigrants (such as general abilities or the ability to integrate into the host country's society). By surveying employers, they found evidence that the former is more likely to be the case.

3.3 Potential Contribution of the Thesis

This literature review documents that the existing studies observe different patterns regarding the impact of immigrants'/refugees' language proficiency on labor market outcomes - varying among countries, genders, or occupation types. Therefore, the main contribution of this thesis is to add to the existing research by examining the case of the Czech Republic, which, to the best of our knowledge, has not been explored yet. The only related studies focusing on the Czech settings are theses[1] by Roy (2023) and Pasichnyk (2023). However, both of them experimentally investigate the issue of discrimination against Ukrainian citizens (specifically, Ukrainian refugees in the former case, and long-term Ukrainian immigrants in the latter case), not their language skills. The conclusions made by Roy (2023) indicate the presence of discrimination against Ukrainian refugees in the Czech Republic. In this regard, our study may also prompt a discussion on the role of language skills in mitigating this discriminatory behavior.

Furthermore, the research uses an experimental approach of a correspondence experiment, an increasingly popular method often claimed to yield more reliable results than observational studies.

Finally, specific features of the experimental design (documented in Section 4.2) may allow us to determine whether improved language skills could minimize the issue of Ukrainian refugees currently working in positions for which they are overqualified. Therefore, the results could potentially help determine the effectiveness of potential policy interventions dealing with this problem, such as subsidizing language courses for refugees.

[1] The findings of these theses are elaborated on in Chapter 2.

Chapter 4

Methodology

This chapter is devoted to further clarification of the methods employed for the data collection. The first section aims to elaborate on concepts mentioned in the previous chapter, while the second one provides a detailed description of our experiment's design.

4.1 Controlled Experiments: Some Theory

According to Harrison & List (2004), controlled experiments represent a powerful way to estimate treatment effects[1]. This is achieved by creating a control group through randomization, i.e., assigning the subjects in the sample randomly either to groups receiving treatment or to groups not receiving treatment (the so-called control groups). The authors highlight that controlled experiments encompass laboratory experiments and field experiments, with the latter gaining increased popularity in recent years. Levitt & List (2009) differentiate field experiments from laboratory ones based on their occurrence in real-world settings. As a result, the data gathered from field experiments can be viewed as a compromise between naturally occurring data, characterized by its realism, and the data produced in laboratory experiments, which usually involve a high degree of control over the experimental conditions.

4.1.1 Correspondence and Audit Studies

Our research relies on a specific type of field experiment, a correspondence study (also referred to as a correspondence experiment). As the name implies,

[1] Treatment effect is defined as the average causal effect of a binary variable on an outcome variable (Angrist 2010).

one of the key features of correspondence studies is that they do not involve physical interaction between the tester and the subjects being tested. Instead, the experiment is conducted via phone or e-mail. This is in contrast to an otherwise equivalent type of field experiment, a situation test, which requires the physical presence of real testers. Correspondence studies and situation tests are often collectively referred to as audit studies (Verhaeghe 2022).[1]

The majority of published papers using correspondence experiments focus on the issue of discrimination. Specifically, the most addressed issues include hiring discrimination (e.g., the pioneering correspondence experiment from 1970 by Jowell & Prescott-Clarke) and housing market discrimination (e.g., Ahmed & Hammarstedt 2008). However, the method has also been used, e.g., to examine the impact of language skills on labor market outcomes (e.g., Ek *et al.* 2021, as detailed in Subsection 3.2.2), the influence of entrepreneurial experience on success rates in job application processes (Botelho & Chang 2023), or to investigate whether companies use social media profiles of job candidates during the recruitment process (Manant *et al.* 2014). Regardless of the topic in scope, the experimental design always involves preparing manipulated requests of fictitious persons and sending them as responses to, e.g., real job openings or rental offers.

4.1.2 Matched and Non-Matched Designs

Researchers use various designs of correspondence studies, with the most significant categorization being into matched and non-matched approaches. Taking the example of sending job applications to employers (sample units), the former approach involves submitting multiple experimental applications per sample unit (typically one treated and one control), while the latter approach is characterized by sending only one application to each sample unit, Although the majority of correspondence studies on discrimination favor the matched method (specifically, the paired method), there is a growing inclination towards adopting the alternative single-inquiry approach (Larsen 2020).

Regarding the relative statistical efficiency of the two methods, Vuolo *et al.*

[1]Following the conclusion of Verhaeghe (2022), relevant terminology varies in the existing literature. Therefore, the term "audit studies" may encompass both correspondence experiments and situation tests, or it may only serve as a synonym for situation tests. For consistency, we use the broader definition going forward.
In addition, it should be noted that the author's article addressed correspondence studies in the context of identifying discriminatory behavior. Nonetheless, we believe that the majority of conclusions could be extended to cover correspondence experiments in general.

(2018) emphasize the role of the level of concordance of outcomes between inquiries in a matched pair (e.g., the result of a job application process of a "treatment" applicant compared to the result of a "control" applicant). They propose that if the concordance exceeds 0.5 in the population, the matched approach should be adopted, and vice versa. Additionally, the authors discuss other substantive criteria for choosing a method. For example, they argue that matched designs are less sensitive to potential imperfections in randomization and are more convenient when dealing with a limited population to be sampled. In contrast, the non-matched approach carries a lower risk of the experiment being detected, potentially influencing the behavior of the tested subjects. Furthermore, as Verhaeghe (2022) points out, non-matched designs may be considered ethically superior in cases where the tested units bear a significant burden, such as the time required for application evaluation.

Finally, Larsen (2020) identifies another potential limitation of the matched approach, using the example of correspondence experiments on hiring discrimination. The author proposes that the utilization of the matched approach might produce different estimates compared to its alternative since the likelihood of the "treatment" applicant receiving a callback could be directly influenced by the level of competition from the "control" candidate. This issue might occur in cases when the number of candidates for a particular job opening is small, and experimental applicants thus constitute a significant share of total applicants.

4.2 Experimental Design: Description of the Controlled Experiment Used

Following the literature described in the previous chapter, a correspondence experiment was designed to uncover labor market preferences toward refugees with different knowledge of the local language. Curricula vitae (hereafter referred to as "CVs") of three types of fictitious job applicants (hereafter referred to as "applicants" or "candidates") were created: Ukrainian citizens with good Czech language knowledge, Ukrainian citizens with poor Czech language knowledge, and native Czech speakers. These CVs were sent as replies to selected job offers posted on two well-known Czech job advertising portals, namely `www.jobs.cz`, and `www.prace.cz`. The "paired approach" was utilized, i.e., two distinct CVs were sent as a response to each chosen job offer.

4.2.1 Fictitious Identities

Language Skills

Three different treatment conditions were utilized in our experiment - the baseline "prototypes" of candidates, "A", "B", and "C", were distinguished based on the level of Czech language proficiency, using the CEFR (Common European Framework of Reference for Languages, Council of Europe n.d.) classification and/or nationality. "A" corresponds to a Ukrainian applicant whose reported level of Czech language proficiency is A2 (Treatment A); "B" corresponds to a Ukrainian applicant whose reported level of Czech language proficiency is B2 (Treatment B); and "C" corresponds to an applicant whose reported level of Czech language proficiency is specified as "native". The prototype "C" is represented by a native Czech citizen, and serves as a control group for this experiment.

It should also be clarified why specifically levels A2 and B2 were chosen as the treatment types. The levels should be sufficiently distinct to represent different levels of readiness to work in a mostly Czech-dominated environment. However, they should also be realistic, considering that the candidates have been working in the Czech Republic for around two years, as described further. Therefore, A2 and B2 appeared to be appropriate choices.

To signalize the level of language proficiency in the CVs, the CEFR classification was utilized consistently across all cases to prevent any ambiguity, assuming that recruiters are either familiar with the classification or that they are able to look up the meaning of individual levels. This explicit statement (e.g., "Czech language - B2") was the only signal of applicants' language skills. We are aware that this approach, relying on self-reported information without any objective proof, might create space for potential bias, as recruiters might not fully trust the information provided. Nevertheless, we suggest that the bias might be smaller compared to observational studies using self-reported data - in a survey with virtually no stakes, a respondent has fewer incentives for reporting accurate information. In contrast, it is plausible that a candidate states their real level (or at most slightly overestimated one) in the CV since they would be then expected to prove that they possess the reported skills. Clearly, it would have been possible to minimize the potential bias by including information about Czech language courses or certificates. One option would have been to include such information for treatment B only. However, this approach has a drawback as attendance at such courses may be interpreted as a signal of motivation, for instance, rather than language proficiency *per se*. The second approach would have included reporting the attendance of language courses (at different levels) for both treatment A and treatment B. Nonetheless, it would then also be appropriate to include, e.g., the name of the institution organizing the given course (since there is no centralized language training for refugees in the Czech Republic) and the date of completion to ensure that the pieces of information are trustworthy and up-to-date. Nonetheless, this might increase the risk of excessive similarity of the CVs. Ultimately, we decided that the risks of alternative approaches described above outweigh the potential benefits. Further, similarly to the approach of Ek *et al.* (2021), we decided that it would be appropriate to write all CVs in Czech without any mistakes since it can be assumed that Ukrainian applicants have access to good-quality online translators or AI or that they have Czech acquaintances who could potentially check the linguistic quality of the document.

In addition to Ukrainian or Czech as a mother tongue and the level of Czech as a foreign language for treatments A and B, all candidates additionally indicated knowledge of English at level B1. This level corresponds to the minimum requirement for Czech students at the national school-leaving examination.

A list of other personal characteristics and, where possible, their different variants was then created and later assigned to each prototype in various combinations to ensure adequate randomization. This is described in what follows.

Other Personal Characteristics

A total of four different names were used - two for Czech candidates, and two for Ukrainian candidates. The reason for including two distinct names for each nationality was to minimize the bias resulting from a potential preference for a specific name. All first names and surnames were chosen from lists of the most prevalent names in respective countries.[1] However, to prevent raising suspicion, the names from the very top of the lists were avoided. Moreover, all applicants were female, considering the fact that adult women constitute a major portion of Ukrainian refugees in the Czech Republic (as mentioned in Chapter 2). An e-mail address was subsequently created on the "Gmail" domain for each name, resulting in the combinations listed in Table 4.1. An

[1] The lists were retrieved on May 27, 2024, from the following websites:
`https://www.czso.cz/csu/czso/srovnani_krestni_jmena_2003`,
`https://www.prijmeni.cz/oblast/3000-ceska_republika`,
`http://database.ukrcensus.gov.ua/dw_name/top10archive2.asp`,
`https://ridni.org/karta`

e-mail address was the only piece of contact information included in all CVs; phone numbers and home addresses were excluded as they would significantly complicate the execution of the experiment.

Table 4.1: Names and e-mail addresses of fictitious applicants

Nationality	**Name and surname**	**E-mail address**
UA	Viktorija Ševčenko	sevcenko.viktorijaa@gmail.com
UA	Yuliya Kovalchuk	yuliya.kovalchuk.38@gmail.com
CZ	Tereza Benešová	terezabenesova417@gmail.com
CZ	Karolína Marková	karolinamarkova417@gmail.com

Regarding the age of applicants, we decided that they would all be 20 years old. The main reasons for including such young applicants were the minimization of potential concerns about their maternity and parental leave, as well as the convenience of having only a short employment history, without much space for significant career development or specialization.

The systems of education in the Czech Republic and Ukraine exhibit certain differences (see, e.g., Ministerstvo školství, mládeže a tělovýchovy n.d.). These variations had to be evaluated to guarantee a level playing field for applicants from each country in terms of their educational backgrounds. Ultimately, the Czech candidates' highest level of education achieved was secondary technical school, with a successful completion of a school-leaving examination. For Ukrainian applicants, it was specialized high school/pre-university education finished with a "Professional Junior Bachelor's Degree". Additionally, each candidate, regardless of the country, was assigned one of two different study paths, business academy or tourism.

As far as professional experience is concerned, Czech applicants always listed only one job, which they have held approximately since graduating high school. In contrast, Ukrainian candidates were assigned two different jobs - specifically, their employment history included a brief work experience in Ukraine in the period between finishing high school and the beginning of the war in Ukraine, and a current job in the Czech Republic starting in the summer of 2022. For the job of Czech candidates and the first job of Ukrainian candidates, the alternatives were a shop assistant at a drugstore and a cashier/receptionist at a public swimming pool. The key feature of the second job of Ukrainian candidates is that it had to require lower qualifications than the job they had in Ukraine, and also had to be suitable for virtually any level of Czech proficiency. Therefore, the variants included a supermarket employee responsible for replenishing and checking goods, and a fast-food employee responsible for food preparation and distribution.

All applicants also reported that their most recent work experience is still ongoing. Indeed, this might have created a potential advantage for candidates in the later stages of the experiment (based on the notion that longer work experience might generally be considered better). Nevertheless, this shortcoming seemed relatively negligible considering that our experiment lasted for approximately six months, meaning there were no significant differences in the length of work experience. Additionally, changing the commencement date of employment regularly as an alternative solution could put applicants in the later stages of the experiment at a disadvantage by creating a longer gap between finishing high school (or arrival in the Czech Republic) and finding employment; setting a termination date of employment could potentially encourage recruiters to consider non-standard reasons for the termination.

Having chosen the above-mentioned alternatives of education and work experience, names of specific schools as well as companies in Kyiv, Odessa, Prague, and Brno were assigned to them and included in the CV.

Other characteristics than the ones described above did not allow for variation since it could potentially have a significant impact on the employability of respective applicants. Thus, these attributes were only formulated differently in the CV. For instance, all candidates disclosed basic knowledge of Microsoft Office software and possession of a driver's license for a personal car. Other specific skills as well as favorite pastimes were excluded to prevent excessive similarity of CVs or putting one candidate in a favorable position. Another non-differentiated characteristic, which has already been mentioned, was the age of the candidates. In this case, the different formulations included disclosing the full date of birth and stating only the individual's age.

All CVs were created in Microsoft Word, utilizing two self-prepared templates to distinguish the CVs in each pair - both visually and by slightly different linguistic formulations. Both templates were simple, and not exactly sophisticated; yet, they were clearly organized and did not include any grammatical or spelling errors.

Randomization

In line with what has already been described, the CVs used in our experiment were randomized according to six features: city (given by the current job location), treatment condition, name, education and first work experience, second job, and CV template. Taking these into account, 80 distinct CVs were created in total, half of them belonging to candidates based in Prague, and half of them corresponding to candidates based in Brno.[1]

These CVs were then combined into pairs, under the restriction that each of the six features (except for the current job location) has to differ between the two CVs. The resulting 96 pairs were then transformed into a total of 192 possible ways of replying to a job offer (for simplicity, further referred to as "combinations"), simply by switching the order in which the CVs would be sent. Specifically, we obtained "Combination_1_Prague" through "Combination_96_Prague" and "Combination_1_Brno" through "Combination_96_Brno", keeping a precisely balanced representation of all three treatment conditions.

Please refer to Appendix A for CV samples. For a complete list of CVs with their features as well as a list of ways of replying to job offers, please refer to Appendix B.

4.2.2 Selection of Job Offers

In what follows, the selection process of individual job offers is clarified. As mentioned, the sole sources of job postings were two well-known Czech job application portals, `www.jobs.cz` and `www.prace.cz`, over the period between December 5, 2023, and June 7, 2024.

Overall, the research was not strictly limited to specific types of occupations; such offers were selected where the application of any of our candidates could be rationally justified. Thus, the selection process was based on two main aspects - firstly, whether the applicants could be claimed to satisfy all unambiguously interpretable requirements specified in the job offer, and secondly, a subjective evaluation of individual job postings, guided by "common sense". Considering the two principles, the research mainly covered offers from the websites' categories "Prodej a obchod" ("Sales and Trade"), "Administrativa" ("Administration"), and "Gastronomie a pohostinství" ("Gastronomy and Hos-

[1] The distinction between applicants based in Prague/Brno is pursuant to the location of the Czech applicants' former school and current job, as well as the location of the Ukrainian candidates' current job.

pitality"). Following the International Standard Classification of Occupations (ISCO) (International Labour Organization n.d.), this corresponds mainly to occupations corresponding to minor groups Shop Salespersons (522), Client Information Clerks (422), and Waiters and Bartenders (513). It should be also mentioned that we considered full-time jobs, part-time jobs as well as temporary part-time jobs (known as "brigáda" in Czech). The reasons for that are the possibility of the applicants having a secondary occupation alongside their current full-time job, as well as the potential switch to a part-time job only, e.g., to gain more time to pursue further education.

Further, we decided to exclude offers where at least one of the following conditions is met:

- The job is offered by a company where one of the applicants is currently working.
- The job offered is almost identical to the past or current occupation of one candidate, putting them in a significantly more favorable position.
- The occupation in question is generally considered to require far less qualification than the past or current one.
- The posting contains a requirement to include a letter of motivation, phone number, home address, or a photograph.
- The offer requires application through an external website or via e-mail.
- An external agency or an employment office is reportedly responsible for the recruitment process.

The idea to exclude low-skilled jobs is related to the phenomenon of "overqualification" of Ukrainian refugees mentioned in Chapter 2. To be able to assess the role refugees' language skills play in mitigating this issue, we focused on jobs corresponding to applicants' qualifications and education (excluding language proficiency) instead. In addition, each chosen job offer had to be suitable for a native-born candidate as well.

Furthermore, no letters of motivation were used throughout the experiment; the exclusive sources of information about the candidates were their CVs. We assumed that if a recruiter requires a letter of motivation, they would most likely not be convinced by a generic text applicable to any company. However, such a letter would be the only option for us to ensure a level playing field for the two applicants in a pair. Moreover, since a similar text could potentially be expected in e-mail applications, we decided to exclude postings requiring application in this form as well. As far as external websites are concerned, they were disregarded because they mostly require the candidates to provide more information than what is included in the CV.

In addition, limitations related to language requirements have to be emphasized. In general, job advertisements on both portals are composed of text written by a recruiter and a standardized summary table with mostly non-mandatory contents. The summary table utilizes the following classification of language proficiency: "Základní" ("Basic"), "Mírně pokročilá" ("Lower Intermediate"), "Středně pokročilá" ("Upper Intermediate"), "Pokročilá" ("Advanced"), "Výborná" ("Excellent"). Nevertheless, it could be argued that this specification allows for subjective interpretation (especially without the knowledge of the official classification of language skills) and that filling out a table is likely a formal step only. Thus, we concluded that the language-related information in the summary tables would be disregarded for the purpose of selection, and in-text descriptions of language requirements would take precedence. Ultimately, we decided that the job offers with the following in-text requirements would be excluded:

- knowledge of Czech at level B1 or higher (so that only one Ukrainian candidate would fulfill this condition),
- knowledge of Czech at a "native" or "perfect" level,
- "advanced" level of Czech or English,
- knowledge of any other language other than English or Czech.

Further, following the idea of subjective evaluation of individual job offers, we also excluded advertisements for positions that could be considered completely unrealistic for Ukrainian applicants with only a basic knowledge of Czech. Examples of such positions might be the ones in call centers or the ones that include more complicated administrative tasks.

It should also be noted that we deliberately did not exclude offers with in-text requirements for Czech or English specified as "velmi dobrá" ("very good"), "výborná" ("excellent"), or similar. Again, an argument in favor of this decision is the possibility of subjective interpretation of these specifications. However, we are aware that this might be considered a debatable step. Therefore, the potential effect of such in-text requirements for language levels is later checked in econometric models.[1]

Another major restriction of the selection process was the location of respective jobs. Situations where, for instance, two experience-wise similar candidates currently living in Prague would apply for a job located in Ostrava, may raise suspicion. As a consequence, only jobs located in the following regions (NUTS 3) of the Czech Republic were considered: Prague, Central Bohemian Region, and South Bohemian Region.

It was also necessary to minimize the risk of ultimately sending multiple pairs of CVs to the same recruiter. Thus, any company was included at most once in our sample. The names of recruiters, if available, were also collected and continuously checked for duplicity.

4.2.3 Data Collection Process

Data collection took place between December 2023 and July 2024, with the selection of vacancies and subsequent sending of corresponding CVs on a regular basis (usually every week) until the beginning of June 2024.

Once the job postings from `www.jobs.cz` and `www.prace.cz` were selected and the necessary pieces of information about them were recorded, they were each assigned a number between 1 and 96 (one by one, in this order). It is also necessary to mention that the offers were entered into the database in the order in which they were found. Next, they were matched with a city depending on the location of the job - Prague for jobs located in regions Prague and Central Bohemian Region, and Brno for jobs located in South Bohemian region. This left each offer with a "combination number" and a city name, which then determined a way to reply to it, either based on the list "Combination_1_Prague" through "Combination_96_Prague", or based on the list "Combination_1_Brno" through "Combination_96_Brno".[1]

The CVs were always submitted directly through `www.jobs.cz` or `www.prace.cz`. To prevent raising suspicion about the candidates being associated with each other, each reply to a given company was sent on a different day - in our case, on two consecutive weekdays.

Subsequently, the e-mail inboxes of applicants were regularly checked for

[1] Please note that due to the insignificance of relevant variables, the results of corresponding regressions are not reported in the thesis.

[1] For details about the lists, please refer to Subsection 4.2.1. To view the lists, see Appendix B

any updates regarding the application process. In case of receiving a request for a certain action (e.g., to contact the employer via phone or to provide more information about the candidate), or in case of receiving an interview invitation, an answer was promptly sent, informing the recruiter that the applicant is no longer interested in the job position. Similarly to the CV submission, we avoided the situation of sending such messages by both applicants on the same day. For examples of these messages, please refer to Appendix C.

Based on the process described above, a set of information was collected about each job posting and the result of the corresponding application process. For a comprehensive list of all variables, including their explanations, please refer to Appendix D.

4.2.4 Challenges and Limitations

Since the data was collected as a part of a small-scale experiment, it would be appropriate to address certain challenges we faced while designing the experiment as well as limitations to the causal inference based on this research.

The first, and most obvious shortcoming is the limited scope of the experiment, covering three out of fourteen regions of the Czech Republic. Not only did this significantly restrict the sample size, but also limited certain analyses, such as the analysis of differences between individual regions, or differences between major Czech cities and smaller towns. This could be solved by creating more CV versions, with candidates based in cities other than Prague or Brno as well.

The variety of job types taken into consideration was also narrow. This was primarily given by the design of CVs - all applicants were relatively young (implying only short work experience), had a high school education in a specific field, and had no university education. Ensuring to make the variants of experience as comparable as possible, this limitation could be potentially dealt with as well.

Moreover, only two treatment groups were included, implying that the general effect of language skills is represented only by the difference between A2 and B2 levels of language proficiency. In order to obtain more reliable results, it would be advisable to introduce a wider range of variation in the level of language skills.

Another factor that unexpectedly curbed the number of suitable job postings was the frequent requirement to send a CV including a photograph. We excluded all job offers with such a restriction from our selection; however, the problem could have been dealt with differently. After careful consideration of possible ethical issues, photographs could have been generated using AI. Nonetheless, it would still have been necessary to address the issue of possible preferences related to applicants' physical appearance.

Given all the criteria we set regarding the selection of job postings, it is clear that the number of suitable offers was significantly limited by them. As one of the consequences, our sample with 932 applications (corresponding to 466 distinct job postings) in the final dataset is relatively small compared to other studies focusing on a similar topic. In light of the sample size as well as the limited scope, one should be careful inferring causal relationships based on our dataset.

In addition, by detailed inspection of individual job offers during the data collection process, we (virtually always) found ourselves in one of two situations, resembling a trade-off. In the first situation, it would seem as if the Czech candidate would not get better off by getting recruited for the position in question, thus possibly raising suspicion about the credibility of the applicant. Conversely, in the second situation, the job offered would seem reasonable for the Czech candidate; in contrast, the Ukrainian applicant would be significantly underqualified only due to their language skills. Of course, job postings representing extreme versions of either of the scenarios were excluded. Nonetheless, in most cases, the former scenario was justified by the idea that one might not seek different employment only to get a higher wage; other factors, such as job location or a wish to try to change career paths, might come into play. The latter situation was more frequent since most occupations in given fields are customer-oriented and thus require good communication skills. In this instance, it was necessary to accept a certain level of "naiveness" (especially of candidates with A2 level of Czech) and assume that she is sending applications to a large number of companies, maximizing her chances of being hired despite the language-based underqualification.

Lastly, the most complicated task in the preparatory phase of the experiment was dealing with the trade-off between making the variants as comparable as possible (to avoid the situation of one applicant having an advantage), and, at the same time, making them as different as possible (to minimize the risk of raising suspicion due to the candidates' CVs being excessively similar). Although every effort was made, situations where one applicant had a potential advantage at a given job offer could not be completely avoided. In further analyses, we try to minimize the bias by categorizing individual job offers and comparing them with the candidates' experience.

4.2.5 Ethical Aspects of the Experiment

Despite being a common practice necessary to conduct a correspondence study, the data collection process still involved a certain form of "deception" of recruiters. Specifically, to be able to observe their realistic behavior, the recruiters were not aware of their participation in the experiment (and thus not remunerated for it either). Nonetheless, the data is presented in a way that does not allow for the identification of the participants.

To minimize the burden placed on recruiters, at most two CVs were sent to each of them. Moreover, as was already described, in case of receiving an interview invitation or a request to provide more information, the recruiter was informed that the applicant was no longer interested in the job offer.

In addition, approval of the Commission for Ethics in Research of the Faculty of Social Sciences, Charles University, was obtained prior to the beginning of the experiment. The approval was granted based on an online questionnaire about the data collection process.[1]

[1]Application number 76, approval granted on August 17, 2023.

Chapter 5

Dataset Description

The entire process of data collection took place between December 2023 and July 2024. The key part, i.e., choosing job offers and sending job applications, took place between December 5, 2023, and June 7, 2024. During this period, a total of 480 job offers were entered into our database, with at least one experimental response sent to each of them. This way, we went through the list of CV combinations 1 through 96 (regardless of the differentiation between Prague and Brno versions) exactly five times to keep the distribution of all CV features (but the city) balanced in the raw dataset.[1]

The dataset was last updated on the results of job application processes on July 6, 2024, nearly a month after the last CVs were sent. We do not reject the possibility of receiving more replies even after this date. However, considering the observed patterns from earlier stages of the experiment, it is expected to be an insignificant number at most.

5.1 Cleaning the Raw Dataset

Prior to conducting any analyses, it was necessary to clean the raw dataset. We removed a total of 14 entries (i.e., job offers and all data related to them). In 8 instances, the reason for deletion was that only one CV was sent as a response to a given job posting since the advertisement was deleted from the portal before we could send the second reply. It would have been possible to carry out analyses even with these observations being included in the clean dataset. However, we decided to exclude them to be able to examine differences between CVs sent to the same company without any complications. Further,

[1]For details regarding CV combinations, please refer to Subsection 4.2.1 and Appendix B.

2 cases corresponded to situations where an automatic reply including further instructions (filling out a questionnaire or paying a visit to a given company) was received immediately after the CV submission. These cases were deleted since apparently, no CV evaluation took place and none would if the instructions were not followed. Lastly, 4 job offers were deleted since an error on our end occurred during the sending process.

Several adjustments were also made to the variables collected. The raw dataset included more variables than those in the dataset submitted along with the thesis. Variables that could allow the identification of individual companies (such as company name or exact job location) were deleted, and only the unique "job ID" was retained to identify the applications corresponding to the same job offer. Further, it was necessary to unify a large portion of the information from job advertisements - for instance, this included evaluating different formulations of in-text requirements for language skills and assigning them to values of a new categorical variable. Lastly, multiple new variables were created - either based on the evaluation of individual job advertisements (such as the case of categorizing jobs into ISCO minor groups, as will be described later) or simply by transforming categorical variables into dummy variables to facilitate further analyses.[1]

After completing the process described above, we ended up with 932 job applications (corresponding to 466 job offers) in the dataset, which will be referred to as the "dataset" or "full dataset" going forward. Some of the variables from the dataset will be discussed in what follows. For a comprehensive list of all variables, along with their explanations, please see Appendix D.

5.2 Description of Chosen Variables

5.2.1 Variables Representing the Application Outcome

The categorical variable *cv_reply_type* represents the type of response received for a given candidate and job opening. The possible values are summarized in Table 5.1. To conduct the main data analysis, it was essential to convert this variable into a binary form, which would act as a response variable in regressions. Two definitions of a callback (i.e., a positive response

[1]Please note that further adjustments were made to the dataset after conducting all analyses. Specifically, the variables that were not used in any reported analyses were deleted before the submission.

to a job application) were set - a broader one, represented by a binary variable *cv_callback_main*, and a stricter one, represented by a binary variable *cv_callback_strict*.

The values of these variables based on response types can be found in the last two columns of Table 5.1. The use of two different definitions is justified by two reasons: firstly, there is no clear consensus in the existing literature about the proper definition of a callback - specifically, whether a request for more information about a candidate should be viewed as a positive signal (see, e.g., Ek *et al.* (2021), who also use two definitions of a callback). Secondly, this approach also functions as a sensitivity check for our analyses.

5.2.2 Variables Representing CV Features and Sending Conditions

The categorical variable *cv_treatment* is vital for our analysis, allowing us to estimate the impact of language proficiency on callback probability. Taking values A, B, or C, it represents the treatment condition of a given candidate (i.e., treatment A, treatment B, or control). For simplicity, corresponding dummy variables (*cv_treatment_a_dummy*, *cv_treatment_b_dummy*, and *cv_treatment_c_dummy*) were created.

Multiple other variables related to CV features and sending conditions were defined - specifying the candidate's full name (*cv_name*), education and work experience (*cv_educwork*, *cv_secondjob*), type of CV template (*cv_template*) or whether the CV was sent as the first or second response to a given job offer. For obvious reasons, corresponding dummy variables (listed in Appendix D) were preferred in the regressions

5.2.3 Variables Representing Features of Job Offers and Interactions

The selected job offers were classified based on occupation types. This was done on the basis of a "minor ISCO group", defined by the International Labour Organization (n.d.), to which a given position, according to the authors, most likely belongs. Since some groups occurred only sparsely in the dataset, they were further categorized into larger, self-defined groups (represented by *vacancy_isco_st*), which were used for further analyses. The transformation is displayed in Table 5.2.

Table 5.1: Types of responses and their transformation into binary variables

Response type	Description	cv_ outcome_ main	cv_ outcome_ strict
A	no response	0	0
B	mass e-mail informing that selected candidates will be contacted soon or that the admission procedure has already been terminated (and no further reply has been received)	0	0
C	explicit rejection	0	0
D	immediate automatic response including further instructions	N/A	N/A
E	request for further information (no mention of an interview)	1	0
F	question whether the candidate is still interested in the position (without mentioning an interview), sometimes including a request to contact the employer	1	0
G	requesting the candidate to contact the employer via phone to arrange an interview	1	1
H	requesting the candidate to provide a phone number to be able to arrange an interview	1	1
I	rejection of the candidate for a given position but offering a different position at the same company	1	1
J	explicit interview invitation	1	1

Note: As already mentioned, job offers with replies of type D were removed from the dataset.

Table 5.2: Transformation of "minor ISCO groups" into self-defined categories

ISCO minor group	**Self-defined category**
Shop Salespersons Cashiers and Ticket Clerks	SalesCash
Client Information Clerks	Info
Food Preparation Assistants Waiters and Bartenders	FoodWaiter
General Office Clerks Sales and Purchasing Agents and Brokers Sales, Marketing and Public Relations Professionals	Office
Material Recording and Transport Clerks Textile, Fur and Leather Products Machine Operators Manufacturing Labourers Other Craft and Related Workers	Other

Further, the jobs are categorized based on location (*vacancy_location*) into Praha (Prague), Středočeský kraj (Central Bohemian Region), Brno or Jihomoravský kraj (South Moravian Region). Note that in our case, the category "Jihomoravský kraj" refers to jobs located in the South Moravian Region, but outside of Brno.

Other relevant variables (categorical variables and corresponding dummy variables) represent, e.g., language requirements (*vacancy_cz_intext_st*, *vacancy_cz_intext_mentioned_dummy*, *vacancy_en_intext_mentioned_dummy*), education requirements (*vacancy_education_dummy*), computer skills requirements (*vacancy_software_req_dummy*), driver's license requirements (*vacancy_drive_req_dummy*), type of contract offered (*vacancy_emplform*), employment length (*vacancy_duration*), whether the job is full-time or part-time (*vacancy_ftpt*), of whether the job was labeled as "suitable for Ukrainian refugees" (*vacancy_ualabel_dummy*).

Following the idea mentioned in Subsection 4.2.4, we wanted to control for the potential advantage of one applicant when applying for a job that is closely related to her work experience. Therefore, three dummy variables (*interaction_salescash_dummy*, *interaction_info_dummy*, and *interaction_foodwaiter_dummy*) were created, defined as interactions between applicant's work experience and the type of job in question for each relevant field.

Sample means of chosen dummy variables are summarized in Table 5.3.

Table 5.3: Means of chosen dummy variables

Variable name	**Mean**
vacancy_isco_foodwaiter_dummy	0.144
vacancy_isco_salescash_dummy	0.545
vacancy_isco_info_dummy	0.234
vacancy_isco_office_dummy	0.060
vacancy_isco_other_dummy	0.017
vacancy_location_praha_dummy	0.663
vacancy_location_stredoc_dummy	0.118
vacancy_location_brno_dummy	0.122
vacancy_location_jihom_dummy	0.097
vacancy_cz_intext_mentioned_dummy	0.097
vacancy_en_intext_mentioned_dummy	0.369
vacancy_education_dummy	0.661
vacancy_ualabel_dummy	0.109
vacancy_software_req_dummy	0.315
vacancy_drive_req_dummy	0.039
vacancy_ftpt_ft_dummy	0.635
vacancy_ftpt_pt_dummy	0.054
vacancy_ftpt_both_dummy	0.189
vacancy_ftpt_brigada_dummy	0.122
vacancy_emplform_emplonly_dummy	0.631
vacancy_emplform_altonly_dummy	0.152
vacancy_emplform_emplalt_dummy	0.191
vacancy_duration_open_dummy	0.506
vacancy_duration_close_dummy	0.182
interaction_salescash	0.273
interaction_info	0.117
interaction_foodwaiter	0.049

Chapter 6

Data Analysis

Having prepared the dataset in Microsoft Excel, the data was subsequently imported into RStudio, where all analyses were conducted. [1] At this point, it would also be appropriate to reiterate the main research question formalized by the two versions of **Hypothesis 1**, as these are the focus of the analyses:

> **Hypothesis 1a:** Czech language proficiency of Ukrainian applicants has no impact on callback probability.
>
> **Hypothesis 1b:** Better Czech language proficiency of Ukrainian applicants increases the callback probability.

6.1 Randomization Checks

To make valid inferences from our sample, it is crucial to verify whether the randomization process (which involves assigning candidates with different treatment conditions to other CV characteristics and job offers in an unbiased manner) was successful.

Check #1: Number of Each Combination Sent

As a first step, a basic check was performed to assess the number of combinations of treatment conditions sent in total - i.e., how many recruiters received CVs from applicants A and B, A and C, or B and C, regardless of the order.[2]

[1] The majority of the tables were created using the *stargazer* package, available at `https://CRAN.R-project.org/package=stargazer`.

[2] "Applicant A" refers to an applicant receiving treatment A, "applicant B" refers to an applicant receiving treatment B, and "applicant C" refers to an applicant belonging to the control group.

Referring to Table 6.1, we can conclude that the distribution is fairly even; the slight imbalance is attributed solely to the cleaning of the raw dataset by removing problematic observations (as described in Section 4.1).

Table 6.1: Number of job offers for each combination of treatment conditions, regardless of the order

Combination	**Number of job offers**
A and B	156
A and C	157
B and C	153
Total	466

Check #2: Randomization Check of CV Features and Sending Conditions

Had there been no problematic observations in the raw dataset, the randomization of CVs' characteristics (e.g., name or work experience) would have been perfect, except for the distribution of Prague versus Brno versions, which was beyond our control. This is given by the design of the experiment and by the fact that each combination from the list of combinations 1 through 96 (Table B.4 and Table B.5) was used exactly five times.

However, as discussed in the previous chapter, 14 job offers were removed to obtain the final dataset. Consequently, it is important to ensure that this adjustment did not significantly disrupt the randomization of CV features. To accomplish this, a table was created to show the means of relevant CV characteristics (in the form of dummy variables) for each treatment group and the control group. Subsequently, the means for the groups were compared using a simple two-tailed t-test (where possible). The high p-values reported in the corresponding table (Table E.1) indicate no significant issues with the randomization of CV features.

Check #3: Randomization Check of Job Features

In contrast to the randomization of CV features, we had almost no control over the success of the randomization of job features, as the job offers were assigned to treatment conditions based solely on the order in which they were found (as explained in Subsection 4.2.3).

Similar to the check of CV features' randomization, we tested whether the means of job characteristics were statistically equal for each treatment/control group using a two-tailed t-test. The results are available in Table E.2.

The check revealed certain discrepancies in distributions of some CV features (if measured by p-values below 0.100). Specifically, the proportions of jobs in Prague, jobs in the "SalesCash" and "FoodWaiter" categories, and jobs labeled "suitable for Ukrainian refugees," displayed imbalances. However, for the remaining features, the randomization process appears to have been successful.

To control for the imperfections in the randomization of the above-mentioned features, we decided to employ two approaches: first, to include job offer characteristics as control variables in the regressions (if possible), and second, to run regressions (with slight adjustments where necessary) on chosen subsets of the sample, focusing on features for which the randomization was imperfect.

6.2 Statistical Analysis

The following section describes the results of the statistical analysis, serving as an exploratory step to gain a better understanding of the dataset and provide suggestions for testing in subsequent econometric analysis.

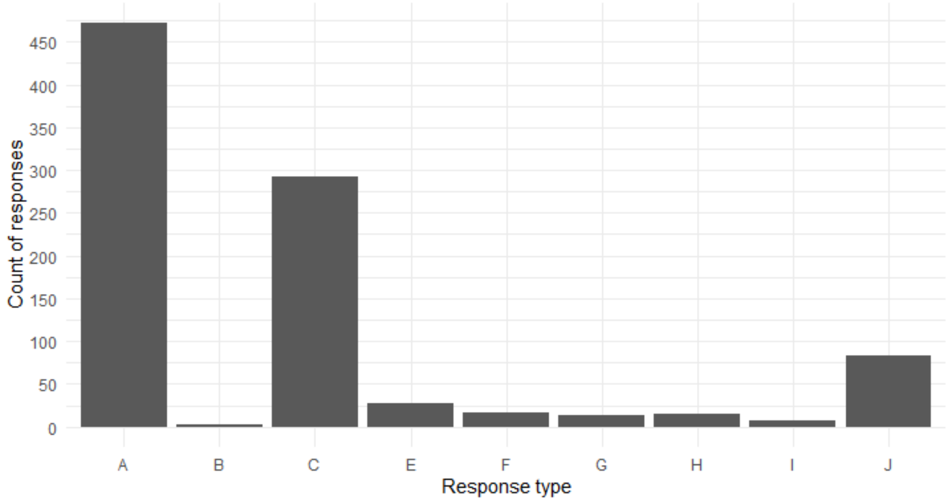
6.2.1 Analysis of Responses and Callback Rates

Figure 6.1 visually represents the frequency of each response type across the full dataset. The most common outcome is no reply, followed by explicit rejection and explicit interview invitation. Other response types were rather infrequent. Regarding cases with responses of type "E" (request for further information without mentioning an interview), in over half of them, the requested information pertained to a phone number.

Relationship between Callback Rates and Treatment Conditions

Table 6.2 displays callback rates (i.e., proportions of job applications that received a callback) for each treatment/control group as well as the full sample, based on both the main and strict definitions of a callback. A two-tailed t-test was subsequently used to compare the callback rates within each pair of groups.

Figure 6.1: Distribution of response types in the full dataset



Note: The explanation of individual response types can be found in Table 5.1. The chart was created based on the "clean" dataset - therefore, it does not include cases with response type "D".

Table 6.2: Callback rates by treatment/control groups and the overall callback rate by different definitions of a callback

	Treatment A	**Treatment B**	**Control**	***Full dataset***
Main def.	0.128	0.097	0.303	0.176
Strict def.	0.096	0.052	0.235	0.128

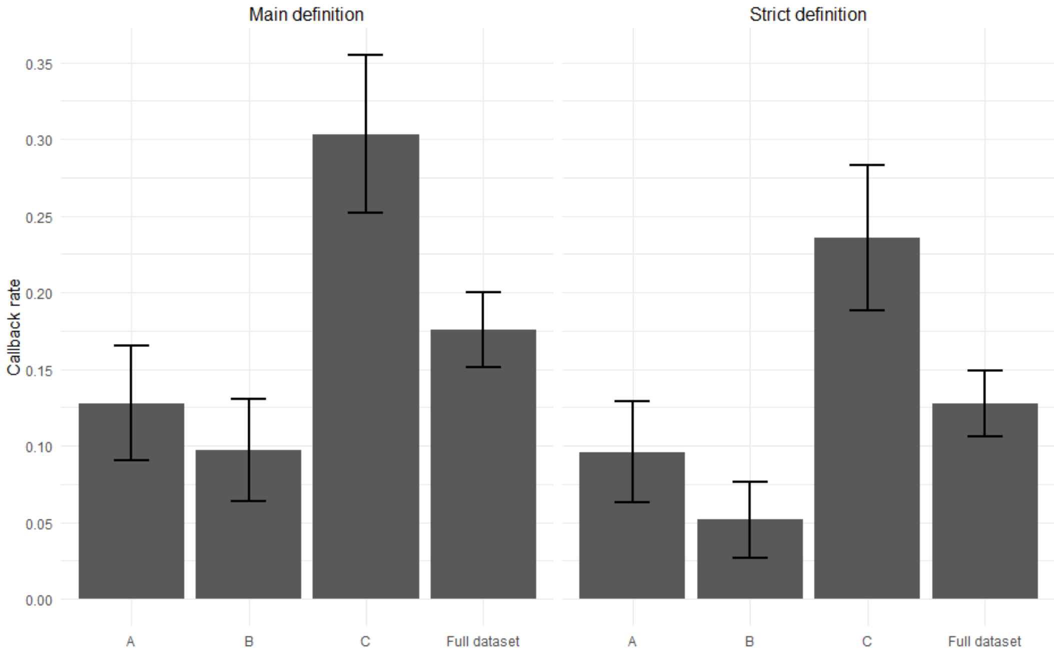
The resulting p-values are shown in Table 6.3. Further, the callback rates and corresponding 95% confidence intervals are visualized in Figure 6.2.

Table 6.3: Resulting p-values of two-tailed t-tests for equality of callback rates among treatment/control groups

	p-value A vs. B	**p-value A vs. C**	**p-value B vs. C**
Main def.	0.226	8.071e-08	8.614e-11
Strict def.	0.035	2.472e-06	4.579e-11

Note: Null hypotheses of given t-tests were defined as the callback rate of one group being equal to the callback rate of the other group. The comparison of treatment group A and treatment group B directly corresponds to testing Hypothesis 1a against its two-sided alternative.

Figure 6.2: Callback rates by treatment conditions with 95% confidence intervals



Note: "A" refers to treatment group A (Ukrainian applicants with poor knowledge of Czech), "B" refers to treatment group B (Ukrainian applicants with a good command of Czech), and "C" refers to the control group (native applicants).

The comparison of the callback rates observed in our study and the ones revealed in similar correspondence experiments might bring interesting insights. For instance, Ek *et al.* (2021) focused exclusively on refugees in Sweden and reported an overall callback rate of 3.9% using the broad definition of a callback and 1.3% using the strict definition. Even when considering only refugee applicants in our study, the callback rates observed by us are notably higher. This difference may be caused by various factors, such as differing labor market conditions in the Czech Republic and Sweden, or the types of occupations under consideration. Further, in a discrimination-focused correspondence experiment in the Czech Republic, Pasichnyk (2023) included both native applicants and long-term Ukrainian immigrants fluent in Czech. According to the broad definition, the author reported a callback rate of 33.7% for natives and 19.5% for immigrants, and 16.6% for natives and 9.5% for immigrants according to the strict definition. We conclude that the callback rates observed by us are reasonable when compared with the above-mentioned study and that the disparities could be attributed, for instance, to different perceptions of refugees and immigrants, possibly influenced by language skills or variations in the studies' scopes regarding occupation types and the different levels of qualification of fictitious applicants.[1]

Another observation is that callback rates of the control group (Czech applicants) are significantly higher than those of the treatment groups (Ukrainian applicants), which aligns with our expectations and could be explained by a preference for native workers, native applicants' fluency in Czech, or other reasons. A similar pattern was observed, for instance, by Oreopoulos (2011), who conducted a correspondence experiment in Canada. The resulting callback rate was approx. 0.157 for fictitious candidates with English-sounding names, Canadian education, and Canadian work experience, while it was only approx. 0.060 for fictitious applicants with foreign-sounding names, foreign education, and foreign experience. The author attributes this difference to discrimination, with signals about language proficiency failing to offset its effect.

Surprisingly, treatment group A (Ukrainian applicants with poor knowledge of Czech) shows a slightly higher callback rate than treatment group B

[1]The definitions of callbacks used by Ek *et al.* (2021) and Pasichnyk (2023) are directly comparable to ours. Specifically, Ek *et al.* (2021) defined a callback as an interview invitation or a request for more information (main definition) or only an interview invitation (strict definition). Pasichnyk (2023) used a very similar approach to Ek *et al.* (2021), but her main definition of a callback was narrowed down to an interview invitation, a phone call request, or a request to provide a phone number.

(Ukrainian applicants with good knowledge of Czech), with a difference of approx. 3.1 percentage points for the main callback definition and approx. 4.4 percentage points for the strict callback definition. However, the p-values of two-tailed t-tests analyzing the equality of means yield rather inconclusive results. Specifically, the null hypothesis of equal callback rates is not rejected against the two-sided alternative at a 10% significance level according to the main definition, but it is rejected at the same significance level when applying the strict definition. Consequently, no definitive conclusions can be drawn regarding Hypothesis 1a at this point.

Next, a one-tailed t-test was performed, with the null hypothesis of equal callback rates of treatment groups A and B (corresponding to Hypothesis 1a) and the alternative hypothesis of the callback rate of treatment group A being lower than that of treatment group B (corresponding to Hypothesis 1b). The resulting p-values are 0.887 and 0.982 for the main and strict callback definitions, respectively. Based on these results, we cannot reject Hypothesis 1a in favor of Hypothesis 1b at any reasonable significance level.

Relationship between Callback Rates and Chosen Job Features

Further, we analyzed distributions of selected job characteristics and their relation to callback rates. Table 6.4 displays data on occupation types, Table 6.5 focuses on job locations, and Table 6.6 differentiates between part-time, full-time, and other job alternatives.

The above-mentioned tables indicate that certain characteristics are unevenly distributed in the dataset. "Salescash" is by far the most frequent occupation type, Prague is by a large margin the most common job location[1], and full-time positions are clearly the most prevalent. Due to the imbalanced distributions as well as imperfections in randomization discussed in Section 6.1, the following paragraph serves only exploratory purposes, and no conclusions are drawn based on them.

The callback rates are relatively similar across different occupation types, except for jobs categorized as "Office", which have the lowest callback rates, likely due to higher qualifications required for such positions. Additionally, callback rates for jobs located outside of Prague and Brno are higher, possibly

[1] As described in Subsection 6.3.1, multiple regressions are performed using datasets restricted to include only jobs corresponding to the "SalesCash" category or only jobs located in Prague, for the purpose of a robustness check.

Table 6.4: Distribution of occupation types and callback rates for each occupation type

	SalesCash	Info	FoodWaiter	Office	Other
Number of jobs	254	109	67	28	8
Callback rate (main)	0.187	0.174	0.179	0.071	0.188
Callback rate (strict)	0.130	0.128	0.157	0.054	0.062

Note: The classification of occupation types is based on self-defined categories described in Table 5.2 .

Table 6.5: Distribution of job locations and callback rates for each location

	Prague	Brno	Central Boh.	South Mor.
Number of jobs	309	57	55	45
Callback rate (main)	0.167	0.053	0.300	0.244
Callback rate (strict)	0.118	0.035	0.227	0.189

Note: The fourth column corresponds to jobs located in the Central Bohemian Region. The last column refers to jobs located in the South Moravian Region, but outside of Brno.

due to lower levels of competition outside major cities. Further, jobs located in Brno have significantly lower callback rates compared to those in Prague. Lastly, positions advertised as part-time only show the highest callback rates.

Table 6.6: Distribution of types of jobs (full-time, part-time, etc.) and callback rates for each type

	FT only	PT only	FT or PT	Temporary PT
Number of jobs	296	25	88	57
Callback rate (main)	0.181	0.260	0.142	0.167
Callback rate (strict)	0.125	0.240	0.097	0.140

Note: The last column corresponds to temporary part-time jobs (known as "brigáda" in Czech), which represent a separate category on both job portals in question.

6.2.2 Language Requirements

In our examination of the influence of language proficiency on callback rates, it would be pertinent to investigate the language-related requirements that employers specify in job advertisements. In line with the ideas expressed in Subsection 4.2.2, we have chosen to concentrate solely on requirements stated in the texts written by employers.

Approximately 9.7% of employers in our sample make reference to the need for Czech language proficiency in some form, with a detailed breakdown provided in Table 6.7. Furthermore, 36.9% of employers mention the knowledge of English. The comparison between the frequencies of Czech and English language requirements may suggest that Czech proficiency is so integral that it is not explicitly mentioned, or it could indicate a preference for native workers.

Table 6.7: Frequency of in-text requirements for Czech language skills

	Number of jobs
Knowledge of Czech not mentioned	421
Knowledge of Czech required, level not specified	11
Knowledge of Czech claimed to be an advantage	1
Basic knowledge of Czech required	1
Intermediate level of Czech required	20
Very good knowledge of Czech required	12

Note: The offers were categorized by formulations/wording that could be considered content-wise equivalent.

6.2.3 Efficiency of the Matched Design

As described in Section 4.1, Vuolo *et al.* (2018) suggest comparing the efficiency of matched and non-matched designs of correspondence experiments based on the level of concordance of outcomes within matched pairs. They suggest that if the expected concordance of outcomes in a given population exceeds 0.5, the matched design should be preferred. We decided to assess our decision to use the matched approach *post hoc*, assuming that our sample is somewhat representative of the population (i.e., vacancies available in given fields and given locations).

When examining the full sample, the outcomes within pairs aligned in approx. 83.7% of cases for the main definition of callback, and 86.5% of cases for the strict definition of callback. If the sample of jobs is restricted to offers for which only the CVs of treated (Ukrainian) applicants were sent as responses, the level of concordance of outcomes is 96.8% for the main definition and 97.4% for the strict definition. Therefore, we conclude that using the matched approach was an optimal decision.

6.3 Econometric Analysis

The following section focuses on the econometric analysis. Our approach is primarily influenced by two crucial features of the data. Firstly, both alternatives of the dependent variable (*cv_callback_main* and *cv_callback_ strict*) are binary. Therefore, we apply three methods commonly applied in such cases: a linear probability model, a logit model, and a probit model. All of them are examples of binary response models, in which the probability of a "success" (in our case, the probability of receiving a callback) is defined as a function of the explanatory variables (Wooldridge 2013). Secondly, as a result of applying the matched approach (i.e., sending two CVs in response to each selected job offer), our data exhibits a panel structure. In practical terms, it is likely that the outcomes of the two applications sent to the same employer are related due to unobservable, job-offer-specific characteristics - e.g., the recruiter's personal preferences or the company's general idea of a suitable candidate, not directly specified in the job advertisement. To account for these job-offer-specific fixed effects, dummy variables representing individual job offers are included in multiple presented models.

This section offers a theoretical introduction to each estimation method, the rationale for individual model specifications, and most importantly, the results of estimations. Linear probability models, constituting the core of our econometric analysis, are described first and more profoundly. Subsequently, logit and probit models are discussed, followed by a comparison of all three estimation methods.

6.3.1 Linear Probability Model

We start by introducing a simple linear model representing the relationship between callback probability and applicants' affiliation to a specific control/treatment group:

$$\begin{aligned} cv\_outcome_i = &\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ &+ \beta_2 \cdot cv\_treatment\_c\_dummy_i + u_i, \end{aligned}$$

where $cv\_outcome_i$ is the dependent variable equal to 1 if the i^{th} applicant receives a callback[1], $cv\_treatment\_b\_dummy_i$ is equal to 1 if the i^{th} applicant belongs to treatment group B (i.e., Ukrainian applicant with a good command

[1] Note that for simplicity, *cv_outcome* is used to denote either *cv_outcome_main* or *cv_outcome_strict* in all equations presented in the thesis.

of Czech), and $cv\_treatment\_c\_dummy_i$ is equal to 1 if the i^{th} applicant belongs to the control group (i.e., native Czech applicant). Further, β_0 is the intercept, β_1 and β_2 are slope coefficients representing treatment effects, and u_i is the error term.

In all models, including this one, treatment group A (i.e., Ukrainian applicant with a poor knowledge of Czech) is used as a comparison group. Therefore, the coefficient β_1 can be interpreted as the difference between the callback probabilities of applicants with treatment A and applicants with treatment B.

Assumptions and Shortcomings

To ensure the unbiasedness of estimators in a linear probability model (LPM), the following assumptions must be fulfilled: linearity in parameters, no perfect collinearity among independent variables, random sampling, and exogeneity (i.e., zero correlation between explanatory variables and the error term) (Wooldridge 2013).

The first two assumptions are considered satisfied for our purposes. Due to the exogenous sample selection - and further supported by randomization checks (which exhibit only a few discrepancies that will be controlled for) - the condition of random sampling is also considered fulfilled. Lastly, exogeneity is ensured by employing an experimental approach, and thus having full control over a large portion of explanatory variables. For instance, when considering the simple model presented at the beginning of Subsection 6.3.1, it is obvious that neither of the explanatory variables is correlated with the error term. However, we are aware that once other regressors (more specifically, the ones that were not under our control) are introduced to the model, a slight violation of this assumption may potentially occur.

To make valid inferences based on t- and F-statistics obtained from any linear regression model, two additional assumptions must be fulfilled: homoskedasticity (i.e., constant variance of errors) and normality (i.e., normal distribution of errors) (Wooldridge 2013). These assumptions cannot be satisfied in LPM as the errors are inherently heteroskedastic, and binomially distributed. However, the former issue is resolved by calculating heteroskedasticity-robust standard errors. The non-compliance with the latter may be overcome by the fact that our sample is reasonably large ($N = 932$), and we can thus rely on the central limit theorem.

It would be also appropriate to mention two additional shortcomings of

LPM. Firstly, the predicted probabilities are not necessarily restricted to the interval between 0 and 1. Further, in some instances, it might be unrealistic to expect that the effect of changes in the values of explanatory variables on the success probability is constant for all values of explanatory variables (Wooldridge 2013). Despite this, it may be concluded that LPM still represents a computationally simple approach when dealing with binary regressands - especially with the possibility of a direct interpretation of coefficients as the change in probability of a "success" when increasing the value of the independent variable by one unit, *ceteris paribus*.

Model Specifications

In all presented models, the explained variable is either *cv_outcome_main* or *cv_outcome_strict*, depending on the callback definition under consideration. Further, all of the models include explanatory variables *cv_treatment_b_dummy* and *cv_treatment_c_dummy*. The estimated coefficient of the former variable is crucial for the analysis, representing the difference between the predicted callback probabilities of applicants with treatment A and applicants with treatment B.

Based on preliminary analyses, five different model specifications were selected for further investigation:

LPM *(1)* - "basic model without fixed effects"

$$\begin{aligned} cv\_outcome_i = &\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ &+ \beta_2 \cdot cv\_treatment\_c\_dummy_i + u_i \end{aligned}$$

LPM *(2)* - "large model without fixed effects"

$$\begin{aligned} cv\_outcome_i = &\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ &+ \beta_2 \cdot cv\_treatment\_c\_dummy_i + \zeta \cdot \mathbf{Z_i} + u_i \end{aligned}$$

LPM *(3)* - "smaller model without fixed effects"

$$\begin{aligned} cv\_outcome_i = &\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ &+ \beta_2 \cdot cv\_treatment\_c\_dummy_i + \upsilon \cdot \mathbf{V_i} + u_i \end{aligned}$$

LPM *(4)* - "model with fixed effects and interactions"

$$\begin{aligned} cv\_outcome_i = & \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ & + \beta_2 \cdot cv\_treatment\_c\_dummy_i + \omega \cdot \mathbf{W_i} + \pi_\mathbf{i} + u_i \end{aligned}$$

LPM *(5)* - "basic model with fixed effects"

$$\begin{aligned} cv\_outcome_i = & \beta_1 \cdot cv\_treatment\_b\_dummy_i \\ & + \beta_2 \cdot cv\_treatment\_c\_dummy_i + \pi_\mathbf{i} + u_i \end{aligned}$$

where β_0 is the intercept, β_1 and β_2 are slope coefficients representing treatment effects. $\mathbf{Z_i}$, $\mathbf{V_i}$, and $\mathbf{W_i}$ (where $\mathbf{V_i}$ is a subset of $\mathbf{Z_i}$) are vectors of control variables representing other characteristics of applicants, features of job offers, and sending conditions. ζ, υ, and ω are vectors of corresponding slope coefficients, respectively. $\pi_\mathbf{i}$ corresponds to job-offer-specific fixed effects and u_i is the error term.

In the baseline model *(1)*, only the regressors representing affiliation to a given treatment/control group are included. In specification *(2)*, additional control variables (representing sending conditions, job characteristics as well as interactions of work experience and occupation types) were incorporated. Specification *(3)* is a slightly constrained version of specification *(2)* and was established based on the evaluation of the significance of estimated coefficients in specification *(2)*. Additionally, the inclusion of the variables representing features for which the randomization was imperfect was ensured.[1] Specification *(4)* includes dummy variables representing control/treatment groups, interactions of work experience and occupation types, and dummy variables representing individual job offers, allowing for the identification of job-offer-specific fixed effects. Finally, specification *(5)* comprises only dummy variables related to control/treatment groups and dummy variables representing job offers.

Results of Regressions on the Full Dataset

As the starting point as well as the core element of our econometric analysis, the models *(1)* through *(5)* were estimated using the full dataset (i.e., 932 observations). For the purpose of a sensitivity check, each regression was performed twice - once with *cv_outcome_main* as the response variable, and once

[1] Specifically, these variables include *vacancy_location_praha_dummy*, *vacancy_isco_salescash_dummy*, *vacancy_isco_foodwaiter_dummy*, and *vacancy_ualabel_dummy*.

with *cv_outcome_strict* as the response variable. The results can be viewed in Table 6.8 (for the main callback definition) and Table 6.9 (for the strict callback definition).

The first observation is that regardless of the model specification or callback definition, $\hat{\beta}_1$ (i.e., the estimated coefficient of *cv_treatment_b_dummy*) is consistently negative.[1] In addition, the estimates of β_1 from models using the main definitions are generally closer to zero than in the models with the strict definition. Regarding the regression results of the models using the main callback definition, $\hat{\beta}_1$ is always insignificant at a 10% significance level. In contrast, a different pattern is observed for models using the strict callback definition: for all models without job-offer-specific fixed effects (i.e., *(1)*, *(2)*, and *(3)*), $\hat{\beta}_1$ is significant at a 10% significance level. Therefore, the resulting coefficient estimates of these models can be interpreted as follows: if a candidate reports knowledge of Czech at level B2, the probability of receiving a callback decreases by 4.4 (3.6, 3.6, respectively) percentage points compared to the situation when she specifies knowledge of Czech at level A2. However, it is clear that once the job-offer-specific fixed effects are accounted for, $\hat{\beta}_1$ is no longer significant at a 10% significance level and its value is comparable to the one for the main definition. This might support the idea that the higher callback rate of treatment group A compared to treatment group B (elaborated on in Subsection 6.2.1) is not primarily driven by the direct preference of candidates belonging to treatment group A over candidates belonging to treatment group B.

Furthermore, it is noticeable that the coefficients are much less stable across model specifications in models using the strict callback definition compared to models using the main definition. For instance, when focusing on the estimation results of models *(1)* and *(5)* using the strict callback definition, $\hat{\beta}_1$ is equal to -0.044 and -0.021, respectively, with the only difference between the specifications being the inclusion of fixed effects in model *(5)*. Together with the observed increases in adjusted R^2 after adding fixed effects, this observation provides evidence that these effects have a substantial explanatory power. In essence, certain companies are more likely to invite candidates for interviews,

[1] The sign of the estimated coefficient is counter-intuitive since it suggests that improved language skills decrease the callback probability. However, it is not surprising given the results of the statistical analysis.

and it appears that we (inadvertently) sent a higher number of "treatment A CVs" compared to "treatment B CVs" to these companies.

As far as Hypothesis 1a is concerned, its validity compared to its two-sided alternative can be directly assessed by examining the corresponding p-values in regression results. In line with what has been stated above, in most cases (i.e., across different model specifications and callback definitions), the hypothesis cannot be rejected against its two-sided alternative at a 10% significance level. However, the opposite can be concluded for models without fixed effects and using the strict definition. Nevertheless, since the job-offer-specific fixed effects most likely have high explanatory power, it may be more appropriate to rely on the results of models where these effects are accounted for. Hence, considering that in the preferred models, $\hat{\beta_1}$ is invariably insignificant, we are inclined towards not rejecting Hypothesis 1a against its two-sided alternative. This may be interpreted as Ukrainian applicants having the same probability of receiving an interview invitation, irrespective of their reported level of Czech language proficiency. Furthermore, given the consistently negative estimated coefficients of *cv_treatment_b_dummy*, it is clear that it would not be possible to reject Hypothesis 1a in favor of Hypothesis 1b at any conventional significance level.[1]

It might be insightful to discuss the estimated coefficients of some control variables as well. In all models presented so far, the estimated coefficients of *cv_treatment_c_dummy* are positive and significant at a 10% level. This suggests that being a native increases the callback probability by 13.5 to 18.6 (depending on the specification and callback definition in question) percentage points compared to being a Ukrainian applicant with poor knowledge of Czech.[2]

The coefficients of dummy variables representing job locations are always positive and significant at a 10% level, indicating that the callback probability increases when the job is located in any location (within the scope of our research) other than Brno. However, we refrain from drawing any conclusions, emphasizing the uneven distribution of job locations in the dataset and the

[1] A one-sided test with $H_0 : \hat{\beta_1} = 0$ and $H_A : \hat{\beta_1} > 0$ was used to verify this expectation formally for specification *(5)* and using the main callback definition. The resulting p-value is 0.821, suggesting that Hypothesis 1a cannot be rejected against Hypothesis 1b at any conventional significance level. The same result is expected for other model specifications and callback definitions.

[2] To compare the callback probabilities of a native applicant and a Ukrainian applicant with good knowledge of Czech, it would suffice to replace *cv_treatment_b_dummy* with *cv_treatment_a_dummy* and then evaluate the estimated coefficient of *cv_treatment_c_dummy*. Based on the results presented so far, this predicted difference in callback rates is expected to be even higher in this case.

imperfections in randomization.

Interestingly, none of the estimated coefficients corresponding to occupation types are significant at a 10% significance level.[3] The same can be concluded about variables representing interactions between occupation types and applicants' work experience. This might imply that the CVs were designed relatively well, with the job experience of applicants in matched pairs being comparable enough to not provide a significant advantage to one of them. Lastly, it is worth mentioning that the fact that a specific job offer is labeled as "suitable for Ukrainian refugees" does not significantly influence the callback probability.

Robustness Checks

Where possible, or with some necessary adjustments, all the selected models were also estimated on four subsets of the full dataset - specifically the "Prague", "SalesCash", "AB/BA", and "SentFirst" datasets.[1] These analyses primarily serve as a robustness check of our findings so far. In the first two cases, another objective is to control for the imperfections in the randomization of job locations and occupation types reported in Section 6.1. Regarding the "AB/BA" dataset, the rationale is to completely exclude the control group from the analysis in order to investigate solely the comparison between the two treatment groups. However, it should be emphasized that this adjustment restricted the original sample size to a third. Lastly, performing the selected regressions on the "SentFirst" dataset allows us to test the impacts of multiple potential scenarios - such as the recruiter's potential adjustments in behavior after receiving the first experimental CV, raising suspicions about its credibility, or the potential advantage of the first applicant as a result of a "first come - first serve" principle. The results of the corresponding regressions are documented in Appendix F.

No particularly surprising patterns emerge from the analyses using the restricted datasets. Across all regressions, the coefficient of *cv_treatment_b_*

[3]Please note that these variables were included primarily due to the imperfections in randomization.

[1]The individual subsets are characterized as follows:
"Prague" dataset - jobs located in Prague;
"SalesCash" dataset - jobs belonging to the self-defined "SalesCash" category;
"AB/BA" dataset - jobs offers to which exactly two CVs of Ukrainian applicants were sent as a response;
"SentFirst" dataset - includes only the first experimental application sent as a response to each job offer.

dummy is negative, and mostly statistically insignificant at the 10% level. The case of the "AB/BA" subset should be paid particular attention to. All regressions using this dataset yield $\hat{\beta}_1$ statistically insignificant at a 10% significance level, which suggests that there is no difference in callback probabilities between Ukrainian candidates with varying levels of Czech proficiency. Furthermore, the estimated coefficient values are very stable across specifications, differing only based on the callback definition under consideration - amounting to -0.006 in models using the main definition and -0.013 in models using the strict definition. It is worth noting that these values are substantially lower compared to those obtained from regressions on the full dataset. These observations provide further evidence that the higher callback rates for treatment group A compared to treatment group B are unlikely to be attributed to a direct preference for candidates from treatment group A.

Check of the Experimental Design

One additional check was carried out, based on performing a regression including possible explanatory variables related to applicants' characteristics. The aim was to identify potential shortcomings related to the experimental design - such as a significant systematic preference for applicants with a specific type of education, or a preference for a specific name compared to the other name belonging to a candidate of the same nationality. Based on the insignificance of relevant coefficients (reported in Table F.8), it can be concluded that no issues of such character are present.

Table 6.8: Regression results: LPM, selected models, full dataset, main callback definition

	Dependent variable:				
	cv_callback_main				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
cv_treatment_b_dummy	−0.031 (0.025)	−0.021 (0.025)	−0.020 (0.025)	−0.020 (0.028)	−0.025 (0.027)
cv_treatment_c_dummy	0.175*** (0.032)	0.183*** (0.034)	0.181*** (0.032)	0.186*** (0.038)	0.171*** (0.037)
cv_sentfirst_dummy		−0.015 (0.024)		−0.015 (0.025)	
vacancy_location_praha_dummy		0.136*** (0.027)	0.137*** (0.027)		
vacancy_location_stredoc_dummy		0.260*** (0.050)	0.262*** (0.048)		
vacancy_location_jihom_dummy		0.212*** (0.050)	0.205*** (0.049)		
vacancy_isco_salescash_dummy		0.057 (0.044)	0.041 (0.027)		
interaction_salescash		0.040 (0.033)		0.040 (0.033)	
vacancy_isco_info_dummy		0.056 (0.052)			
interaction_info		−0.013 (0.051)		−0.013 (0.050)	
vacancy_isco_foodwaiter_dummy		0.007 (0.060)	−0.014 (0.041)		
interaction_foodwaiter		0.051 (0.068)		0.118 (0.089)	
vacancy_education_dummy		−0.058* (0.031)	−0.046* (0.028)		
vacancy_cz_intext_mentioned_dummy		0.027 (0.048)			
vacancy_ualabel_dummy		0.065 (0.046)	0.054 (0.044)		
vacancy_ftpt_brigada_dummy		−0.058 (0.052)			
vacancy_ftpt_ft_dummy		0.009 (0.031)			
vacancy_emplform_emplalt_dummy		−0.055* (0.031)	−0.057* (0.029)		
vacancy_duration_open_dummy		−0.040 (0.027)			
Constant	0.128*** (0.019)	−0.008 (0.069)	−0.004 (0.041)		
Fixed effects	No	No	No	Yes	Yes
Observations	932	932	932	932	932
Adjusted R^2	0.055	0.085	0.087	0.603	0.600
F Statistic	27.946*** (df = 2; 929)	5.573*** (df = 19; 912)	9.882*** (df = 10; 921)	4.002*** (df = 472; 460)	3.983*** (df = 468; 464)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table 6.9: Regression results: LPM, selected models, full dataset, strict callback definition

	Dependent variable:				
	cv_callback_strict				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
cv_treatment_b_dummy	-0.044^{**}	-0.036^{*}	-0.036^{*}	-0.017	-0.021
	(0.021)	(0.021)	(0.021)	(0.026)	(0.025)
cv_treatment_c_dummy	0.140^{***}	0.143^{***}	0.142^{***}	0.142^{***}	0.135^{***}
	(0.029)	(0.031)	(0.030)	(0.037)	(0.035)
cv_sentfirst_dummy		-0.001		-0.0005	
		(0.021)		(0.023)	
vacancy_location_praha_dummy		0.101^{***}	0.102^{***}		
		(0.023)	(0.023)		
vacancy_location_stredoc_dummy		0.201^{***}	0.202^{***}		
		(0.045)	(0.044)		
vacancy_location_jihom_dummy		0.169^{***}	0.164^{***}		
		(0.046)	(0.045)		
vacancy_isco_salescash_dummy		0.050	0.026		
		(0.035)	(0.024)		
interaction_salescash		0.030		0.031	
		(0.029)		(0.031)	
vacancy_isco_info_dummy		0.047			
		(0.044)			
interaction_info		0.007		0.008	
		(0.045)		(0.047)	
vacancy_isco_foodwaiter_dummy		0.044	0.015		
		(0.054)	(0.038)		
interaction_foodwaiter		0.026		0.065	
		(0.064)		(0.080)	
vacancy_education_dummy		-0.045	-0.041^{*}		
		(0.027)	(0.025)		
vacancy_cz_intext_mentioned_dummy		0.022			
		(0.044)			
vacancy_ualabel_dummy		0.035	0.032		
		(0.041)	(0.040)		
vacancy_ftpt_brigada_dummy		-0.028			
		(0.045)			
vacancy_ftpt_ft_dummy		-0.004			
		(0.028)			
vacancy_emplform_emplalt_dummy		-0.040	-0.040		
		(0.027)	(0.026)		
vacancy_duration_open_dummy		-0.021			
		(0.023)			
Constant	0.096^{***}	-0.022	0.001		
	(0.017)	(0.057)	(0.036)		
Fixed effects	No	No	No	Yes	Yes
Observations	932	932	932	932	932
Adjusted R^2	0.053	0.071	0.076	0.524	0.524
F Statistic	26.988^{***} (df = 2; 929)	4.767^{***} (df = 19; 912)	8.691^{***} (df = 10; 921)	3.172^{***} (df = 472; 460)	3.195^{***} (df = 468; 464)
Note:	*p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses				

6.3.2 Logit and Probit

Some Theory

While the linear probability model assumes that the response probability is a linear function of the explanatory variables, alternative binary response models allow the response probability to depend on explanatory variables in a nonlinear manner. This can be expressed as

$$P(y_i = 1|\mathbf{X_i}) = G(\beta_0 + \beta \cdot \mathbf{X_i}),$$

where β_0 is the intercept, β is a vector of slope coefficients, $\mathbf{X_i}$ is a vector of independent variables, and G is a function that takes on values strictly between 0 and 1 for all real numbers. In a logit model, G denotes the cumulative distribution function for a standard logistic random variable, while in a probit model, G is defined as the standard normal cumulative distribution function (Wooldridge 2013).

To obtain valid estimates from logit or probit models, several assumptions must be met. The following assumptions are generally considered necessary: random sampling, no perfect collinearity among explanatory variables, a binary character of the explained variable, and no endogeneity. Additionally, it is necessary to assume a linear relationship between explanatory variables and the log odds or z-score of the dependent variable (the former for logit, the latter for probit). The first four conditions are considered fulfilled. The linearity assumption is more complicated since there cannot be a linear relationship between the dependent variable and both the log odds and the z-score simultaneously. However, at this point, it cannot be evaluated which of these assumptions is valid. Therefore, with this reservation, we consider them both as "fulfilled" so that we can estimate both logit and probit models. The decision regarding which version of the linearity assumption is more likely can be subsequently made based on the comparison of the goodness of fit of estimated logit and probit models.

Further, the main difference between logit and probit lies in the assumed distribution of error e in the following latent variable model:

$$y^* = \beta_0 + \mathbf{x} \cdot \beta + e,$$

where y^* is an unobserved latent variable and $y = 1[y^* > 0]$. While logit assumes that e follows a standard logistic distribution, probit assumes that e has a standard normal distribution (Wooldridge 2013). Given that our analysis is based on labor market data, we cannot reject any of these two possibilities. Therefore, under the assumption that either option is plausible, we perform analyses using both logit and probit.

Logit and probit models improve on some issues of the linear probability model, including heteroskedasticity, a constant marginal effect of the explanatory variables on the explained variable, and predicted probabilities outside the interval between 0 and 1. However, they pose challenges in interpreting estimated coefficients directly. Instead, average marginal effects or marginal effects at the average are used for interpretation purposes. In our case, it is necessary to calculate average marginal effects, which are, specifically for a binary independent variable x_k, defined as

$$
\begin{aligned}
n^{-1}\cdot \sum_{i=1}^{n}[&G(\hat{\beta}_0 + \hat{\beta}_1 \cdot x_{i1} + ... + \hat{\beta}_{k-1} \cdot x_{i,k-1} + \hat{\beta}_k) \\
&- G(\hat{\beta}_0 + \hat{\beta}_1 \cdot x_{i1} + ... + \hat{\beta}_{k-1} \cdot x_{i,k-1})],
\end{aligned}
$$

where $i = 1, ..., n$ (Wooldridge 2013).

Model Specifications

In line with the choice of variables based on LPM as well as the corresponding numbering of individual specifications, the following specifications were selected for analysis[1]:

Logit/Probit *(1)* - "basic model without fixed effects"

$$
\begin{aligned}
&P(cv\_outcome_i = 1 | cv\_treatment\_b\_dummy_i, cv\_treatment\_c\_dummy_i) \\
&\quad = G(\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i + \beta_2 \cdot cv\_treatment\_c\_dummy_i)
\end{aligned}
$$

Logit/Probit *(2)* - "large model without fixed effects"

$$
\begin{aligned}
&P(cv\_outcome_i = 1 | cv\_treatment\_b\_dummy_i, cv\_treatment\_c\_dummy_i, \mathbf{Z_i}) \\
&\quad = G(\beta_0 + \beta_1 \cdot cv\_treatment\_b\_dummy_i + \beta_2 \cdot cv\_treatment\_c\_dummy_i + \zeta \cdot \mathbf{Z_i})
\end{aligned}
$$

[1] Please note that specification *(3)* is not presented since it did not produce any particularly noteworthy results.

Logit/Probit *(4)* - "model with fixed effects and interactions"

$$P(cv\_outcome_i = 1|cv\_treatment\_b\_dummy_i, cv\_treatment\_c\_dummy_i, \mathbf{W_i}, \pi_\mathbf{i}) \\ = G(\beta_1 \cdot cv\_treatment\_b\_dummy_i + \beta_2 \cdot cv\_treatment\_c\_dummy_i + \omega \cdot \mathbf{W_i} + \pi_\mathbf{i})$$

Logit/Probit *(5)* - "basic model with fixed effects"

$$P(cv\_outcome_= 1|cv\_treatment\_b\_dummy_i, cv\_treatment\_c\_dummy_i, \pi_\mathbf{i}) \\ = G(\beta_1 \cdot cv\_treatment\_b\_dummy_i + \beta_2 \cdot cv\_treatment\_c\_dummy_i + \pi_\mathbf{i})$$

where G is a logistic function (when specifying logit models) or a probabilistic function (when specifying probit models), β_0 is the intercept, β_1 and β_2 are slope coefficients representing treatment effects. $\mathbf{Z_i}$ and $\mathbf{W_i}$ are vectors of control variables representing other characteristics of applicants, features of job offers, and sending conditions. ζ and ω are vectors of corresponding slope coefficients, respectively, and $\pi_\mathbf{i}$ corresponds to job-offer-specific fixed effects.

Regression Results

The above-defined models were estimated on the full dataset ($N = 932$), through both logit and probit, and considering both the main and strict definitions of a callback. The results are available in Appendix G.

To summarize the pivotal observations from the regression results, the estimated coefficients of *cv_treatment_b_dummy* are consistently negative. In the models using the main callback definition, they are statistically insignificant at the 10% significance level for both logit and probit. However, for logit and probit models using the strict callback definition, a different pattern is visible. While in specifications *(1)*, *(2)*, and *(4)*, $\hat{\beta}_1$ is significant at a 10% significance level, it is not significant at the same significance level for specification *(5)*. This result is in contrast with the findings of the LPM estimation, where $\hat{\beta}_1$ is insignificant at a 10% significance level across all specifications including fixed effects (i.e., model *(4)* as well).[1]

There are no substantial differences between the estimated marginal effects *cv_treatment_b_dummy* between logit and probit when comparing corre-

[1] In other words, due to the influence of nonlinear distributions, both logit and probit models using this specification indicate that language levels play a significant role, despite the job-offer-specific fixed effects. Although these results point towards a different conclusion regarding the impact of varying language skills, they carry the same weight as the results obtained from other comparable models (e.g., logit, probit, and LPM including fixed effects and using the main callback definition). This approach is be particularly important when formulating the answer to the research question (described in Section 7.1).

sponding model specifications. Nonetheless, the corresponding average marginal effects estimated by probit are slightly closer to zero compared to those estimated by logit.

Finally, the estimated average marginal effects of *cv_treatment_b_dummy* will be interpreted. In line with the approach adopted with LPM, only the cases where the estimated coefficient in question is statistically significant at a 10% significance level are considered (i.e., the specifications *(1)*, *(2)*, and *(4)* for the strict callback definition). The relevant marginal effects can be interpreted as follows: if a candidate reports possessing a B2 level of proficiency in Czech, the probability of receiving a callback diminishes by 6.2 (5.3, or 3.6) percentage points compared to the scenario where the candidate reports an A2 level of Czech, as per the logit estimation of model specifications *(1)*, *(2)*, and *(4)*, respectively. For probit models, the values are equal to 5.8, 5.0, and 3.4, respectively. In the case of both logit and probit, the values are relatively high when compared to the results of relevant regressions via LPM. This implies that logit and probit suggest that language skills play a more important role (though in an unexpected direction) compared to LPM. Based on the estimated coefficients in LPM, the values are equal to 4.4, 3.6, and 1.7 (noting that in the last case, $\hat{\beta}_1$ is insignificant at a 10% significance level). However, regardless of the estimation method, it is clear that the effect of language proficiency decreases once the job-offer-specific fixed effects are introduced.

6.3.3 Comparison of LPM, Logit, and Probit

As the final step of the econometric analysis, a test was performed to determine which estimation method - LPM, logit, or probit - has the highest predictive power in the case of our research. Since the conventional goodness-of-fit measures are not suitable for this comparison, the approach of calculating the "percentage correctly predicted" was utilized. For the purpose of the test, model specifications *(1)* and *(2)* were selected.

Fitted values from each model estimated on the full dataset were dichotomized using a 0.5 threshold, setting values below or equal to this threshold to 0 and values above it to 1.[1] The resulting values were subsequently compared to

[1] Please note that there were no other bounds of the two intervals. Therefore, fitted values from LPM could fall outside the interval between 0 and 1, and still be considered correctly predicted. For model *(1)* (both callback definitions), there were no such values. In model *(2)*, there were some fitted values below 0; specifically 52 values for model *(2)* with the main definition, and 74 values for model *(2)* with the strict definition.

the true values of the independent variables, and the percentage of correctly predicted cases was calculated for each model.

Table 6.10: Percentage correctly predicted - model *(1)*

	LPM	**Logit**	**Probit**
Main callback definition	82.4%	82.4%	82.4%
Strict callback definition	87.2%	87.2%	87.2%

Table 6.11: Percentage correctly predicted - model *(2)*

	LPM	**Logit**	**Probit**
Main callback definition	82.3%	82.6%	82.6%
Strict callback definition	87.2%	87.3%	87.2%

As presented in Table 6.10, the percentage of correctly predicted is equal across all three estimation methods and both callback definitions for model specification *(1)*. However, referring to Table 6.11, minor differences in the proportions of correctly predicted values are present for model specification *(2)*, particularly when considering the strict callback definition. Therefore, it could be concluded that logit offers the best fit (albeit marginally) when compared to the other estimation methods. Aside from the comparison of the models' predictive power, the tables offer another interesting insight - that all models under consideration are generally more successful in predicting the correct values when the strict callback definition is considered.[1]

[1]This is in line with the fact that the models using this definition generally result in lower standard errors. Although it could be concluded that this definition is more precise, we do not consider it superior to the main definition. That is because cannot be decided which definition is more trustworthy in determining how each hiring process would continue.

Chapter 7

Discussion of Results

This chapter presents a summary of the results obtained in the statistical and econometric analysis and aims to formulate an answer to the research question. Further, it discusses the reasons for observing certain patterns in our study, while elaborating on the methodological issues mentioned in Subsection 4.2.1.

7.1 Summary of Results

The statistical analysis uncovers a surprising finding pertaining to the research question: the callback rates for Ukrainian applicants with a poor level of Czech are higher than for those with a good command of Czech. The difference is deemed statistically insignificant (at a 10% significance level) when using the main definition of a callback, while it is proven to be significant at the same significance level when considering the strict callback definition.

The results of the econometric analysis align with those obtained from the statistical analysis. In all selected models, regardless of the estimation method, callback definition, or model specification, the estimated coefficients representing the change in the callback probability caused by improved knowledge of Czech are invariably negative. However, an essential trend is observed across most cases: the p-value of the coefficient of interest increases after job-offer-specific fixed effects are introduced to the model. These unobservable effects are intuitively expected to play a significant role in application processes, as evidenced by the improvement in the models' goodness of fit when they are accounted for. Consequently, regressions that address these effects may arguably produce more reliable results. Such regressions are mostly[1] characterized by

[1] As should be clear from Section 6.3, there were certain cases in which a different pattern

the insignificance of the corresponding coefficient at a 10% significance level. This could partially explain (and reduce the emphasis on) the higher callback rate of treatment group A compared to treatment group B, suggesting that it is not primarily driven by the direct preference of one treatment group over the other. In other words, when a recruiter receives CVs from Ukrainian applicants with different proficiency levels in Czech, the varying levels do not play a significant role when deciding which applicant would be invited to an interview (or be given a different positive signal).

The above-stated ideas support the conclusion that Hypothesis 1a should not be rejected against its two-sided alternative. In essence, there is insufficient evidence to dismiss the notion that a Ukrainian applicant's level of Czech language proficiency has no impact on the callback probability. Furthermore, considering the higher callback rates of treatment group B in comparison to treatment group A, and the negative (though sometimes insignificant) estimated coefficients signifying a preference for treatment group A, it is evident that Hypothesis 1a cannot be dismissed in favor of Hypothesis 1b. In other words, we cannot dismiss the assertion that language proficiency has no impact on the callback probability in favor of the statement that improved language proficiency increases the callback probability. *In essence, we conclude that the Czech language skills of Ukrainian refugees do not have a significant effect on callback probabilities.*

Having formulated the answer to the research question, it is imperative to emphasize that our conclusions are certainly not applicable to all job types. This study focuses on very specific occupation types - i.e., jobs similar to those that the Ukrainian applicants had in their home country and which align with their educational background and qualifications (excluding language proficiency). In addition, the current jobs of Ukrainian applicants presented in their CVs cannot be considered to satisfy these criteria. Therefore, our focus is on addressing the situation of Ukrainian refugees currently working in positions for which they are overqualified, rather than the aim of simply securing any employment. Hence, our findings suggest that improved language proficiency has no impact on the mitigation of this particular issue.

Given the diverse findings in existing literature investigating the relation-

was observed (i.e., a negative significant coefficient of interest). Although these cases were considered while formulating the answer to our research question, they could not outweigh the majority results of other comparable models. Furthermore, the assessment was also made with an assumption that neither of the callback definitions is superior, and the results of corresponding models were thus assigned equal weight.

ship between language proficiency and labor market outcomes of immigrants or refugees (elaborated on in Chapter 3), it is impossible to categorize our findings as either consistent or contradictory with similar studies. Therefore, let us briefly revisit some of the relevant experimental studies described in Section 3.2. Some authors draw conclusions comparable to ours. For example, Oreopoulos (2011) concludes, through an empirical analysis, that signals about language proficiency in job applications do not mitigate discriminatory practices against immigrants in Canada. A similar pattern was observed by Edo *et al.* (2017) concerning female French citizens with non-French names, indicating an ethnicity different from that prevailing in France. Ek *et al.* (2021) documents that completing specialized language training may not significantly improve the employability of Syrian refugees in Sweden. On the contrary, it is important to note that our findings contrast with those reported by, e.g., Carlsson *et al.* (2023) and Theys *et al.* (2020).

7.2 Further Reflections on the Results

Having concluded (albeit with some reservations) that the Czech language proficiency of Ukrainian applicants does not have a significant impact on callback probabilities, it would be also appropriate to discuss the possible reasons for observing such a pattern. Upon careful consideration, three possible scenarios have been identified, based on the attitude of the recruiters toward signals of language proficiency in the CVs: indifference, lack of comprehension, or lack of trust.

Indifference to Language-Related Signals

The first scenario, which is arguably the most plausible one, suggests that recruiters may not consider the difference in applicants' language proficiency at level A2 or B2 to be important. This behavior could be attributed to several reasons. Firstly, recruiters may deem even upper-intermediate proficiency to be insufficient, especially given the communication-intensive nature of some of the jobs within the scope of our research. An alternative explanation might be discrimination, i.e., rejecting a candidate based on their nationality, not taking into account their language skills and other credentials. This could supported by the findings of two correspondence experiments focusing on the Czech labor market: Roy (2023) suggests that Ukrainian refugees face discrimination, while

Pasichnyk (2023) highlights discrimination against long-term Ukrainian immigrants with perfect Czech language skills. Another possibility is that recruiters assume Ukrainian refugees may not be counted upon as long-term employees, due to the possibility of returning to Ukraine later on.

In light of the concepts discussed in the previous paragraph, future research could involve, for example, including Ukrainian immigrants with excellent Czech language skills as an additional treatment group. This approach could potentially help to investigate the relationships between language skills and discrimination.

Non-Comprehension of Language-Related Signals

It is also possible that the initial assumption - that the majority of recruiters are familiar with the CEFR classification - might have been incorrect. Therefore, another suggestion for further research is to reconsider the approach toward the signalization of language skills. Two main options should be considered: a short verbal description of language proficiency, or a proof of completion of a language course. The former would have to be done with great care to prevent ambiguous interpretation. The latter is elaborated on in what follows.

Distrust of Language-Related Signals

The third potential explanation for the observed phenomenon may be that recruiters are skeptical regarding the reported language proficiency levels in the candidates' CVs, assuming that the applicants might overstate their language skills to increase their prospects of securing an interview. This possibility was taken into consideration during the preparation of the experiment. It is worth remembering that various methods of indicating language proficiency have been employed in other correspondence studies; for details, please refer to Subsection 3.2.2. However, due to constraints specific to our circumstances, some of these methods were deemed unfeasible. Consequently, we were left with two alternatives - a straightforward declaration of language proficiency unsupported by any means, as utilized by, e.g., Oreopoulos (2011), or the indication of completion of a specific language course, as adopted by, e.g., Ek *et al.* (2021). Although the former approach was ultimately chosen, the rationale for not opting for the latter is elaborated on in Subsection 4.2.1. Nevertheless, we recognize that with greater attention to addressing the potential issues outlined, it would have been feasible to apply the latter approach as well, constituting another suggestion for further research.

Chapter 8

Conclusion

The beginning of the Russian invasion of Ukraine in February 2022 caused millions of Ukrainians to leave their country and seek refuge in other countries, with the Czech Republic emerging as one of the primary destinations for the fleeing populace. Labor market participation may considered one of the vital parts of the refugees' integration into the host country's society. This thesis aims to examine the relationship between the refugees' proficiency in the host country's language and success in a given labor market. By focusing specifically on the, to the best of our knowledge, unexplored case of Ukrainian refugees in the Czech Republic, we aim to contribute to the existing literature on the link between the language skills of immigrants or refugees and their labor market outcomes.

The study was conducted in the form of a correspondence experiment. Manipulated curricula vitae were prepared for three groups of fictitious applicants: Ukrainian refugees with poor Czech language skills, Ukrainian refugees with a good command of the language, and native Czech citizens. These CVs were then submitted in response to relevant job postings on two popular Czech job portals. The matched approach was utilized, i.e., for each job offer, two applications were sent, each representing a different applicant group. Along with details about the positions offered, information on the subsequent responses from employers was collected, focusing especially on whether a callback (i.e., a positive signal from the recruiter) was received in a given case.

The resulting dataset contained information on 932 job applications (corresponding to 466 job offers) collected during the experiment. The statistical analysis of the data primarily examined variations in callback rates among the individual applicant groups. Although this analysis did not offer a clear answer to the research question, it revealed a clear finding of native candidates having a significantly higher callback rate compared to Ukrainian candidates.

In the econometric analysis, we focused on estimating callback probabilities using linear probability models, which were further complemented by logit and probit models. The panel structure of the data (resulting from utilizing the matched approach) was addressed in multiple regressions by incorporating dummy variables representing individual job offers to capture their unobservable fixed effects. These regressions were deemed more reliable due to the intuitive significance of such effects and their numerically better fit. Despite the fact not all components of our analyses consistently yield the same results concerning our research question, the majority of the "reliable" models indicate that varying Czech language proficiency does not significantly impact the callback probability of Ukrainian refugees. This suggests that improved knowledge of the Czech language may not necessarily enhance refugees' labor market prospects.

In addition, the design of the experiment (specifically the design of the CVs belonging to Ukrainian candidates and the criteria used to select job offers) might allow us to further interpret the results in a way that brings insights regarding a significant trend: Ukrainian refugees working in positions for which they are overqualified. Our analyses indicate that having a better knowledge of Czech does not appear to mitigate this issue. Therefore, we suggest that potential interventions in this area, such as subsidized language courses, may not prove to be particularly effective in this respect.

Finally, it is necessary to emphasize the limited scope of our research. To draw more reliable conclusions on this research question, we propose several avenues for future research. Most importantly, it is suggested to include a wider range of occupation types as well as job offers from more regions of the Czech Republic, to incorporate Ukrainian immigrants fluent in Czech as an additional applicant group, or to reevaluate the approach towards the signals of language proficiency in the CVs.

Bibliography

Ahmed, A. M. & M. Hammarstedt (2008): "Discrimination in the rental housing market: A field experiment on the Internet." *Journal of Urban Economics* **64(2)**: pp. 362–372.

Aldashev, A., J. Gernandt, & S. L. Thomsen (2009): "Language usage, participation, employment and earnings." *Labour Economics* **16(3)**: pp. 330–341.

Angrist, J. D. (2010): *Treatment Effect*, pp. 329–338. Palgrave Macmillan UK.

Auer, D. (2017): "Language roulette - the effect of random placement on refugees' labour market integration." *Journal of Ethnic and Migration Studies* **44(3)**: pp. 341–362.

Becker, G. S. (2009): *Human Capital*. Chicago: University of Chicago Press. Description based upon print version of record.

Botelho, T. L. & M. Chang (2023): "The Evaluation of Founder Failure and Success by Hiring Firms: A Field Experiment." *Organization Science* **34(1)**: pp. 484–508.

Budría, S., A. Colino, & C. Martínez de Ibarreta (2018): "The impact of host language proficiency on employment outcomes among immigrants in Spain." *Empirica* **46(4)**: pp. 625–652.

Carlsson, M., S. Eriksson, & D.-O. Rooth (2023): "Language Proficiency and Hiring of Immigrants: Evidence from a New Field Experimental Approach." *IZA Discussion Papers 15950*, Bonn.

Chiswick, B. R. (2008): "The Economics of Language: An Introduction and Overview." *IZA Discussion Papers 3568*, Bonn.

Chiswick, B. R. & P. W. Miller (2009): "The international transferability of immigrants' human capital." *Economics of Education Review* **28(2)**: pp. 162–169.

Cohen-Goldner, S. & Z. Eckstein (2008): "Labor Mobility of Immigrants: Training, Experience, Language, and Opportunities." *International Economic Review* **49(3)**: pp. 837–872.

Council of Europe (n.d.): "The CEFR Levels." `https://www.coe.int/en/web/common-european-framework-reference-languages/level-descriptions`. Accessed May 27, 2024.

Delander, L., M. Hammarstedt, J. Månsson, & E. Nyberg (2005): "Integration of Immigrants: The Role of Language Proficiency and Experience." *Evaluation Review* **29(1)**: pp. 24–41.

Dustmann, C. & F. Fabbri (2003): "Language Proficiency and Labour Market Performance of Immigrants in the UK." *The Economic Journal* **113(489)**: pp. 695–717.

Dustmann, C. & A. Van Soest (2002): "Language and the Earnings of Immigrants." *ILR Review* **55(3)**: pp. 473–492.

Edo, A., N. Jacquemet, & C. Yannelis (2017): "Language skills and homophilous hiring discrimination: Evidence from gender and racially differentiated applications." *Review of Economics of the Household* **17(1)**: pp. 349–376.

Ek, S., M. Hammarstedt, & P. Skedinger (2021): "Low-Skilled Jobs, Language Proficiency and Refugee Integration: An Experimental Study." *IFN Working Paper 1398*, Stockholm.

Foged, M., L. Hasager, G. Peri, J. N. Arendt, & I. Bolvig (2022): "Language Training and Refugees' Integration." *The Review of Economics and Statistics* pp. 1–41.

Foged, M., L. Hasager, G. Peri, J. N. Arendt, & I. Bolvig (2023): "Intergenerational spillover effects of language training for refugees." *Journal of Public Economics* **220**: p. 104840.

Harrison, G. W. & J. A. List (2004): "Field Experiments." *Journal of Economic Literature* **42(4)**: pp. 1009–1055.

HAYFRON, J. E. (2001): "Language training, language proficiency and earnings of immigrants in Norway." *Applied Economics* **33(15)**: pp. 1971–1979.

HELLER, B. H. & K. S. MUMMA (2023): "Immigrant Integration in the United States: The Role of Adult English Language Training." *American Economic Journal: Economic Policy* **15(3)**: pp. 407–437.

HIMMLER, O. & R. JÄCKLE (2017): "Literacy and the Migrant-Native Wage Gap." *Review of Income and Wealth* **64(3)**: pp. 592–625.

INTERNATIONAL LABOUR ORGANIZATION (n.d.): "International Standard Classification of Occupations (ISCO)." `https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/`. Accessed May 27, 2024.

JOWELL, R. & P. PRESCOTT-CLARKE (1970): "Racial Discrimination and White-collar Workers in Britain." *Race* **11(4)**: pp. 397–417.

LARSEN, E. N. (2020): "Induced competition in matched correspondence tests: Conceptual and methodological considerations." *Research in Social Stratification and Mobility* **65**: p. 100475.

LEVITT, S. D. & J. A. LIST (2009): "Field experiments in economics: The past, the present, and the future." *European Economic Review* **53(1)**: pp. 1–18.

LINDEMANN, K. & I. KOGAN (2013): "The Role of Language Resources in Labour Market Entry: Comparing Estonia and Ukraine." *Journal of Ethnic and Migration Studies* **39(1)**: pp. 105–123.

LOCHMANN, A., H. RAPOPORT, & B. SPECIALE (2019): "The effect of language training on immigrants' economic integration: Empirical evidence from France." *European Economic Review* **113**: pp. 265–296.

LØNSMANN, D. (2020): "Language, employability and positioning in a Danish integration programme." *International Journal of the Sociology of Language* **2020(264)**: pp. 49–71.

MANANT, M., S. PAJAK, & N. SOULIÉ (2014): "Online social networks and hiring: a field experiment on the French labor market." .

Mergener, A. & T. Maier (2018): "Immigrants' Chances of Being Hired at Times of Skill Shortages: Results from a Factorial Survey Experiment Among German Employers." *Journal of International Migration and Integration* **20(1)**: pp. 155–177.

Ministerstvo školství, mládeže a tělovýchovy (n.d.): "Základní informace ke vzdělávacímu systému Ukrajiny v porovnání s českým vzdělávacím sytémem." `https://www.npi.cz/images/ukrajina/vzdelavaci_system.pdf`. Accessed May 27, 2024.

Miyar-Busto, M., F. J. Mato Díaz, & R. Gutiérrez (2020): "Immigrants' educational credentials leading to employment outcomes: The role played by language skills." *Revista Internacional de Organizaciones* **(23)**: pp. 167–191.

Oreopoulos, P. (2011): "Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes." *American Economic Journal: Economic Policy* **3(4)**: pp. 148–171.

Pasichnyk, V. (2023): *Discrimination of Ukrainian Citizens in the Czech Labor Market: A Field Experiment.* Bachelor's Thesis, Univerzita Karlova, Fakulta sociálních věd, Institut ekonomických studií.

Pieroni, L., G. d'Agostino, D. Lanari, & M. Scarlato (2022): "Immigrant Labour Market Outcomes: New Insights from a Lack of Language Proficiency in Italy." *Italian Economic Journal* **10(1)**: pp. 293–327.

Rooth, D.-O. & J. Saarela (2007): "Native Language and Immigrant Labour Market Outcomes: An Alternative Approach to Measuring the Returns for Language Skills." *Journal of International Migration and Integration / Revue de l'integration et de la migration internationale* **8(2)**: pp. 207–221.

Roy, R. (2023): *Ukrainian Refugees and Labor Market Discrimination over Time.* Master's thesis, Masarykova univerzita, Ekonomicko-správní fakulta.

Schmaus, M. (2019): "Ethnic Differences in Labour Market Outcomes - The Role of Language-Based Discrimination." *European Sociological Review* .

Tam, K. W. & L. Page (2016): "Effects of language proficiency on labour, social and health outcomes of immigrants in Australia." *Economic Analysis and Policy* **52**: pp. 66–78.

Theys, T., S. Adriaenssens, D. Verhaest, N. Deschacht, & S. Rousseau (2020): "Disentangling language from ethnic preferences in the recruitment of domestic workers: A discrete choice experiment." *Journal of Business Research* **117**: pp. 144–151.

Verhaeghe, P.-P. (2022): *Correspondence Studies*, pp. 1–19. Springer International Publishing.

Vuolo, M., C. Uggen, & S. Lageson (2018): *To Match or Not to Match? Statistical and Substantive Considerations in Audit Design and Analysis*, pp. 119–140. Springer International Publishing.

Wooldridge, J. M. (2013): *Introductory Econometrics: A Modern Approach.* South-Western Cengage Learning, 5th edition.

Yao, Y. & J. C. van Ours (2015): "Language skills and labor market performance of immigrants in the Netherlands." *Labour Economics* **34**: pp. 76–85.

Appendix A

Sample CVs

The following pages include examples of four CVs, where Figure A.1 corresponds to CV_1 (PRG-A-V-KY-ZB-T1), Figure A.2 corresponds to CV_17 (PRG-B-Y-OD-OB-T2), Figure A.3 corresponds to CV_74 (BRN-C-T-OA-NA-T1), and Figure A.4 corresponds to CV_79 (BRN-C-K-CR-NA-T2). For a list of all CV types as well as an explanation of individual CV features, please refer to Appendix B.

Figure A.1: Sample CV 1

Viktorija Ševčenko

Věk: 20 let

Kontakt: sevcenko.viktorijaa@gmail.com

Pracovní zkušenosti

srpen 2022 – dosud **Asistentka prodejny, Kaufland, Praha**

- doplňování zboží do regálů, kontrola štítků a kvality

červenec 2021 – únor 2022 **Pokladní, Plavecký bazén Sportrend, Kyjev**

- prodej vstupenek, zajištění chodu recepce, zaznamenávání rezervací, ztráty a nálezy

Vzdělání

2018 – 2021 **Kyjevská odborná škola cestovního ruchu a hospodářství**

- střední škola, obor Cestovní ruch
- zakončeno jako "mladší bakalář"

Dovednosti

Jazyky	ukrajinský jazyk: rodilý mluvčí
	český jazyk: úroveň A2
	anglický jazyk: úroveň B1
PC	uživatelská znalost PC, práce v Microsoft Office
Řidičský průkaz	skupina B

Figure A.2: Sample CV 2

YULIYA KOVALCHUK

Datum narození: 3. 7. 2003

VZDĚLÁNÍ

Polytechnická odborná škola Národní univerzity "Odesa Polytechnic" (2018 - 2021)

- odborné středoškolské vzdělání s titulem *junior bakalář* v oboru Podnikání a obchod

PŘEDCHOZÍ ZAMĚSTNÁNÍ

UGO Salaterie (Praha) - OBSLUHA (09/2022 - současnost)

- příprava, servírování a roznáška pokrmů

Drogerie EVA (Oděsa) - OBSLUHA PRODEJNY (08/2021 - 03/2022)

- obsluha pokladny, vyřizování dotazů zákazníků, kontrola cenovek apod.

DALŠÍ

Práce s PC

- MS Word, PowerPoint, Excel jako běžný uživatel

Jazykové znalosti

- ukrajinština – mateřský jazyk
- angličtina – B1
- čeština – B2

Řidičské oprávnění

- osobní auto

Kontaktní e-mail: yuliya.kovalchuk.38@gmail.com

Figure A.3: Sample CV 3

Tereza Benešová

Věk: 20 let

Kontakt: terezabenesova417@gmail.com

Pracovní zkušenosti

srpen 2022 – dosud **Obsluha prodejny, Drogerie TETA, Brno**

- obsluha pokladny, vyřizování dotazů zákazníků, kontrola cenovek apod.

Vzdělání

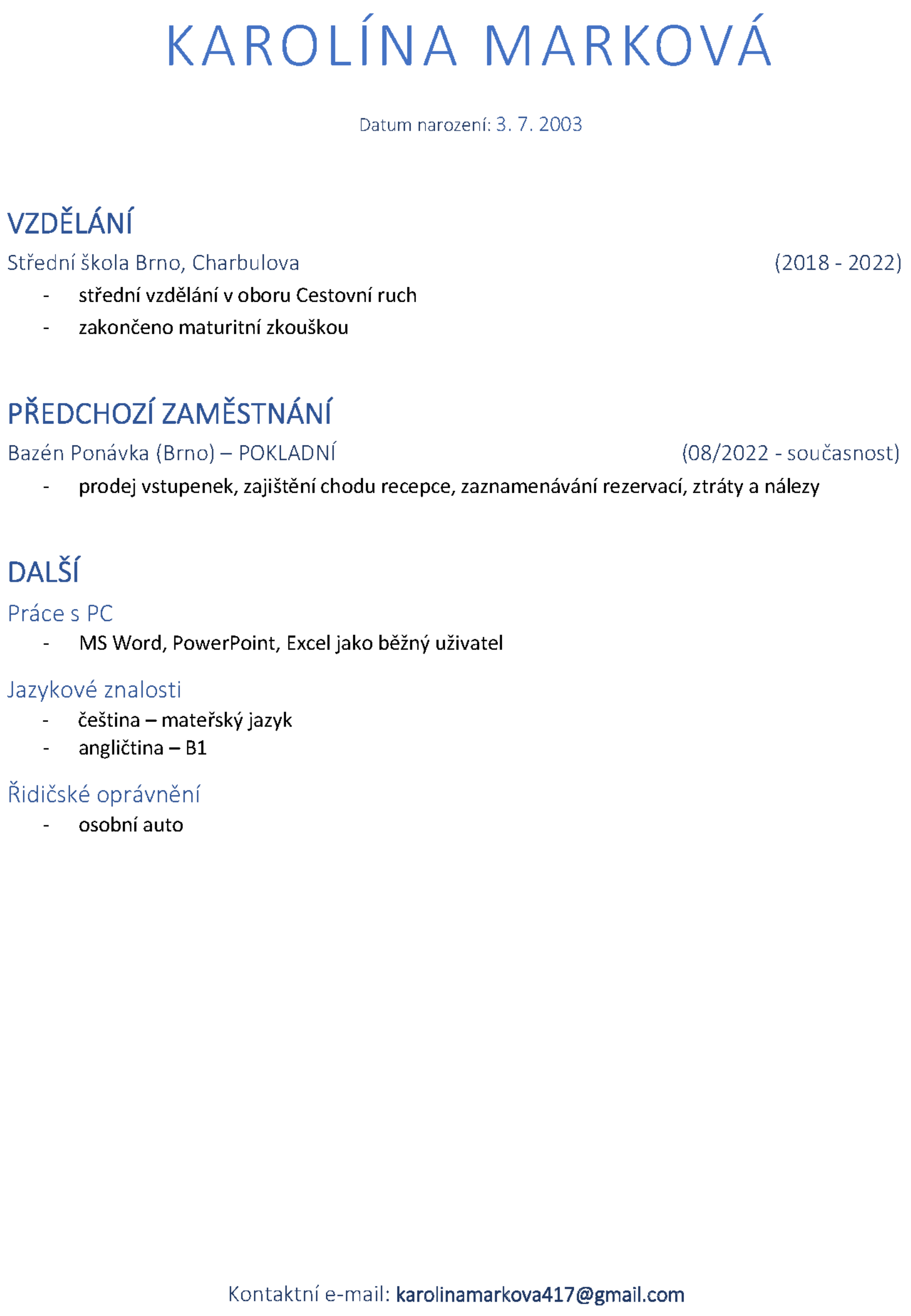
2018 – 2022 **Obchodní akademie a vyšší odborná škola Brno, Kotlářská**

- střední vzdělání s maturitní zkouškou v oboru Obchodní akademie

Dovednosti

Jazyky	český jazyk: rodilý mluvčí
	anglický jazyk: úroveň B1
PC	uživatelská znalost PC, práce v Microsoft Office
Řidičský průkaz	skupina B

Figure A.4: Sample CV 4



KAROLÍNA MARKOVÁ

Datum narození: 3. 7. 2003

VZDĚLÁNÍ

Střední škola Brno, Charbulova (2018 - 2022)

- střední vzdělání v oboru Cestovní ruch
- zakončeno maturitní zkouškou

PŘEDCHOZÍ ZAMĚSTNÁNÍ

Bazén Ponávka (Brno) – POKLADNÍ (08/2022 - současnost)

- prodej vstupenek, zajištění chodu recepce, zaznamenávání rezervací, ztráty a nálezy

DALŠÍ

Práce s PC

- MS Word, PowerPoint, Excel jako běžný uživatel

Jazykové znalosti

- čeština – mateřský jazyk
- angličtina – B1

Řidičské oprávnění

- osobní auto

Kontaktní e-mail: karolinamarkova417@gmail.com

Appendix B

CV Characteristics and Combinations

This appendix provides additional information related to our experimental design - specifically, the creation of CVs and their subsequent assignment to pairs. Table B.1 and Table B.2 present all CV types used throughout the experiment (identified by their unique "CV IDs") and corresponding "CV codes", which specify applicants' characteristics in abbreviated form. Table B.3 then provides an explanation for individual letters included in the CV codes. Table B.4 and Table B.5 list all possible ways of replying to a job offer by specifying the ID of the CV which is sent on the first day and the ID of the CV that is sent on the following day.

Table B.1: CV IDs and CV codes - Prague

CV ID	CV code
CV_1	PRG-A-V-KY-ZB-T1
CV_2	PRG-A-V-KY-ZB-T2
CV_3	PRG-A-V-KY-OB-T1
CV_4	PRG-A-V-KY-OB-T2
CV_5	PRG-A-V-OD-ZB-T1
CV_6	PRG-A-V-OD-ZB-T2
CV_7	PRG-A-V-OD-OB-T1
CV_8	PRG-A-V-OD-OB-T2
CV_9	PRG-A-Y-KY-ZB-T1
CV_10	PRG-A-Y-KY-ZB-T2
CV_11	PRG-A-Y-KY-OB-T1
CV_12	PRG-A-Y-KY-OB-T2
CV_13	PRG-A-Y-OD-ZB-T1
CV_14	PRG-A-Y-OD-ZB-T2
CV_15	PRG-A-Y-OD-OB-T1
CV_16	PRG-A-Y-OD-OB-T2
CV_17	PRG-B-Y-OD-OB-T2
CV_18	PRG-B-Y-OD-OB-T1
CV_19	PRG-B-Y-OD-ZB-T2
CV_20	PRG-B-Y-OD-ZB-T1
CV_21	PRG-B-Y-KY-OB-T2
CV_22	PRG-B-Y-KY-OB-T1
CV_23	PRG-B-Y-KY-ZB-T2
CV_24	PRG-B-Y-KY-ZB-T1
CV_25	PRG-B-V-OD-OB-T2
CV_26	PRG-B-V-OD-OB-T1
CV_27	PRG-B-V-OD-ZB-T2
CV_28	PRG-B-V-OD-ZB-T1
CV_29	PRG-B-V-KY-OB-T2
CV_30	PRG-B-V-KY-OB-T1
CV_31	PRG-B-V-KY-ZB-T2
CV_32	PRG-B-V-KY-ZB-T1
CV_33	PRG-C-T-OA-NA-T2
CV_34	PRG-C-T-OA-NA-T1
CV_35	PRG-C-T-CR-NA-T2
CV_36	PRG-C-T-CR-NA-T1
CV_37	PRG-C-K-OA-NA-T2
CV_38	PRG-C-K-OA-NA-T1
CV_39	PRG-C-K-CR-NA-T2
CV_40	PRG-C-K-CR-NA-T1

Table B.2: CV IDs and CV codes - Brno

CV ID	CV code
CV_41	BRN-A-V-KY-ZB-T1
CV_42	BRN-A-V-KY-ZB-T2
CV_43	BRN-A-V-KY-OB-T1
CV_44	BRN-A-V-KY-OB-T2
CV_45	BRN-A-V-OD-ZB-T1
CV_46	BRN-A-V-OD-ZB-T2
CV_47	BRN-A-V-OD-OB-T1
CV_48	BRN-A-V-OD-OB-T2
CV_49	BRN-A-Y-KY-ZB-T1
CV_50	BRN-A-Y-KY-ZB-T2
CV_51	BRN-A-Y-KY-OB-T1
CV_52	BRN-A-Y-KY-OB-T2
CV_53	BRN-A-Y-OD-ZB-T1
CV_54	BRN-A-Y-OD-ZB-T2
CV_55	BRN-A-Y-OD-OB-T1
CV_56	BRN-A-Y-OD-OB-T2
CV_57	BRN-B-Y-OD-OB-T2
CV_58	BRN-B-Y-OD-OB-T1
CV_59	BRN-B-Y-OD-ZB-T2
CV_60	BRN-B-Y-OD-ZB-T1
CV_61	BRN-B-Y-KY-OB-T2
CV_62	BRN-B-Y-KY-OB-T1
CV_63	BRN-B-Y-KY-ZB-T2
CV_64	BRN-B-Y-KY-ZB-T1
CV_65	BRN-B-V-OD-OB-T2
CV_66	BRN-B-V-OD-OB-T1
CV_67	BRN-B-V-OD-ZB-T2
CV_68	BRN-B-V-OD-ZB-T1
CV_69	BRN-B-V-KY-OB-T2
CV_70	BRN-B-V-KY-OB-T1
CV_71	BRN-B-V-KY-ZB-T2
CV_72	BRN-B-V-KY-ZB-T1
CV_73	BRN-C-T-OA-NA-T2
CV_74	BRN-C-T-OA-NA-T1
CV_75	BRN-C-T-CR-NA-T2
CV_76	BRN-C-T-CR-NA-T1
CV_77	BRN-C-K-OA-NA-T2
CV_78	BRN-C-K-OA-NA-T1
CV_79	BRN-C-K-CR-NA-T2
CV_80	BRN-C-K-CR-NA-T1

Table B.3: Explanation of acronyms in CV codes

Feature type	Acronym in CV code	Meaning
City	PRG	applicant based in Prague
	BRN	applicant based in Brno
Treatment	A	treatment A (A2 level of Czech)
	B	treatment B (B2 level of Czech)
	C	control group (native speaker of Czech)
Name	V	Viktorija Ševčenko
	Y	Yuliya Kovalchuk
	T	Tereza Benešová
	K	Karolína Marková
Education, work experience	KY	Ukrainian applicant; high school and first job in Kyiv; study path: tourism; first work experience: cashier at a public swimming pool
	OD	Ukrainian applicant; high school and first job in Odessa; study path: business academy; first work experience: shop assistant at a drugstore
	OA	Czech applicant; study path: business academy; work experience: shop assistant at a drugstore
	CR	Czech applicant; study path: tourism; work experience: cashier at a public swimming pool
Second job	OB	Ukrainian applicant; second work experience (in the Czech Republic): fast-food employee
	ZB	Ukrainian applicant; second work experience (in the Czech Republic): supermarket employee
	NA	Czech applicant; no second job
CV template	T1	CV template 1 used
	T2	CV template 2 used

Note: The "City" feature of an applicant is given by current job location (for Czech candidates by high school location as well).

Table B.4: CV combinations - Prague

Combination ID	CV ID - sent first	CV ID - sent second
Combination_1_Prague	CV_1	CV_17
Combination_2_Prague	CV_2	CV_18
Combination_3_Prague	CV_3	CV_19
Combination_4_Prague	CV_4	CV_20
Combination_5_Prague	CV_5	CV_21
Combination_6_Prague	CV_6	CV_22
Combination_7_Prague	CV_7	CV_23
Combination_8_Prague	CV_8	CV_24
Combination_9_Prague	CV_9	CV_25
Combination_10_Prague	CV_10	CV_26
Combination_11_Prague	CV_11	CV_27
Combination_12_Prague	CV_12	CV_28
Combination_13_Prague	CV_13	CV_29
Combination_14_Prague	CV_14	CV_30
Combination_15_Prague	CV_15	CV_31
Combination_16_Prague	CV_16	CV_32
Combination_17_Prague	CV_17	CV_1
Combination_18_Prague	CV_18	CV_2
Combination_19_Prague	CV_19	CV_3
Combination_20_Prague	CV_20	CV_4
Combination_21_Prague	CV_21	CV_5
Combination_22_Prague	CV_22	CV_6
Combination_23_Prague	CV_23	CV_7
Combination_24_Prague	CV_24	CV_8
Combination_25_Prague	CV_25	CV_9
Combination_26_Prague	CV_26	CV_10
Combination_27_Prague	CV_27	CV_11
Combination_28_Prague	CV_28	CV_12
Combination_29_Prague	CV_29	CV_13
Combination_30_Prague	CV_30	CV_14
Combination_31_Prague	CV_31	CV_15
Combination_32_Prague	CV_32	CV_16

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Table B.4: CV combinations - Prague - continued

Combination ID	**CV ID - sent first**	**CV ID - sent second**
Combination_33_Prague	CV_1	CV_33
Combination_34_Prague	CV_2	CV_34
Combination_35_Prague	CV_3	CV_33
Combination_36_Prague	CV_4	CV_34
Combination_37_Prague	CV_5	CV_35
Combination_38_Prague	CV_6	CV_36
Combination_39_Prague	CV_7	CV_35
Combination_40_Prague	CV_8	CV_36
Combination_41_Prague	CV_9	CV_37
Combination_42_Prague	CV_10	CV_38
Combination_43_Prague	CV_11	CV_37
Combination_44_Prague	CV_12	CV_38
Combination_45_Prague	CV_13	CV_39
Combination_46_Prague	CV_14	CV_40
Combination_47_Prague	CV_15	CV_39
Combination_48_Prague	CV_16	CV_40
Combination_49_Prague	CV_37	CV_1
Combination_50_Prague	CV_38	CV_2
Combination_51_Prague	CV_37	CV_3
Combination_52_Prague	CV_38	CV_4
Combination_53_Prague	CV_39	CV_5
Combination_54_Prague	CV_40	CV_6
Combination_55_Prague	CV_39	CV_7
Combination_56_Prague	CV_40	CV_8
Combination_57_Prague	CV_33	CV_9
Combination_58_Prague	CV_34	CV_10
Combination_59_Prague	CV_33	CV_11
Combination_60_Prague	CV_34	CV_12
Combination_61_Prague	CV_35	CV_13
Combination_62_Prague	CV_36	CV_14
Combination_63_Prague	CV_35	CV_15
Combination_64_Prague	CV_36	CV_16

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Table B.4: CV combinations - Prague - continued

Combination ID	CV ID - sent first	CV ID - sent second
Combination_65_Prague	CV_32	CV_33
Combination_66_Prague	CV_31	CV_34
Combination_67_Prague	CV_30	CV_33
Combination_68_Prague	CV_29	CV_34
Combination_69_Prague	CV_28	CV_35
Combination_70_Prague	CV_27	CV_36
Combination_71_Prague	CV_26	CV_35
Combination_72_Prague	CV_25	CV_36
Combination_73_Prague	CV_24	CV_37
Combination_74_Prague	CV_23	CV_38
Combination_75_Prague	CV_22	CV_37
Combination_76_Prague	CV_21	CV_38
Combination_77_Prague	CV_20	CV_39
Combination_78_Prague	CV_19	CV_40
Combination_79_Prague	CV_18	CV_39
Combination_80_Prague	CV_17	CV_40
Combination_81_Prague	CV_37	CV_32
Combination_82_Prague	CV_38	CV_31
Combination_83_Prague	CV_37	CV_30
Combination_84_Prague	CV_38	CV_29
Combination_85_Prague	CV_39	CV_28
Combination_86_Prague	CV_40	CV_27
Combination_87_Prague	CV_39	CV_26
Combination_88_Prague	CV_40	CV_25
Combination_89_Prague	CV_33	CV_24
Combination_90_Prague	CV_34	CV_23
Combination_91_Prague	CV_33	CV_22
Combination_92_Prague	CV_34	CV_21
Combination_93_Prague	CV_35	CV_20
Combination_94_Prague	CV_36	CV_19
Combination_95_Prague	CV_35	CV_18
Combination_96_Prague	CV_36	CV_17

Table B.5: CV combinations - Brno

Combination ID	**CV ID - sent first**	**CV ID - sent second**
Combination_1_Brno	CV_41	CV_57
Combination_2_Brno	CV_42	CV_58
Combination_3_Brno	CV_43	CV_59
Combination_4_Brno	CV_44	CV_60
Combination_5_Brno	CV_45	CV_61
Combination_6_Brno	CV_46	CV_62
Combination_7_Brno	CV_47	CV_63
Combination_8_Brno	CV_48	CV_64
Combination_9_Brno	CV_49	CV_65
Combination_10_Brno	CV_50	CV_66
Combination_11_Brno	CV_51	CV_67
Combination_12_Brno	CV_52	CV_68
Combination_13_Brno	CV_53	CV_69
Combination_14_Brno	CV_54	CV_70
Combination_15_Brno	CV_55	CV_71
Combination_16_Brno	CV_56	CV_72
Combination_17_Brno	CV_57	CV_41
Combination_18_Brno	CV_58	CV_42
Combination_19_Brno	CV_59	CV_43
Combination_20_Brno	CV_60	CV_44
Combination_21_Brno	CV_61	CV_45
Combination_22_Brno	CV_62	CV_46
Combination_23_Brno	CV_63	CV_47
Combination_24_Brno	CV_64	CV_48
Combination_25_Brno	CV_65	CV_49
Combination_26_Brno	CV_66	CV_50
Combination_27_Brno	CV_67	CV_51
Combination_28_Brno	CV_68	CV_52
Combination_29_Brno	CV_69	CV_53
Combination_30_Brno	CV_70	CV_54
Combination_31_Brno	CV_71	CV_55
Combination_32_Brno	CV_72	CV_56

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Table B.5: CV combinations - Brno - continued

Combination ID	**CV ID - sent first**	**CV ID - sent second**
Combination_33_Brno	CV_41	CV_73
Combination_34_Brno	CV_42	CV_74
Combination_35_Brno	CV_43	CV_73
Combination_36_Brno	CV_44	CV_74
Combination_37_Brno	CV_45	CV_75
Combination_38_Brno	CV_46	CV_76
Combination_39_Brno	CV_47	CV_75
Combination_40_Brno	CV_48	CV_76
Combination_41_Brno	CV_49	CV_77
Combination_42_Brno	CV_50	CV_78
Combination_43_Brno	CV_51	CV_77
Combination_44_Brno	CV_52	CV_78
Combination_45_Brno	CV_53	CV_79
Combination_46_Brno	CV_54	CV_80
Combination_47_Brno	CV_55	CV_79
Combination_48_Brno	CV_56	CV_80
Combination_49_Brno	CV_77	CV_41
Combination_50_Brno	CV_78	CV_42
Combination_51_Brno	CV_77	CV_43
Combination_52_Brno	CV_78	CV_44
Combination_53_Brno	CV_79	CV_45
Combination_54_Brno	CV_80	CV_46
Combination_55_Brno	CV_79	CV_47
Combination_56_Brno	CV_80	CV_48
Combination_57_Brno	CV_73	CV_49
Combination_58_Brno	CV_74	CV_50
Combination_59_Brno	CV_73	CV_51
Combination_60_Brno	CV_74	CV_52
Combination_61_Brno	CV_75	CV_53
Combination_62_Brno	CV_76	CV_54
Combination_63_Brno	CV_75	CV_55
Combination_64_Brno	CV_76	CV_56

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Table B.5: CV combinations - Brno - continued

Combination ID	**CV ID - sent first**	**CV ID - sent second**
Combination_65_Brno	CV_72	CV_73
Combination_66_Brno	CV_71	CV_74
Combination_67_Brno	CV_70	CV_73
Combination_68_Brno	CV_69	CV_74
Combination_69_Brno	CV_68	CV_75
Combination_70_Brno	CV_67	CV_76
Combination_71_Brno	CV_66	CV_75
Combination_72_Brno	CV_65	CV_76
Combination_73_Brno	CV_64	CV_77
Combination_74_Brno	CV_63	CV_78
Combination_75_Brno	CV_62	CV_77
Combination_76_Brno	CV_61	CV_78
Combination_77_Brno	CV_60	CV_79
Combination_78_Brno	CV_59	CV_80
Combination_79_Brno	CV_58	CV_79
Combination_80_Brno	CV_57	CV_80
Combination_81_Brno	CV_77	CV_72
Combination_82_Brno	CV_78	CV_71
Combination_83_Brno	CV_77	CV_70
Combination_84_Brno	CV_78	CV_69
Combination_85_Brno	CV_79	CV_68
Combination_86_Brno	CV_80	CV_67
Combination_87_Brno	CV_79	CV_66
Combination_88_Brno	CV_80	CV_65
Combination_89_Brno	CV_73	CV_64
Combination_90_Brno	CV_74	CV_63
Combination_91_Brno	CV_73	CV_62
Combination_92_Brno	CV_74	CV_61
Combination_93_Brno	CV_75	CV_60
Combination_94_Brno	CV_76	CV_59
Combination_95_Brno	CV_75	CV_58
Combination_96_Brno	CV_76	CV_57

Appendix C

Examples of Responses to Interview Invitations

The texts provided below are the standard replies used to respond to employers' messages (interview invitations or requests for additional information about the candidates). "Version 1" was always utilized for applicants using CV template "T1," while "Version 2" was consistently employed for candidates with CV template "T2." In certain instances, the texts were slightly modified as needed.

Version 1
Dobrý den,
moc děkuji za reakci, ale ve výběrovém řízení na Vámi nabízenou pozici nebudu pokračovat.
S pozdravem (V. Ševčenko)

Version 2
Dobrý den, bohužel už o tuto pracovní nabídku nemám zájem.
Děkuji a přeji pěkný den.
(Yuliya Kovalchuk)

Appendix D

List of Variables

Table D.1: List of variables and their description

Name	Type	Description	Corresponding dummy variables (if created)
vacancy_id	categorical	unique identifier of a job offer	
vacancy_isco_st	categorical	job type (self-defined categories based on ISCO minor groups)	vacancy_isco_foodwaiter_dummy, vacancy_isco_salescash_dummy, vacancy_isco_info_dummy, vacancy_isco_office_dummy, vacancy_isco_other_dummy
vacancy_location	categorical	job location given by city/region - Praha, Středočeský, Brno or Jihomoravský. Note that jobs located Brno are categorized as "Brno", not "Jihomoravský"	vacancy_location_praha_dummy, vacancy_location_stredoc_dummy, vacancy_location_brno_dummy, vacancy_location_jihom_dummy
vacancy_cz_intext_st	categorical	level of Czech required specified in the text of a job ad; standardized for the purpose of classification into groups	
vacancy_cz_intext_mentioned_dummy	dummy	indicating whether knowledge of Czech (regardless of the level) is mentioned in the text of a job advertisement	
vacancy_en_intext_mentioned_dummy	dummy	indicating whether knowledge of English (regardless of the level) is mentioned in the text of a job advertisement	
vacancy_education_dummy	dummy	indicating whether high-school education or vocational school education is required	
vacancy_ualabel_dummy	dummy	indicating whether a given job advertisementhas a label "suitable for Ukrainian refugees"	
vacancy_software_req_dummy	dummy	indicating whether knowledge of basic software is required	
vacancy_drive_req_dummy	dummy	indicating whether driver's licence for a car is required	
vacancy_ftpt	categorical	employment type - full-time only/part-time only/full-time or part-time/temporary part-time ("brigáda")	vacancy_ftpt_ft_dummy, vacancy_ftpt_pt_dummy, vacancy_ftpt_both_dummy, vacancy_ftpt_brigada_dummy
vacancy_emplform	categorical	contract offered - employment contract only/alternative contract (e.g., agreement on working activity) only/employment or alternative contract/not specified	vacancy_emplform_emplonly_dummy, vacancy_emplform_altonly_dummy, vacancy_emplform_emplalt_dummy
vacancy_duration	categorical	duration of employment - open-ended contract/close-ended contract/not specified	vacancy_duration_open_dummy, vacancy_duration_close_dummy
comb_city	categorical	determining which "CV versions" would be sent - Prague or Brno	
comb_number	categorical	determining the "combination number" (between 1 and 96)	
comb_city_number	categorical	determines the way of responding to a given offer (i.e., "combination ID", consiting of "CV version" and "combination number")	
comb_treatment	categorical	treatment conditions of candidates matched to a given offer, regardless of the order (AB, BC, or AC)	

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Table D.1: List of variables and their description - continued

Name	Type	Description	For categorical variables: corresponding dummy variables
cv_sent_date *	N/A	date of application submission	
cv_reply_type *	categorical	type of response received (A-J) - explained in chapter "Dataset Description"	
cv_reply_info *	categorical	type of additional information required (for response type E only)	
cv_callback_main *	dummy	application process result according to the main definition of callback	
cv_callback_strict *	dummy	application process result according to the strict definition of callback	
cv_cvnumber *	categorical	unique CV identifier ("CV ID")	
cv_cvcode *	categorical	"CV code" corresponding to the "CV ID"	
cv_treatment *	categorical	treatment condition	cv_treatment_a_dummy, cv_treatment_b_dummy, cv_treatment_c_dummy
cv_name *	categorical	candidate's name	cv_viktorija_dummy, cv_yuliya_dummy, cv_tereza_dummy, cv_karolina_dummy
cv_educwork *	categorical	candidate's education and first job based on the "CV code" (taking nationality into account)	cv_kyiv_dummy, cv_odessa_dummy, cv_oa_dummy, cv_cr_dummy
cv_secondjob *	categorical	candidate's second job based on the "CV code" (taking nationality into account)	cv_supermarket_dummy, cv_exp_foodwaiter_dummy, cv_cvjobna_dummy
cv_template *	categorical	type of CV template	cv_t1_dummy, cv_t2_dummy
cv_exp_salescash_dummy	dummy	indicating whether the applicant studied at a business academy and worked as a shop assistant, regardless of nationality	
cv_exp_info_dummy	dummy	indicating whether the applicant studied tourism and worked as a receptionist/cashier, regardless of nationality	
cv_order_sent	categorical	specifying whether the CV was sent as the first or second experimental response to a given job offer	cv_sentfirst_dummy
vacancy_id_cv_order	categorical	"job ID" and the information whether the CV was sent first or second	
interaction_salescash	dummy	interaction of cv_exp_salescash_dummy and vacancy_isco_salescash_dummy	
interaction_foodwaiter	dummy	interaction of cv_exp_foodwaiter_dummy and vacancy_isco_foodwaiter_dummy	
interaction_info	dummy	interaction of cv_exp_info_dummy and vacancy_isco_info_dummy	

Note: The names of variables with an asterisk might also begin with "first_" or "second_" instead of "cv_", depending on the dataset version in question.

Appendix E

Randomization Checks

Table E.1: Randomization check of CV features and sending conditions

	Mean A	**Mean B**	**Mean C**	**p-val. A vs. B**	**p-val. A vs. C**	**p-val. B vs. C**	**p-val. C**
Viktorija (A, B only)	0.505	0.508	0.000	0.935	N/A	N/A	N/A
Tereza (C only)	0.000	0.000	0.500	N/A	N/A	N/A	1.000
Experience - SalesCash	0.502	0.492	0.506	0.809	0.904	0.718	N/A
Kyiv (A, B only)	0.498	0.508	0.000	0.809	N/A	N/A	N/A
Business academy (C only)	0.000	0.000	0.506	N/A	N/A	N/A	0.821
Supermarket (A, B only)	0.495	0.505	0.000	0.810	N/A	N/A	N/A
Template 1	0.505	0.498	0.497	0.873	0.842	0.968	N/A
Sent first	0.498	0.505	0.497	0.872	0.968	0.841	N/A

Note: The columns labeled "Mean" display the mean of a given dummy variable for each treatment/control group. Due to the experimental design, some features were considered either for the control group only or the two treatment groups only, resulting in some values being equal to zero. The columns labeled "p-val." show the p-values of two-tailed t-tests. In the first three cases, the null hypotheses were defined as the mean being equal for the two groups in question. Missing values indicate cases where no test was performed, due to one of the means being equal to zero. The last column is relevant only for the characteristics defined exclusively for the control group, displaying p-values of two-tailed t-tests with the null hypotheses of the mean being equal to 0.500.

Table E.2: Randomization check of job features

	Mean A	**Mean B**	**Mean C**	**p-val. A vs. B**	**p-val. A vs. C**	**p-val. B vs. C**
Location: Prague	0.687	0.696	0.606	0.811	0.036	0.020
Location: Central Bohemia	0.125	0.100	0.129	0.339	0.868	0.263
Location: Brno	0.102	0.120	0.145	0.488	0.104	0.352
Type: SalesCash	0.581	0.540	0.513	0.304	0.086	0.493
Type: Info	0.217	0.243	0.242	0.451	0.465	0.982
Type: FoodWaiter	0.125	0.129	0.177	0.856	0.066	0.098
Type: Office	0.058	0.074	0.048	0.396	0.612	0.178
CZ mentioned in text	0.089	0.100	0.100	0.645	0.654	0.989
EN mentioned in text	0.355	0.382	0.371	0.482	0.672	0.780
UA label	0.089	0.094	0.145	0.850	0.031	0.049
Education required	0.649	0.667	0.668	0.635	0.614	0.977
Software required	0.323	0.314	0.310	0.815	0.728	0.910
Driving required	0.038	0.042	0.035	0.813	0.850	0.672
FT/PT: Full-time only	0.626	0.644	0.635	0.645	0.811	0.825
FT/PT: Part-time only	0.054	0.045	0.061	0.606	0.710	0.377
FT/PT: Temporary part-time only	0.141	0.113	0.113	0.307	0.300	0.989
Contract: Employment only	0.629	0.625	0.639	0.902	0.810	0.716
Contract: Alternative only	0.169	0.142	0.145	0.355	0.408	0.922
Contract: Employment or alternative	0.173	0.214	0.187	0.195	0.636	0.411
Length: Open-ended	0.505	0.482	0.532	0.574	0.493	0.214
Length: Close-ended	0.176	0.188	0.184	0.699	0.791	0.903

Note: The columns labeled "Mean" display the mean of a given dummy variable for each treatment/control group. The columns labeled "p-val." show p-values of two-tailed t-tests, with the null hypotheses defined as the mean being equal for the two groups in question.

Appendix F

Additional Regression Results: LPM

The following pages include the results of OLS regressions using multiple different subsets. The specifications of individual models, *(1)* through *(5)*, follow the definitions stated in Subsection 6.3.1 - in cases where the exact same specification would not be meaningful, some variables were removed or the regression was not performed at all.

Table F.1: Regression results: LPM, selected models, "Prague" dataset, main callback definition

	Dependent variable:				
	cv_callback_main				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.014	−0.012	−0.010	−0.024	−0.030
	(0.029)	(0.030)	(0.029)	(0.034)	(0.033)
cv_treatment_c_dummy	0.212***	0.223***	0.220***	0.195***	0.177***
	(0.040)	(0.044)	(0.041)	(0.050)	(0.048)
cv_sentfirst_dummy		−0.037		−0.034	
		(0.029)		(0.030)	
vacancy_isco_salescash_dummy		0.024	0.052		
		(0.053)	(0.032)		
interaction_salescash		0.049		0.049	
		(0.040)		(0.041)	
vacancy_isco_info_dummy		0.005			
		(0.063)			
interaction_info		−0.009		−0.009	
		(0.057)		(0.061)	
vacancy_isco_foodwaiter_dummy		−0.031	−0.001		
		(0.077)	(0.051)		
interaction_foodwaiter		0.056		0.144	
		(0.088)		(0.115)	
vacancy_education_dummy		−0.065*	−0.031		
		(0.038)	(0.032)		
vacancy_cz_intext_mentioned_dummy		0.042			
		(0.050)			
vacancy_ualabel_dummy		−0.014	−0.036		
		(0.055)	(0.053)		
vacancy_ftpt_brigada_dummy		−0.117*			
		(0.061)			
vacancy_ftpt_ft_dummy		0.009			
		(0.038)			
vacancy_emplform_emplalt_dummy		−0.049	−0.035		
		(0.039)	(0.035)		
vacancy_duration_open_dummy		−0.039			
		(0.033)			
Constant	0.107***	0.172**	0.105***		
	(0.021)	(0.079)	(0.040)		
Fixed effects	No	No	No	Yes	Yes
Observations	618	618	618	618	618
Adjusted R^2	0.070	0.073	0.072	0.578	0.570
F Statistic	24.371*** (df = 2; 615)	4.039*** (df = 16; 601)	7.834*** (df = 7; 610)	3.688*** (df = 315; 303)	3.639*** (df = 311; 307)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.2: Regression results: LPM, selected models, "Prague" dataset, strict callback definition

	Dependent variable:				
	cv_callback_strict				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.037	−0.039	−0.035	−0.024	−0.027
	(0.023)	(0.024)	(0.023)	(0.031)	(0.029)
cv_treatment_c_dummy	0.171***	0.173***	0.175***	0.150***	0.141***
	(0.037)	(0.040)	(0.038)	(0.047)	(0.044)
cv_sentfirst_dummy		−0.016		−0.014	
		(0.025)		(0.028)	
vacancy_isco_salescash_dummy		0.032	0.034		
		(0.039)	(0.027)		
interaction_salescash		0.037		0.039	
		(0.034)		(0.039)	
vacancy_isco_info_dummy		0.034			
		(0.050)			
interaction_info		−0.022		−0.021	
		(0.050)		(0.056)	
vacancy_isco_foodwaiter_dummy		0.021	0.018		
		(0.068)	(0.047)		
interaction_foodwaiter		0.014		0.079	
		(0.080)		(0.098)	
vacancy_education_dummy		−0.053	−0.033		
		(0.033)	(0.028)		
vacancy_cz_intext_mentioned_dummy		0.050			
		(0.047)			
vacancy_ualabel_dummy		−0.031	−0.039		
		(0.048)	(0.046)		
vacancy_ftpt_brigada_dummy		−0.114**			
		(0.055)			
vacancy_ftpt_ft_dummy		−0.043			
		(0.035)			
vacancy_emplform_emplalt_dummy		−0.052	−0.027		
		(0.032)	(0.030)		
vacancy_duration_open_dummy		−0.042			
		(0.029)			
Constant	0.079***	0.153**	0.086**		
	(0.018)	(0.064)	(0.036)		
Fixed effects	No	No	No	Yes	Yes
Observations	618	618	618	618	618
Adjusted R^2	0.072	0.073	0.072	0.499	0.498
F Statistic	25.042*** (df = 2; 615)	4.038*** (df = 16; 601)	7.857*** (df = 7; 610)	2.951*** (df = 315; 303)	2.972*** (df = 311; 307)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.3: Regression results: LPM, selected models, "SalesCash" dataset, main callback definition

	Dependent variable:				
	cv_callback_main				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.042	−0.037	−0.033	−0.055	−0.056
	(0.034)	(0.033)	(0.033)	(0.037)	(0.035)
cv_treatment_c_dummy	0.220***	0.216***	0.221***	0.173***	0.176***
	(0.046)	(0.046)	(0.046)	(0.051)	(0.051)
cv_sentfirst_dummy		0.008		0.010	
		(0.033)		(0.034)	
cv_exp_salescash_dummy		0.038		0.039	
		(0.033)		(0.033)	
vacancy_location_praha_dummy		0.166***	0.151***		
		(0.039)	(0.038)		
vacancy_location_stredoc_dummy		0.253***	0.246***		
		(0.070)	(0.070)		
vacancy_location_jihom_dummy		0.202***	0.199***		
		(0.067)	(0.067)		
vacancy_education_dummy		−0.063	−0.024		
		(0.040)	(0.037)		
vacancy_cz_intext_mentioned_dummy		0.031			
		(0.104)			
vacancy_ualabel_dummy		0.196**	0.171*		
		(0.086)	(0.089)		
vacancy_ftpt_brigada_dummy		−0.233***			
		(0.067)			
vacancy_ftpt_ft_dummy		0.035			
		(0.037)			
vacancy_emplform_emplalt_dummy		−0.117***	−0.120***		
		(0.041)	(0.039)		
vacancy_duration_open_dummy		−0.048			
		(0.035)			
Constant	0.132***	0.017	0.009		
	(0.025)	(0.066)	(0.049)		
Fixed effects	No	No	No	Yes	Yes
Observations	508	508	508	508	508
Adjusted R^2	0.080	0.133	0.120	0.639	0.638
F Statistic	23.085*** (df = 2; 505)	6.555*** (df = 14; 493)	9.608*** (df = 8; 499)	4.489*** (df = 258; 250)	4.494*** (df = 256; 252)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.4: Regression results: LPM, selected models, "SalesCash" dataset, strict callback definition

	Dependent variable:				
	cv_callback_strict				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.063**	−0.061**	−0.057**	−0.047	−0.047
	(0.025)	(0.026)	(0.025)	(0.033)	(0.032)
cv_treatment_c_dummy	0.183***	0.181***	0.186***	0.153***	0.155***
	(0.042)	(0.042)	(0.042)	(0.050)	(0.050)
cv_sentfirst_dummy		0.014		0.013	
		(0.029)		(0.032)	
cv_exp_salescash_dummy		0.027		0.029	
		(0.029)		(0.031)	
vacancy_location_praha_dummy		0.130***	0.121***		
		(0.032)	(0.030)		
vacancy_location_stredoc_dummy		0.181***	0.178***		
		(0.062)	(0.062)		
vacancy_location_jihom_dummy		0.180***	0.178***		
		(0.063)	(0.063)		
vacancy_education_dummy		−0.025	0.003		
		(0.034)	(0.031)		
vacancy_cz_intext_mentioned_dummy		0.076			
		(0.103)			
vacancy_ualabel_dummy		0.076	0.057		
		(0.076)	(0.077)		
vacancy_ftpt_brigada_dummy		−0.160***			
		(0.052)			
vacancy_ftpt_ft_dummy		0.037			
		(0.034)			
vacancy_emplform_emplalt_dummy		−0.059	−0.063*		
		(0.037)	(0.036)		
vacancy_duration_open_dummy		−0.029			
		(0.031)			
Constant	0.093***	−0.030	−0.020		
	(0.022)	(0.050)	(0.038)		
Fixed effects	No	No	No	Yes	Yes
Observations	508	508	508	508	508
Adjusted R^2	0.089	0.113	0.106	0.530	0.530
F Statistic	25.882*** (df = 2; 505)	5.620*** (df = 14; 493)	8.553*** (df = 8; 499)	3.222*** (df = 258; 250)	3.238*** (df = 256; 252)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.5: Regression results: LPM, selected models, "AB/BA" dataset, main callback definition

	Dependent variable:				
	cv_callback_main				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.006	−0.006	−0.006	−0.006	−0.006
	(0.035)	(0.035)	(0.033)	(0.024)	(0.020)
cv_treatment_c_dummy					
cv_sentfirst_dummy		−0.006		−0.006	
		(0.033)		(0.022)	
vacancy_location_praha_dummy		0.050*	0.075***		
		(0.028)	(0.023)		
vacancy_location_stredoc_dummy		0.348***	0.387***		
		(0.086)	(0.089)		
vacancy_location_jihom_dummy		0.131	0.135		
		(0.100)	(0.089)		
vacancy_isco_salescash_dummy		0.016	−0.072*		
		(0.064)	(0.042)		
interaction_salescash		0.010		0.010	
		(0.040)		(0.027)	
vacancy_isco_info_dummy		0.106			
		(0.089)			
interaction_info		−0.001		−0.001	
		(0.093)		(0.068)	
vacancy_isco_foodwaiter_dummy		−0.056	−0.148**		
		(0.087)	(0.061)		
interaction_foodwaiter		−0.003		−0.003	
		(0.087)		(0.013)	
vacancy_education_dummy		−0.024	−0.045		
		(0.042)	(0.038)		
vacancy_cz_intext_mentioned_dummy		0.062			
		(0.074)			
vacancy_ualabel_dummy		0.175*	0.185*		
		(0.105)	(0.099)		
vacancy_ftpt_brigada_dummy		0.081			
		(0.058)			
vacancy_ftpt_ft_dummy		0.082**			
		(0.034)			
vacancy_emplform_emplalt_dummy		−0.018	−0.060		
		(0.046)	(0.043)		
vacancy_duration_open_dummy		−0.086**			
		(0.039)			
Constant	0.109***	−0.016	0.095*		
	(0.025)	(0.086)	(0.053)		
Fixed effect	No	No	No	Yes	Yes
Observations	312	312	312	312	312
Adjusted R^2	−0.003	0.126	0.112	0.844	0.848
F Statistic	0.034 (df = 1; 310)	3.502*** (df = 18; 293)	5.373*** (df = 9; 302)	11.498*** (df = 161; 151)	12.061*** (df = 157; 155)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.6: Regression results: LPM, selected models, "AB/BA" dataset, strict callback definition

	Dependent variable:				
	cv_callback_strict				
	(1)	(2)	(3)	(4)	(5)
cv_treatment_b_dummy	−0.013 (0.027)	−0.013 (0.026)	−0.013 (0.025)	−0.013 (0.022)	−0.013 (0.018)
cv_treatment_c_dummy					
cv_sentfirst_dummy		0.0001 (0.025)		0.0001 (0.020)	
vacancy_location_praha_dummy		0.028 (0.024)	0.036^{*} (0.021)		
vacancy_location_stredoc_dummy		0.227^{***} (0.075)	0.245^{***} (0.076)		
vacancy_location_jihom_dummy		0.140 (0.090)	0.148^{*} (0.089)		
vacancy_isco_salescash_dummy		0.021 (0.029)	-0.068^{**} (0.034)		
interaction_salescash		−0.001 (0.028)		−0.001 (0.021)	
vacancy_isco_info_dummy		0.139^{**} (0.066)			
interaction_info		−0.003 (0.083)		−0.003 (0.068)	
vacancy_isco_foodwaiter_dummy		−0.008 (0.063)	-0.092^{*} (0.055)		
interaction_foodwaiter		−0.007 (0.082)		−0.007 (0.012)	
vacancy_education_dummy		-0.054^{*} (0.031)	-0.070^{**} (0.032)		
vacancy_cz_intext_mentioned_dummy		−0.067 (0.056)			
vacancy_ualabel_dummy		0.215^{*} (0.112)	0.251^{**} (0.108)		
vacancy_ftpt_brigada_dummy		0.044 (0.047)			
vacancy_ftpt_ft_dummy		0.020 (0.025)			
vacancy_emplform_emplalt_dummy		−0.002 (0.034)	−0.033 (0.034)		
vacancy_duration_open_dummy		-0.049^{*} (0.029)			
Constant	0.064^{***} (0.020)	0.009 (0.049)	0.096^{*} (0.049)		
Fixed effects	No	No	No	Yes	Yes
Observations	312	312	312	312	312
Adjusted R^2	−0.002	0.162	0.145	0.772	0.778
F Statistic	0.234 (df = 1; 310)	4.342^{***} (df = 18; 293)	6.868^{***} (df = 9; 302)	7.560^{***} (df = 161; 151)	7.955^{***} (df = 157; 155)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Table F.7: Regression results: LPM, selected models, "SentFirst" dataset, main and strict callback definitions

	Dependent variable:			
	cv_callback_main		cv_callback_strict	
	(1)	(2)	(3)	(4)
cv_treatment_b_dummy	−0.031	−0.029	−0.050	−0.049
	(0.037)	(0.035)	(0.033)	(0.031)
cv_treatment_c_dummy	0.152***	0.148***	0.099**	0.097**
	(0.047)	(0.045)	(0.043)	(0.042)
vacancy_location_praha_dummy	0.106***	0.121***	0.084**	0.096***
	(0.038)	(0.036)	(0.033)	(0.031)
vacancy_location_stredoc_dummy	0.287***	0.298***	0.224***	0.235***
	(0.072)	(0.069)	(0.067)	(0.064)
vacancy_location_jihom_dummy	0.206***	0.200***	0.167**	0.166***
	(0.072)	(0.070)	(0.066)	(0.064)
vacancy_isco_salescash_dummy	0.057	0.083**	0.055	0.063**
	(0.053)	(0.036)	(0.041)	(0.032)
interaction_salescash	0.147***		0.101**	
	(0.047)		(0.042)	
vacancy_isco_info_dummy	0.052		0.047	
	(0.061)		(0.050)	
interaction_info	0.016		0.021	
	(0.069)		(0.060)	
vacancy_isco_foodwaiter_dummy	0.065	0.054	0.117	0.095
	(0.082)	(0.060)	(0.077)	(0.059)
interaction_foodwaiter	0.096		0.057	
	(0.109)		(0.110)	
vacancy_education_dummy	−0.062	−0.052	−0.058	−0.050
	(0.045)	(0.039)	(0.041)	(0.036)
vacancy_cz_intext_mentioned_dummy	0.037		0.022	
	(0.069)		(0.062)	
vacancy_ualabel_dummy	0.029	0.032	0.022	0.028
	(0.066)	(0.062)	(0.063)	(0.060)
vacancy_ftpt_brigada_dummy	−0.040		−0.034	
	(0.079)		(0.071)	
vacancy_ftpt_ft_dummy	−0.018		−0.023	
	(0.044)		(0.041)	
vacancy_emplform_emplalt_dummy	−0.095**	−0.086**	−0.079**	−0.068*
	(0.044)	(0.040)	(0.039)	(0.036)
vacancy_duration_open_dummy	0.011		0.025	
	(0.037)		(0.032)	
Constant	−0.031	−0.012	−0.022	−0.002
	(0.091)	(0.057)	(0.075)	(0.051)
Observations	466	466	466	466
Adjusted R^2	0.100	0.089	0.077	0.075
F Statistic	3.861*** (df = 18; 447)	5.532*** (df = 10; 455)	3.156*** (df = 18; 447)	4.786*** (df = 10; 455)
Note:	*p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses			

Table F.8: Regression results: LPM, model with CV features, full dataset, main and strict callback definitions

	Dependent variable:			
	cv_callback_main		cv_callback_strict	
	(1)	(2)	(3)	(4)
cv_treatment_b_dummy	−0.029	−0.025	−0.043**	−0.021
	(0.026)	(0.027)	(0.021)	(0.025)
cv_treatment_c_dummy	0.159***	0.171***	0.122***	0.135***
	(0.043)	(0.037)	(0.039)	(0.035)
cv_prg_dummy	0.067**		0.046*	
	(0.028)		(0.025)	
cv_viktorija_dummy	0.009		0.023	
	(0.026)		(0.021)	
cv_tereza_dummy	0.065		0.059	
	(0.052)		(0.048)	
cv_exp_salescash_dummy	0.028		0.017	
	(0.024)		(0.021)	
cv_exp_foodwaiter_dummy	0.013		−0.007	
	(0.026)		(0.021)	
cv_t1_dummy	0.014		−0.006	
	(0.024)		(0.021)	
cv_sentfirst_dummy	−0.016		−0.001	
	(0.024)		(0.021)	
Constant	0.049		0.045	
	(0.039)		(0.033)	
Fixed effects	No	Yes	No	Yes
Observations	932	932	932	932
Adjusted R^2	0.058	0.600	0.053	0.524
F Statistic	7.335*** (df = 9; 922)	3.983*** (df = 468; 464)	6.812*** (df = 9; 922)	3.195*** (df = 468; 464)

Note: *p<0.1; **p<0.05; ***p<0.01, robust standard errors in parentheses

Appendix G

Regression Results: Logit and Probit

Table G.1: Regression results: logit, selected models, full dataset, main callback definition

	(1)		(2)		(4)		(5)	
	AME	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*
cv_treatment_b_dummy	-0.041	2.08e-01	-0.028	3.80e-01	-0.010	5.39e-01	-0.007	6.71e-01
cv_treatment_c_dummy	0.165	1.57e-06	0.177	6.18e-07	0.128	3.41e-31	0.124	2.05e-26
cv_sentfirst_dummy			-0.015	5.17e-01	0.001	8.82e-01		
vacancy_location_praha_dummy			0.166	1.13e-05				
vacancy_location_stredoc_dummy			0.398	4.48e-06				
vacancy_location_jihom_dummy			0.355	1.49e-04				
vacancy_isco_salescash_dummy			0.074	1.91e-01				
interaction_salescash			0.038	2.58e-01	0.022	9.22e-02		
vacancy_isco_info_dummy			0.082	2.67e-01				
interaction_info			-0.014	7.59e-01	0.004	8.27e-01		
vacancy_isco_foodwaiter_dummy			0.037	6.17e-01				
interaction_foodwaiter			0.049	5.53e-01	0.072	1.18e-10		
vacancy_education_dummy			-0.057	5.83e-02				
vacancy_cz_intext_mentioned_dummy			0.023	6.12e-01				
vacancy_ualabel_dummy			0.059	1.87e-01				
vacancy_ftpt_brigada_dummy			-0.047	2.67e-01				
vacancy_ftpt_ft_dummy			0.013	6.52e-01				
vacancy_emplform_emplalt_dummy			-0.049	1.13e-01				
vacancy_duration_open_dummy			-0.042	1.00e-01				
Fixed effects	No		No		Yes		Yes	
McFadden R^2	0.058		0.115		0.897		0.879	

Table G.2: Regression results: logit, selected models, full dataset, strict callback definition

	(1)		(2)		(4)		(5)	
	AME	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*
cv_treatment_b_dummy	-0.062	1.86e-02	-0.053	4.75e-02	-0.036	7.46e-02	-0.026	2.17e-01
cv_treatment_c_dummy	0.122	2.68e-05	0.129	2.36e-05	0.091	1.71e-11	0.089	3.64e-10
cv_sentfirst_dummy			-0.001	9.78e-01	0.012	1.29e-01		
vacancy_location_praha_dummy			0.134	6.02e-04				
vacancy_location_stredoc_dummy			0.346	6.59e-04				
vacancy_location_jihom_dummy			0.319	2.76e-03				
vacancy_isco_salescash_dummy			0.076	1.76e-01				
interaction_salescash			0.027	3.65e-01	0.012	2.93e-01		
vacancy_isco_info_dummy			0.087	2.66e-01				
interaction_info			0.004	9.31e-01	0.030	6.93e-02		
vacancy_isco_foodwaiter_dummy			0.087	2.97e-01				
interaction_foodwaiter			0.036	6.15e-01	0.052	4.61e-04		
vacancy_education_dummy			-0.044	1.04e-01				
vacancy_cz_intext_mentioned_dummy			0.016	6.82e-01				
vacancy_ualabel_dummy			0.024	5.11e-01				
vacancy_ftpt_brigada_dummy			-0.020	6.10e-01				
vacancy_ftpt_ft_dummy			-0.000	9.88e-01				
vacancy_emplform_emplalt_dummy			-0.034	2.06e-01				
vacancy_duration_open_dummy			-0.024	3.00e-01				
Fixed effects	No		No		Yes		Yes	
McFadden R^2	0.070		0.122		0.883		0.867	

Table G.3: Regression results: probit, selected models, full dataset, main callback definition

	(1)		(2)		(4)		(5)	
	AME	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*
cv_treatment_b_dummy	-0.038	2.14e-01	-0.025	4.11e-01	-0.013	4.39e-01	-0.006	6.97e-01
cv_treatment_c_dummy	0.168	7.73e-07	0.182	1.77e-07	0.126	3.03e-01	0.124	1.14e-03
cv_sentfirst_dummy			-0.016	5.08e-01	0.000	9.87e-01		
vacancy_location_praha_dummy			0.157	4.98e-06				
vacancy_location_stredoc_dummy			0.370	1.52e-06				
vacancy_location_jihom_dummy			0.326	7.65e-05				
vacancy_isco_salescash_dummy			0.065	2.22e-01				
interaction_salescash			0.038	2.51e-01	0.020	1.02e-01		
vacancy_isco_info_dummy			0.068	3.14e-01				
interaction_info			-0.007	8.83e-01	0.004	8.21e-01		
vacancy_isco_foodwaiter_dummy			0.023	7.30e-01				
interaction_foodwaiter			0.050	5.31e-01	0.071	5.85e-01		
vacancy_education_dummy			-0.061	4.31e-02				
vacancy_cz_intext_mentioned_dummy			0.030	5.01e-01				
vacancy_ualabel_dummy			0.061	1.69e-01				
vacancy_ftpt_brigada_dummy			-0.050	2.48e-01				
vacancy_ftpt_ft_dummy			0.012	6.82e-01				
vacancy_emplform_emplalt_dummy			-0.047	1.20e-01				
vacancy_duration_open_dummy			-0.041	1.06e-01				
Fixed effects	No		No		Yes		Yes	
McFadden R^2	0.058		0.116		0.897		0.879	

Table G.4: Regression results: probit, selected models, full dataset, strict callback definition

	(1)		(2)		(4)		(5)	
	AME	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*	*AME*	*p-val.*
cv_treatment_b_dummy	-0.058	2.31e-02	-0.050	5.30e-02	-0.034	8.19e-02	-0.024	2.07e-01
cv_treatment_c_dummy	0.125	1.93e-05	0.135	9.49e-06	0.090	2.43e-05	0.089	1.27e-09
cv_sentfirst_dummy			-0.001	9.58e-01	0.009	2.50e-01		
vacancy_location_praha_dummy			0.123	2.77e-04				
vacancy_location_stredoc_dummy			0.312	2.05e-04				
vacancy_location_jihom_dummy			0.287	1.22e-03				
vacancy_isco_salescash_dummy			0.063	2.11e-01				
interaction_salescash			0.029	3.34e-01	0.013	2.35e-01		
vacancy_isco_info_dummy			0.069	3.04e-01				
interaction_info			0.009	8.32e-01	0.029	7.81e-02		
vacancy_isco_foodwaiter_dummy			0.067	3.45e-01				
interaction_foodwaiter			0.034	6.15e-01	0.049	1.33e-02		
vacancy_education_dummy			-0.046	8.33e-02				
vacancy_cz_intext_mentioned_dummy			0.020	5.98e-01				
vacancy_ualabel_dummy			0.030	4.17e-01				
vacancy_ftpt_brigada_dummy			-0.025	5.14e-01				
vacancy_ftpt_ft_dummy			-0.007	7.86e-01				
vacancy_emplform_emplalt_dummy			-0.032	2.31e-01				
vacancy_duration_open_dummy			-0.024	2.95e-01				
Fixed effects	No		No		Yes		Yes	
McFadden R^2	0.070		0.124		0.882		0.867	