DEPARTMENT
OF POLITICAL AND
SOCIAL SCIENCES

Duration dependence and discrimination in the youth labour market.

Experimental evidence from the decision-making of Italian employers.

Mario Spiezio

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Political and Social Sciences
of the European University Institute

Florence, 26 January 2023

European University Institute
Department of Political and Social Sciences

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Examining Board
Prof. Klarita Gërxhani, European University Institute (EUI Supervisor)
Prof. Alicia Adsera, Princeton University
Prof. Michèle Belot, Cornell University
Prof. Bernhard Kittel, University of Vienna

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Department of Political and Social Sciences - Doctoral Programme

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Abstract

The International Labour Organization estimates that there will be 52 million jobs missing in 2022 and an additional 21 million people in unemployment compared to the pre-pandemic period. Women and those with an immigrant background will be adversely affected. These workers already faced a higher risk of losing jobs before the COVID-19 outbreak. The question then is whether, during the recovery, women and those with an immigrant background will also take longer to find a job than men and native workers. Longer job search entails increasing time in unemployment and employers may be less likely to consider hiring someone with extended periods of joblessness. Thus, longer unemployment duration might become an additional liability for women and workers with an immigrant background when looking for jobs. Research has documented the negative effect of unemployment duration on employment prospects, namely duration dependence, but some studies show this relationship might be spurious. Further, research on discrimination looked at the differential impact of unemployment duration based on gender or immigrant background but rarely investigated their intersection. This thesis, therefore, looks at the relationship between duration dependence and discrimination. It assesses how employers utilize unemployment duration, gender, and immigrant background, and their intersection in hiring processes. Using a correspondence study, 4,079 resumes were sent to 1,041 Italian employers who posted online vacancies between September 2019 and May 2020. Responses to these resumes show that duration dependence and discrimination are independent phenomena: unemployment duration is not more detrimental for any group of job seekers. Discrimination stems from employers' bias and whether employers use gender to sort applicants depends on the immigrant background. Nonetheless, who gets discriminated against varies with job quality and the formalization of the hiring process. Overall, results suggest that Italian employers help push women and those with an immigrant background toward low-quality jobs.

Acknowledgments

In the past six years, I am not sure how many times I thought that the day of submitting this thesis will ever come. The journey has been very long and bumpy with so many life-changing events. I started this Ph.D. as a researcher and by its end, I have become a husband and a parent. I am therefore very grateful to all of you who helped me along the way. Particularly, I want to thank you Klarita for your mentorship and support throughout the past years. I know I must have caused quite a few of your headaches, but you kept my motivation high and changed the way I approach research. Without your guidance, I would have not had the opportunity to work with Arianna who has made this project possible thanks to her passion and competencies. Arianna, I enjoyed our discussions on how to improve the design of the data collection and our continuous exchange even after the end of that process. I will always be indebted to you and I hope I will have the chance to return the favor one day.

This project also benefitted from the many encounters and friends I made at the EUI and those, like Simone, who I met way before starting the Ph.D. If I am going to defend this dissertation, it is also because you told me about the EUI and your project. Those chats were a great source of inspiration. Without your help, I would have never met good friends and research buddies such as Marco, Carlos, Ilze, Francesco, Ezgi, and Krzys with whom I shared the joy and the pain of doing research. I also want to thank Diego, Fabrizio, and Elias for what I have learned during your courses and for the rich discussions with other researchers attending your classes. Likewise, I want to thank the jurors of the defense committee and Valentina Di Stasio for taking the time to read my manuscript and for providing valuable feedback.

Last but not least, I want to share this achievement with my family who has always been standing by me throughout this journey. Without the love, persistence, and sacrifices of my parents, I could have never dreamed of pursuing a Ph.D. Erica, you are my partner in crime and you have also been my compass. You helped me balance things out while supporting me when I needed it the most. I also want to dedicate this achievement to my brother and sister and my daughter Agata.

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1 Discrimination and duration dependence: are they (in)dependent?

The International Labour Organization estimates that there will be 52 million jobs missing in 2022 compared to the pre-pandemic period, as well as an additional 21 million people in unemployment worldwide (Dewan, Ernst, and Achkar Hilal 2022). The ILO also shows that the impact of this employment crisis has been larger among women and those with an immigrant background/ethnic minorities. Women and those with an immigrant background experienced a higher risk of losing their jobs compared to men and native workers in the European Union (Fasani and Mazza 2020). Such a higher risk of losing jobs and income stems from the fact that women (Hurley 2021) and migrant workers/ethnic minorities (OECD 2022) were more likely to hold, even before the pandemic, low-paid jobs with short-term contracts that could not be performed remotely. Women were also more likely to have to take care of family members and leave their jobs (Tooze 2021).

The question then is whether, during the recovery from the COVID-19 pandemic, women and those with an immigrant background/ethnic minorities will also take longer to find a job than men and native workers. Providing an answer matters given that a longer job search entails increasing time in unemployment, which in turn may reduce the likelihood of finding employment (Ellwood 1979). During the Great Recession, the average time spent in unemployment increased (Krueger, Cramer, and Cho 2014) and exit rates from joblessness were lower among individuals in long-term unemployment compared to those in unemployment for less than 12 months (Elsby, Smith, and Wadsworth 2016). Thus, if women and those with immigrant backgrounds/ethnic minorities spend more time out of work than, respectively, men and native-born workers, increasing unemployment duration can become an additional liability when looking for jobs in the post-COVID-19 pandemic.

However, is unemployment duration (more) detrimental to job prospects for women and those with immigrant backgrounds/ethnic minorities? While there is abundant evidence of the adverse effect of unemployment duration on employment prospects, namely duration dependence (Arulampalam, Booth, and Taylor 2000; Gregg 2001; Gangl 2004), research also shows that this relationship could be spurious (Machin and Manning 1999). Those remaining out of work for longer, for example, might not be as productive as those who remained in unemployment for shorter periods (Heckman and Borjas 1980). Unobserved heterogeneity of the pool of workers in unemployment would then drive duration dependence (Devine and Kiefer 1991).

This proposition also resonates with statistical discrimination models, which aim to explain differential labour market outcomes (Arrow 1973). The key tenet behind these models is that groups of workers, like women and ethnic minorities, have different productivity distributions than their respective counterparts (Phelps 1972). These underlying differences, which are known in the labor market, make women and ethnic minorities less likely to be considered for jobs than men and native workers (Correll and Benard 2006). Women and ethnic minorities would then spend more time searching for jobs and experience longer periods of unemployment than those groups known to be, on average, more productive. Consequently, longer unemployment duration would not be more harmful to women and ethnic minorities compared to their respective counterparts. Between-group differences in time spent out of work would simply stem from differences in unobserved characteristics between men and women and ethnic minorities and native workers.

The discussion on unobserved heterogeneity illustrates that isolating true duration dependence, and any differential impact of unemployment duration on employment prospects, remains challenging. Observational studies necessitate detailed information on candidates' employment histories and life events and when these are not available, or data are truncated, strong assumptions need to be made about what happened before the first available data point (Heckman and Borjas 1980). Further, in contexts where all this information on workers' employment histories is available, data on individual productivity are still hard to measure and obtain (Arrow 1973). This suggests, and may also imply, that group differences in productivity distributions could just be stereotypical representations of the competencies and social worth of women versus men and ethnic minorities vis-à-vis native workers (Berger, Cohen, and Zelditch 1972; Correll and Ridgeway 2006; Ridgeway 2014).

Due to these limitations in the literature on the supply side of the labour market, researchers have turned increasingly to the study of employers and hiring processes to isolate duration dependence (Oberholzer-Gee 2008; Ghayad 2013; Kroft et al. 2014) and to understand what would make unemployment detrimental for job prospects (Bills 1990; Bonoli 2014; Van Belle et al. 2017). Likewise, researchers working on discrimination have been looking at employers and hiring processes to disentangle differential treatment (Azmat and Petrongolo 2014; Neumark 2018) and whether unemployment duration was more (less) detrimental for women and ethnic minorities compared to men and native workers (Eriksson and Rooth 2014; Pedulla 2016; Birkelund, Heggebø, and Rogstad 2017; Carlsson, Fumarco, and Rooth 2018).

Such growing interest acknowledges that employers influence the number of available vacancies (Moss and Tilly 2001) and make decisions about who can gain access to job opportunities (Bills, Di Stasio, and Gërxhani 2017). Importantly, employers define with job requirements and credentials who qualify for the job (Modestino, Shoag, and Ballance 2015) and decide who will be called for an interview, which is an opportunity to show qualities that cannot be directly seen in written job applications (Protsch and Solga 2015). Those who are not selected for the interview stage will not have that chance and will have to move on to the next job application while staying longer in unemployment. However, efforts and time spent on job search go down as unemployment duration lengthens up to the point of stopping job search (Krueger and Mueller 2008; Krueger et al. 2011).

Thus, looking at how employers review written information about prospective candidates, in the first step of the hiring process, namely screening, can be critical to isolate and explain duration dependence. First, it could help reconcile contrasting research findings from the literature on duration dependence, given that a lot of efforts have gone into methodological debates drifting away from more substantive discussions. Second, it would help get a better understanding of employers' motives that might make unemployment duration a salient piece of information in their decision to call back a candidate for an interview. In this regard, there are research gaps in the literature on duration dependence on how employers use, understand, and aggregate details about applicants' employment histories, such as unemployment duration, with additional information available in resumes like gender and ethnicity (Pedulla 2018b).

While there are some studies on the intersection of ethnicity and gender, with mixed findings (Zschirnt and Ruedin 2016), as well as on race, gender, and type of occupation (Valentina Di Stasio and Larsen 2020), little research, and just in the US, has been carried out on how employers deal with the intersection of unemployment duration, gender, and ethnicity (Pedulla 2020). As such, studying the screening phase of the hiring process can tell whether what employers infer from unemployment duration depends on gender and ethnicity/immigrant background. Importantly, providing evidence on the relationship between duration dependence and discrimination, in the aftermath of COVID-19 and contexts other than the US, will be critical to understanding whether employers contribute to deepening pre-existing inequalities in the labour market.

This thesis, therefore, focuses on employers and how they carry out the screening phase of the hiring process. First, the thesis looks at whether and how employers use unemployment duration, gender, and immigration background to select prospective job candidates before and

after the start of the COVID-19 pandemic. Second, the thesis assesses the relationship between duration dependence and discrimination. Particularly, the thesis analyses how employers bring together inferences they make about unemployment duration, gender, and immigration background when deciding who will move to the interview stage of the hiring process. In this regard, the thesis will assess the extent that what employers "learn" from unemployment duration depends on gender and immigration background, as well as on their intersection.

To understand how employers identify prospective job applicants during the screening phase of the hiring process, the thesis relies on data collected through a correspondence study. In this research design, employers are contacted using fictitious resumes in response to real job vacancies (Gaddis 2018). Resumes sent to employers in this study were designed to be of equivalent quality (age, education, length of work experience). Nonetheless, using a factorial approach (Valentina Di Stasio and Lancee 2020), key variables, namely gender, immigrant background, and unemployment duration, were randomly assigned to fictitious resumes[1]. In real life, these characteristics are strongly interdependent making it very hard to isolate duration dependence and discrimination, let alone any potential interaction between the two. Random variation of characteristics in this study, therefore, ensures that details provided in resumes, particularly gender, migration background, and unemployment duration are not correlated.

Randomization also means that the analysis of the data generated by this correspondence study can gauge the impact of every single characteristic, and their interaction, on employers' decision to call back an applicant for an interview. This variable is the key outcome of interest in this thesis. By looking at differences in callback rates between applicants with varying configurations of unemployment duration, gender, and immigrant background the thesis aims to grasp whether and how employers use available information to screen prospective job applicants. Ultimately, this analysis would help answer the question of the relationship between duration dependence and discrimination.

Overall, 4,079 resumes were sent to 1,041 Italian employers who published vacancies on online job portals focusing on 11 of the most populous cities in Italy: five cities in the North, namely Bologna, Genova, Milan, Turin, and Verona; two cities in the central region (Florence and Rome), as well as four cities in the Southern region (Bari, Catania, Naples, and Palermo). Data collection concentrated on the private service sector. Resumes targeted employers posting vacancies for entry-mid level jobs in Human Resources (HR), Administration, and Marketing.

[1] Other characteristics generally available in resumes were also randomized within- and between-vacancies. See Chapter 4 for greater detail on the structure of resumes and the randomization routine that has been leveraged in this correspondence study.

data collection was carried out between September 2019 and May 2020, which help factor in the impact of COVID-19 on employers' decision-making. Particularly, by comparing employers' responses and use of information before and after the restrictions that the Italian Government put in place to "flatten the curve."

Italy was selected as the sole case study of this research. The country is characterized by within-country differences in (youth) long-term unemployment rates (ISTAT 2018b), in the functioning of the labour market (Lupi and Ordine 2002), and with regards to gender inequality (Amici and Stefani 2013; Curci and Mariani 2013). Italy has also an increasing number of new labour market entrants who have an immigrant background, particularly of Romanian origins (Colucci 2019). Importantly, youth unemployment is widespread across the Italian labour market, but outcomes of the school-to-work transition and its duration are quite heterogenous, particularly among Italian young graduates (Pastore, Quintano, and Rocca 2021). There are also very few correspondence studies carried out in Italy on discrimination (Allasino et al. 2004; Busetta, Campolo, and Panarello 2018; 2020), but none on duration dependence, which has been studied in stronger labour markets with just some exceptions (Bentolila, Garcia-Perez, and Jansen 2017). In this regard, Italy, which has a generalized high level of unemployment, with sharp within-country variations in rates and duration, provides a unique case study to generate evidence in a type of context that is often overlooked.

Overall, results from this research show that Italian employers use unemployment duration in the screening phase when they have limited time to review resumes. Also, when employers emphasize motivation as a job requirement and applicants provide evidence about meeting it, employers grow wary of applicants in long-term unemployment. Importantly, the study shows no regional variations in how Italian employers use unemployment duration in the screening phase, neither before, nor after the COVID-19 outbreak.

Results on discrimination instead indicate that employers consistently prefer women to men and Italians to Romanian-Italians (before and after COVID-19). Nonetheless, these "preferences" are strongly tied to job quality. Employers discriminate against Romanian-Italian applicants for jobs matching their qualifications. However, no differential treatment is detected when Romanian-Italians are overqualified or apply for jobs offering short-term contracts. Employers also tend to strongly prefer women to men, but such differential treatment is driven by employers offering low-quality jobs, as well as by employers who believe that women are the best workers to perform the job that is advertised. From a substantive standpoint, results

suggest that employers and their decision-making help push women and second-generation Italians into a loop of low-quality jobs.

After intersecting time out of work, with gender and immigrant background, the study shows that unemployment duration informs employer decision-making, but time out of work is not more detrimental for any group of applicants. Therefore, in the Italian context, duration dependence does not hinge on discrimination. However, the analysis indicates clearly that employers use the immigrant background as a sorting criterion when deciding who to call back. In this regard, what employers infer from gender and how they use it in the decision to interview an applicant depends on the immigrant background of that applicant. Nonetheless, on a positive note, results indicate that greater formalization of the hiring process is associated with decreasing rates of discrimination.

The results of this thesis contribute to the growing literature on the demand side of the labour market, which looks at hiring processes to shed light on labour market inequalities (Bills, Di Stasio, and Gërxhani 2017). By bringing together the existing body of research on duration dependence and discrimination, this thesis informs the literature looking at what could make unemployment duration salient for employers when choosing who will move to the interview stage (Van Belle et al. 2017); how employers' beliefs on gender and immigrant background/ethnicity shape decision-making in hiring processes (Correll and Benard 2006; Pedulla 2018b); how intersectionality influence employers' decision-making, a topic currently understudied (Pedulla 2018a).

Importantly, the study of employers' motives can help reconcile mixed findings on duration dependence, as well as on discrimination, especially those on gender. Observational studies point to pervasive discrimination in contrast with experimental evidence (Azmat and Petrongolo 2014). Findings from previous correspondence studies on gender discrimination, which focus on the screening phase of the hiring process, do not point to differences between men and women in terms of callbacks (Riach and Rich 2002; Neumark 2018). Nonetheless, evidence from a harmonized cross-country correspondence study shows that employers in Germany, the Netherlands, Spain, and the UK consistently prefer women to men, while they do not find any gender differential treatment in Norway (Birkelund et al. 2021). In this regard, the current study helps explain these contrasting findings from the literature on gender discrimination by incorporating the role of employers' beliefs, job quality, and formalization in the hiring process. Importantly, this is done in a context, namely Italy, that is not part of any previous experimental studies on hiring processes.

Similarly, focusing on how employers assess young second-generation wo(men) can contribute to the literature that focuses on their integration or lack thereof (Portes and Zhou 1993; Alba 2005) and more specifically to research on second generations in the Italian context (Ballarino and Panichella 2015). Existing correspondence studies in Italy in fact focus on first-generation only (workers born abroad) (Busetta, Campolo, and Panarello 2018). These cannot inform us directly about how new generations of Italians will fare in the labour market. Employers might be extremely reluctant to hire first-generation workers because of perceived differences in core skills and competencies compared to natives (Oreopoulos 2011). Second-generation Italians instead share their education and culture with their prospective employers, being born and raised in the same country. Their number is also projected to increase (Colucci 2019) and this trend will deeply modify and increasingly characterize the Italian society over the next decades (ISTAT 2020b). However, the evidence base on migration and integration in the Italian context remains rather limited regardless of its relevance (Mariani, Pasquini, and Rosati 2020). As such, the current project complements previous correspondence studies on first generations while informing the substantive question about how employers are going to deal with changes in the composition of the labour force.

In this regard, the current thesis concentrates on young graduates in the initial stages of their employment histories because the first decade of work experience shapes dramatically future labour market participation (Luijkx and Wolbers 2009) and earning trajectories (Bernhardt et al. 2001). Given that youth unemployment has increasingly become an endemic feature of the Italian labour market (ISTAT 2018b), it is fundamental to better understand the implications of this phenomenon on the labour market participation of young people. Research in Europe on long-term unemployment remains scant despite of the size of the phenomenon and the heightened risk of economic and social exclusion (Bentolila and Jansen 2016).

Research shows that in a context where the structural rate of unemployment is lower, employers' screening practices contribute directly to duration dependence (Ghayad 2013; Kroft, Lange, and Notowidigdo 2013; Eriksson and Rooth 2014; Nunley et al. 2017). There are instead fewer papers, mainly based on observational data, that look at contexts where the structural rate of unemployment is higher, like Italy (Lupi and Ordine 2002) and Spain (Bentolila, Garcia-Perez, and Jansen 2017), which still find duration dependence. The results in the thesis complement these papers showing that the direct role employers play with their hiring practices in the generation of duration dependence is limited in a context with very high levels of (youth) unemployment (duration).

Nonetheless, it is worth highlighting that employers' discriminatory practices may still contribute to unemployment dynamics. Some applicants like Romanian-Italians who are more likely to be rejected have to send more applications to get an interview and while doing that they end up spending more time out of work. This is problematic if we consider research showing that applicants tend to send fewer applications as their unemployment duration lengthens while the risk of dropping out of the labour force increases (Krueger and Mueller 2008; Krueger et al. 2011). As such, even if employers generally do not look at unemployment duration, screening practices generate differential risks of experiencing long periods out of work. It follows that the risk of dropping out of the labour force also stratifies along gender and ethnicity.

Also, it is striking, given the context of the study, that some employers still rely on unemployment duration to assess information such as individual motivation. Similarly, employers do not call back candidates in unemployment (short vs long) at the same rates when they need to hire somebody urgently. These two findings still suggest that even in contexts of high unemployment where long spells are quite common across the labour force, employers use and learn something from unemployment duration to the detriment of job applicants. This confirms the importance of considering explicitly external conditions (structural rate of unemployment), employers' beliefs (on motivation), and constraints characterizing the hiring processes (time/urgency) to isolate the signaling value of unemployment duration.

In this regard, the thesis factors in regional differences, as well as employers' heterogeneity, and by doing that it contributes to research that assesses the influence of these contextual factors on duration dependence and discrimination (Baert et al. 2013; Kroft, Lange, and Notowidigdo 2013; Carlsson, Fumarco, and Rooth 2018). Similarly, having collected data during the initial stages of the COVID-19 outbreak brings new evidence informing research that looks at the impact of crises, like the Great Recession, on discrimination dynamics in hiring processes (Vuolo, Uggen, and Lageson 2017). Ultimately, it is important to note that graduates are in great demand in the Italian Labour market (being 61% of the new expected hires) and that the size of the new cohort of graduates was smaller than the expected number of jobs requiring this level of education (UNIONCAMERE 2019). It seems that job demand for graduates is there, but employers have a challenging time finding them and likewise, young graduates take some time before getting a proper job. Thus, the results of this thesis on Italian graduates can help expand the literature on youth unemployment from the employer's perspective while trying to wrestle with this Italian puzzle.

The remainder of this first chapter provides an overview of the structure and content of the thesis. The thesis is organized around eight chapters, including this one. In the next one (Chapter 2), the thesis reviews the literature on duration dependence and discrimination, as well as on the relationship between these two mechanisms. Chapter 2 looks at the available evidence and theoretical frameworks to elaborate on a set of hypotheses that the thesis aims to test. Hypotheses are clustered around leading questions of this project, namely whether and why employers contribute to duration dependence; what drives employers' discrimination in the screening phase; how labour market conditions influence employers' decision-making and the emergence of duration dependence and discrimination, as well as what is the relationship between duration dependence and discrimination. Thus, the thesis assesses first duration dependence and discrimination separately and how they play out under different labour market conditions. Understanding how duration dependence and discrimination "work" in the Italian context will help better understand their relationship, how employers deal with intersectionality, and the outcomes of their decision-making.

Chapter 3 looks at the country context of this thesis. The Chapter starts by focusing on the existing evidence from correspondence studies on discrimination that were carried out in Italy and how this thesis complements them. Chapter 3 then provides an eye-bird view of the conditions of the Italian labour market focusing on unemployment dynamics and the situation of young Italians. This section also looks at job search trends in the country and the extent that Italians rely on online job portals. The Chapter then discusses gender inequalities in the Italian context and employment outcomes among migrant workers and those with an immigrant background before delving into a discussion on regional differences in the Italian context. Chapter 3 also presents descriptive evidence of employers' expectations regarding job creation and the extent that women or foreigners could be the best fit.

Chapter 4 instead narrows down the focus on the research design of this thesis and its operationalization. In the first section, Chapter 4 explains that the current project relies on a correspondence study to address the research questions comparing this choice with other potential designs that could have been selected. Given that employers do not know that they are part of a research project, the Chapter also discusses the ethics of correspondence studies. The last two sections of Chapter 4 then give a detailed description of how the correspondence study was designed and implemented. These sections provide the rationale behind the design choices that have been made, especially those concerning the scope of the study, for example, economic sectors and the type of jobs that have been targeted. Also, these sections explain in

detail how resumes were designed by looking at their structure and the randomization of content, especially gender, immigration background, and unemployment duration.

Chapter 5 deals with data and methods. It first starts by describing data collected through the correspondence study, particularly the distribution by sector, region, and period. The Chapter then describes the employers who have been reached with fictitious resumes. Information from job ads was systematically collected to compare employers and the amount of information they shared on their own company, the characteristics of the job they were offering (type of contract, salary, etc.), as well as the description of the ideal candidate (i.e. soft and hard skills required). Finally, Chapter 5 presents the empirical strategy that will be followed to test the hypotheses formulated in Chapter 2. Hypotheses are organized around their respective key research question.

Results of the data analysis are detailed in Chapter 6 starting with descriptive findings. The following four sections of Chapter 6 present results on, respectively, duration dependence, discrimination, the influence of labour market conditions on these two mechanisms, and the relationship between duration dependence and discrimination. Chapter 7 discusses the findings from Chapter 6 and provides an overall narrative bringing them together coherently and linking them to the existing body of empirical evidence. The contextualization of findings will provide the basis to draw implications for research and policy debate, which will be presented as part of the conclusions of the thesis in Chapter 8.

2 Literature review, theory, and hypotheses

Chapter 2 provides an overview of the literature on duration dependence and discrimination, as well as on their relationship. It draws on theories and existing evidence to formulate a set of expectations that this thesis aims to test by employing a correspondence study in the Italian context (See Chapters 3 and 4). Chapter 2 is structured around 4 main sections. The first one (2.1) concerns duration dependence and, specifically, how employers use unemployment duration to sort job applicants in the screening phase of the hiring process. This section discusses evidence, theories, and models of duration dependence. Also, it looks at what makes unemployment duration a salient piece of information and what employers infer from it to derive testable hypotheses.

Section (2.2) instead discusses the evidence and presents theoretical frameworks on discrimination borrowing from the literature on statistical discrimination (Phelps 1972) and status (Berger, Cohen, and Zelditch 1972). The section talks about what would make gender and ethnicity/immigrant background relevant for employers, being lack of information or bias. Also, Section 2.2. looks at whether discrimination depends on job requirements and job quality. In this regard, the section puts forward a set of hypotheses on how discrimination would play out depending on the type of contracts that employers offer, as well as on the (mis)match between qualifications employers seek and those of job applicants.

The third section (2.3) builds on the previous two to discuss how duration dependence and discrimination may play out under different labour market conditions, particularly between labour markets with stronger/weaker job creation. The section also talks about variation in discrimination and duration dependence that could occur when a shock, like the COVID-19 pandemic, hits the economy. As such, Section 2.3 builds on some literature that looked at these mechanisms during the Great recession to draw a set of hypotheses.

Finally, the fourth section (2.4) focuses on models and evidence regarding how employers bring together considerations and inferences they make about unemployment duration, gender, and immigrant background. Section 2.4 aims to lay down the theoretical foundations to help understand how employers deal with the intersectionality of prospective job applicants. Ultimately, this section puts forward some empirical expectations on the relationship, or lack thereof, between duration dependence and discrimination.

2.1. Duration dependence and employers' decision-making

2.1.1 (How) do employers use unemployment duration in the screening phase of a hiring process?

The literature on the "scarring" effect of unemployment posits that unemployment begets unemployment increasingly over time (Ellwood 1979; Heckman and Borjas 1980). This process, namely duration dependence, represents a specific case of the general idea of the Mertonian Matthew effect whereby the stock of time spent in unemployment negatively affects the odds of getting a job (Lockwood 1991).

For example, a study finds that in Britain increasing the length of unemployment leads to lower chances to be employed among individuals in the 28-33 age bracket after controlling for comprehensive background factors and using an instrumental variable approach (Gregg 2001). Research in the US also isolates duration dependence in the years of the Great Recession and concludes that the generalized increase in unemployment duration among the labour force could stem just partially from structural factors (Kroft et al. 2014; Krueger, Cramer, and Cho 2014). Similarly, a negative relationship between time spent out of work and employment prospects is also found among young Norwegian workers in a longitudinal study covering the period between 1986-2008 (Nilsen and Reiso 2011). The study shows that increasing unemployment duration made it more likely to be out of work or to drop out of the labour force (stopping job search).

Another study reached similar conclusions studying unemployment dynamics in Spain during the Great Recession (Bentolila, Garcia-Perez, and Jansen 2017). The authors find that longer unemployment spells negatively affect the odds of being in employment. Particularly, they underlined that duration dependence, rather than negative selection, was the driving force behind the lower job-finding rates of job searchers in long-term unemployment. Here, negative selection entails that the composition of job seekers out of work may deteriorate over time as better candidates leave unemployment at faster rates (Heckman and Borjas 1980). Selection would drive the negative relationship between time spent in unemployment and employment rates (Devine and Kiefer 1991), which would help explain why some studies do not detect duration dependence after considering unobserved heterogeneity (Machin and Manning 1999).

Researchers have tried to overcome the issue of unobserved heterogeneity using experimental designs, like correspondence studies, which apply for real job vacancies using fictitious resumes that differ in, at least, one characteristic of interest (Gaddis 2018). The researcher can

thus assess whether employers' responses to prospective candidates, measured as callbacks for an interview, are a function of that characteristic. In the case of unemployment duration, a correspondence study can show whether employers tend to call back less frequently applicants with long unemployment duration, for example, 12 months and above, compared to those with shorter time spent out of work (i.e. 3 months). Using this research design, Oberholzer-Gee (2008) sent resumes of two fictitious job seekers to existing vacancies for administrative assistant positions. The author assigned randomly ongoing unemployment spells of different duration (6-30 months) to the resumes of the two applicants, which were otherwise identical (i.e. education and employment history). Findings point to a negative relationship between the increasing length of unemployment spells and callback rates, especially when job seekers were assigned 24 or 30 months of unemployment. Similar findings were also replicated in the correspondence studies carried out in the US (Kroft, Lange, and Notowidigdo 2013; Ghayad 2013), as well as in Sweden (Eriksson and Rooth 2014). As such, the results of these studies provide evidence in support of duration dependence.

Nonetheless, the experimental literature on duration dependence also includes studies that find no trace of a significant relationship between the length of current unemployment spells and employers' callbacks. For instance, a correspondence study on US college graduates finds no significant relationship between time in unemployment and employers' interview invitations (Nunley et al. 2017). Another correspondence study also randomly assigned time in unemployment (0-52 weeks) to fictitious female job seekers as part of a correspondence study in the US (Farber, Silverman, and von Wachter 2015). In this study, employers are not more likely to call back applicants with long unemployment duration compared to those with shorter unemployment spells. Overall, while correspondence studies provide a means to circumvent unobserved heterogeneity and negative selection, evidence on duration dependence still seems inconclusive.

Even if the evidence seems mixed, researchers tend to agree that employers would use unemployment duration to quickly narrow down their pool of applicants (Van Belle et al. 2017). Acquiring and assessing an increasing quantity of information is time-consuming for employers (Pedulla 2020) and the marginal return to each of information on any applicant is diminishing (Farber and Gibbons 1991). Importantly, the urgency of the hiring may also constraint the time that employers have at their disposal to carry out the screening. Employers, especially under urgency, would turn to quick sorting devices, for example, unemployment

duration, to optimize screening while maximizing the probability of selecting the best candidates for an interview (Bandiera, Barankay, and Rasul 2011).

In this regard, the literature on duration dependence puts forward two main models to characterize how employers sort applicants based on unemployment duration. The first one suggests that employers *rank* prospective candidates based on the length of their unemployment spell (Blanchard and Diamond 1994). The longer the unemployment spell is, the lower the relative ranking of a candidate will be in comparison with peers who bear shorter periods spent without a job. Consequently, the lower ranking, the lower probability of an employer calling back candidates. The second model, namely *screening*, suggests that instead of ranking candidates, employers would be less likely to consider those with long unemployment duration compared to candidates with short periods spent out of work (Lockwood 1991; Manning 2000). Employers would assess applicants with similar unemployment duration as a type or group of workers rather than looking at duration as a continuous measure. As such, employers would assess in the same manner those with comparable unemployment duration. However, employers would negatively assess the group with longer unemployment spells compared to applicants with shorter periods out of work.

In this regard, it is helpful to look at the results of a correspondence study carried out across 100 cities in the United States using online job applications (Kroft, Lange, and Notowidigdo 2013). Among other characteristics, the resumes the authors sent included an ongoing unemployment spell, which could randomly range from 0 to 32 months. The authors find a major reduction in callback rates during the first 8 months of unemployment. However, after the 8th month without work, the slope of the relationship between time in unemployment and employers' callbacks flattens. The authors do not detect any difference in the callback rate between those in unemployment for 8 or 32 months, which is the maximum length allocated to fictitious profiles. Another correspondence study in the US also finds that no significant difference in callback rates can be detected after 6 months out of work (Ghayad 2013).

These results suggest that as unemployment duration gets long, employers may start to see it negatively reducing the likelihood that they will call back an applicant. After a certain threshold, the reduction would then reach a plateau, and employers would simply contact the "group" with a longer duration less frequently than those with a shorter duration. Interestingly, a study in Sweden shows that employers disregard shorter duration (below 9 months) such that no negative impact on callback is (Eriksson and Rooth 2014). This last result is also in line with other studies, which show that employers are less likely to contact job seekers who are

currently working than those in unemployment for a few months (Oberholzer-Gee 2008; Farber et al. 2019). Short periods of unemployment may thus be a positive factor for employers (Bills 1990), or irrelevant (Eriksson and Rooth 2014), when making comparisons with applicants who are currently working.

In sum, while evidence on duration dependence seems mixed, the theory posits that employers would use unemployment duration as a sorting device to square the pool of prospective candidates, particularly when the available time to carry out the screening is limited. In this regard, employers may either rank applicants based on the number of months out of work or by grouping candidates with similar unemployment duration. Evidence from correspondence studies suggests that, when duration dependence emerges, employers' decision-making seems to conform to screening models. More specifically, employers would consider favorably applications from those in short-term unemployment vis-à-vis those who are currently working. Employers would instead call back at lower rates the group of job seekers who have accumulated longer periods of unemployment. Thus,

> ***H.1****: Employers are more likely to consider applications from candidates in short-term unemployment than from those with a job or in long-term unemployment.*
>
> ***H.2****: When the available time to carry out the screening of resumes is limited, the difference in employers' callbacks between applicants in short-term unemployment vis-à-vis those in long-term unemployment is larger than when employers are not as time constrained.*

2.1.2 What do employers infer from unemployment duration?

The underlying assumption of the previous section is that employers would use unemployment duration as a sorting device because it carries some relevant information. In this regard, ranking and screening models diverge on the mechanics of employers' decision-making because they build on two separate theoretical frameworks, respectively human capital, and signaling. These frameworks put forward different motives that would make unemployment duration salient and informative.

The human capital theory assumes that time spent on an activity, such as education and/or work, translates into skills and competencies (Becker 1962). The accumulation of increasing time on the job should thus equate to the acquisition of greater human capital. Conversely, remaining unemployment would be a missed opportunity for the accumulation of human capital and result instead in a loss of it (Arulampalam, Gregg, and Gregory 2001), similar to the idea of depreciation of physical capital in economics. Thus, spending increasing time in unemployment leads to the erosion of individual competencies, which also become progressively obsolete due to changes in production techniques. Trainability and readiness to learn may also weaken over the unemployment spell (Thurow 1976). Within ranking, months or years of unemployment provide a proxy that employers could rely on to assess and compare applicants' human capital and capacity to acquire new information. It follows that employers would *rank* candidates based on unemployment duration and additional months without work would be matched with lower ranking and decreasing probability of a job call (Blanchard and Diamond 1994).

Screening models instead build on signaling theory, which posits that individuals, in the context of asymmetric information, infer a set of cues about unobservable qualities on another person using what is available (Bacharach and Gambetta 2001). The underlying idea is that individuals incur some costs before being able to leverage a signal and therefore whether the signal is informative for the receiver depends on how hard it is for the sender to acquire it (Gambetta 2009). Higher education represents the textbook example of a signal of productivity and endurance given that not everyone can acquire tertiary education (Spence 1973). Conversely, long spells of unemployment could be interpreted as a negative signal given that not every worker would or could remain out of work for such a long time (Goffman 1963). Employers in fact report that they see those in long-term unemployment as less motivated, as well as less reliable and able to perform on the job (Bills 1990; Bonoli 2014). Also, employers may tend to think that other employers already discarded these candidates with long

unemployment (Oberholzer-Gee 2008). Employers would conclude that if these applicants were good, they would not have been looking for jobs for so long.

Given that human capital and signaling theory provide alternative explanations about what employers learn from unemployment duration, some studies have tried to understand what employers are more likely to see in it. In a vignette, study researchers asked human resources managers to indicate the likelihood of calling back a set of fictitious profiles, which were assigned randomly unemployment duration of 1-36 months (Van Belle et al. 2017). The authors then ask HR managers to rate statements on applicants' erosion of human capital and trainability, as well as on their motivation and previous employers' rejections to disentangle the key motivation behind employers' use of time out of work as a sorting tool.

Findings from this study suggest that HR managers tend to see unemployment duration as a signal of low motivation (Mcfadyen 1998), rather than a proxy of human capital erosion (Becker 1962), or trainability (Thurow 1976), or a clue about other employers' decisions (Oberholzer-Gee 2008). Newton and Pensions (2005) also corroborate these findings highlighting that employers give greater importance to soft skills and attitudes such as motivation than technical ones when hiring among the pool of job seekers in unemployment. Employers who see motivation as an explicit job requirement also say that they are more likely to call back applicants in long-term unemployment with information on their commitment compared to others with similar unemployment duration who do not provide such details (Bonoli and Hinrichs 2010).

However, Sherman and Karren (2012) suggest that employers would tend to stigmatize those who are currently out of work. In other words, employers may perceive extended periods of unemployment as an individual mark of lower worth rather than a temporary condition (Goffman 1963). Within a signaling framework (Gambetta 2009), employers who are interested in motivated candidates may perceive long-term unemployment as a (dormant) sign of motivation. In this regard, there is evidence that when employers see commitment and motivation as key for the vacancy they try to fill, employers discriminate more against those candidates they perceive as lowly motivated (Pedulla 2018b). An applicant may therefore try to "signal" his/her unobserved motivation through additional information.

Nonetheless, the employer may not consider it genuine/trustworthy if coming from a person with long-term unemployment who s/he sees as a mark of lower motivation. As such, the additional piece of information "activates" the sign/expectation that those in long-term

unemployment are not motivated. Employers would think that applicants in long-term unemployment are just trying to be seen as a certain “type” of the applicant (good/ motivated), but the sharing of information helps the employer reveals the applicant's true “type” (bad/not motivated). This eventually would lead to lower callbacks among the “signalers” in long-term unemployment. Providing additional information on soft aspects such as motivation, which are fuzzy concepts and difficult to assess (Moss and Tilly 2001), may thus be a liability when employers emphasize traits such as motivation in job ads. Stigmatization of those in unemployment may imply that employers would not take at face value information that those in long-term unemployment provide and this dynamic would be exacerbated when employers list motivation as a job requirement.

In sum, employers may use unemployment duration as a proxy of unobserved qualities, particularly soft aspects such as motivation. As such, employers who set these soft aspects as job requirements might be less likely to contact applicants in long-term unemployment than employers who do not see these soft aspects, as necessary. Nonetheless, when these requirements are explicit in the job ad and employers get signs and information on them through resumes, employers should be more likely to consider applications from job seekers with long unemployment spells. If, however, employers tend to stigmatize those with long unemployment spells, additional information on soft aspects, such as motivation might be seen suspiciously and reduce the probability of a job interview. Therefore,

> ***H.3*** *Employers who set motivation and commitment to work as a job requirement are less likely than those who do not call back applicants in long-term unemployment.*
>
> ***H.4a*** *Employers who set motivation and commitment to work as a job requirement are more likely to consider applicants with long unemployment spells who provide evidence that they meet this requirement compared to candidates with similar unemployment duration but no information on motivation.*
>
> or
>
> ***H.4b*** *Employers who set motivation and commitment to work as a job requirement are less likely to consider applicants with long unemployment duration who provide evidence that they meet this requirement than applicants with the same duration but no information on motivation.*

2.2 Discrimination in the screening phase

2.2.1 Does bias influence what employers look for and who they call back?

The previous section shows that the constraints employers face, the information they (do not) have and what they look for in a candidate can make unemployment duration something like a sorting device to select candidates for an interview. Nonetheless, unemployment duration is just one detail of individual employment histories, let alone in the whole resume. In this regard, research that looks at hiring processes suggests that gender (González, Cortina, and Rodríguez 2019; Petit 2007; Riach and Rich 2006) and ethnicity (Bertrand and Mullainathan 2004; Pager 2003; Rooth 2007) are key when deciding who should move to the interview stage of the hiring process. Importantly, what employers infer from gender and ethnicity can then influence what employers learn about unemployment duration (Pedulla 2020). Consequently, it is fundamental to isolate first what makes gender and ethnicity salient for employers before assessing the relationship with unemployment duration.

The literature on statistical discrimination suggests that employers use aggregate knowledge about groups to infer the productivity potential of individual candidates (Phelps 1972). The grouping can be based on a characteristic that subsets of individuals share, for example, gender or ethnicity, among others. Any differences in, for instance, calls for an interview between men and women and ethnic minorities vis-à-vis native workers would stem from underlying differences in productivity (Arrow 1973). As such, statistical discrimination models make the point that differential outcomes would be fair as hiring decisions are motivated by considerations of productivity, which in turn stem from employers' knowledge of groups' distributions (Bertrand and Duflo 2016). In sum, statistical discriminations models posit that groups (a) differ in their productivity distributions and (b) employers who know these true differences can make an informed assessment of candidates' productivity.

Researchers, however, often question founding assumptions (a) and (b) of statistical discrimination models. First, doubts have been cast on the existence of true and measurable between-group differences in productivity distributions (Aigner and Cain 1977). The other main critique of statistical discrimination models concerns the quality of employers' knowledge of productivity differentials (Correll and Benard 2006). On the one hand, measuring and assessing productivity is hard (Arrow 1973). On the other hand, the systematic screening out of "lower-productivity" groups makes employers less likely to learn more about changes in the composition of these groups, for example, due to migration and increasing women's

participation in the labour force. Employers' knowledge of groups' productivity may in the end be outdated and not representative. Consequently, supposed group-level differences in productivity distributions may simply stem from subjective inferences that employers make about groups of applicants that share a common trait.

In this regard, the literature on status posits that women and ethnic minorities are believed, generally, to possess lower social worth and prestige than their counterparts (Berger and Fişek 2006). Women (Correll and Ridgeway 2006) and minorities (Pedulla 2018b) are also perceived and expected to be less committed to work and in turn less reliable, as well as less competent than men and native workers (Berger, Cohen, and Zelditch 1972). In this regard, Correll, Benard, and Paik (2007) show that employers are more likely to assess mothers as less competent and committed to work than fathers. This in turn lowers the probability that mothers would be recommended for hire. Thijssen, Coenders, and Lancee (2021) also highlight that employers tend to represent ethnic minorities as less committed and attached to work such that they seek to avoid applicants with these backgrounds. Therefore, rather than a matter of productivity, employers' differential treatment may be the result of evaluators' cognitive bias against groups like women and ethnic minorities (Correll and Benard 2006).

Interestingly, researchers often refer to statistical discrimination as the benchmark framework to assess differential treatment even if the empirical evidence does not seem to provide such strong support. Looking at ethnicity, a meta-analysis of correspondence studies points clearly to bias as the source of discrimination (Zschirnt and Ruedin 2016). The authors find consistently that employers tend to call back native workers at higher rates than ethnic minorities while ruling out explanations related to differences in human capital. Methodological issues may still cast doubts on some of the results from this extensive strand of literature on ethnic discrimination (Neumark 2010; Carlsson, Fumarco, and Rooth 2014; Neumark 2018), but results are not as debated as those from experimental research on gender (Azmat and Petrongolo 2014).

Particularly, Neumark (2018) underlines that results on gender are difficult to interpret solely within statistical discrimination (Arrow 1973) or taste-base models (Becker 1957). Rich (2014) also does not find pervasive gender discrimination, but she highlights that women and men experience discrimination when women and men apply for men- and women-dominated jobs, respectively. The status framework can help understand these findings as it posits that expectations about competence are strongly intertwined with the task to be performed (Correll and Ridgeway 2006). Expectations about a group's competence can be either positive or

negative depending on whether it is believed that the group is better at undertaking a certain activity (Berger, Cohen, and Zelditch 1972). As such, women and men will be respectively preferred for jobs that are seen as women's tasks or men's activities. When a task is not gendered instead, the general expectations that men are more competent than women may still be salient and influence how individuals are assessed (Ridgeway and Smith-Lovin 1999).

This proposition resonates with Midtbøen (2016) finds that Norwegian employers tend to contact fewer times 1) ethnic minorities than natives, and 2) ethnic minority men than ethnic minority women. The author notes that evidence of discrimination against women, as well as against men, in hiring processes points to occupational gender segregation. In other words, women are more likely than men to receive a call for an interview for jobs that are usually held by women, and vice versa. The author then finds that the direction of discrimination changes when the analysis only includes applications to gender-neutral jobs. For these jobs, employers are more likely to call back ethnic minority men than women. The literature on gender discrimination also shows that employers embed gender stereotypes in job advertisements (Rho 2016) and those applicants who do not fit the gendered description of the ideal candidate are less likely to be contacted for a job interview than those whose profiles align with employers stereotypical representation (Tilcsik 2011).

As employers may expect (wo)men to be best suited for specific jobs, Zschirnt and Ruedin (2016) also contend that employers hold stereotypical representations about the competencies of ethnic minorities concerning comprehension and use of language. In some instances, worries about language gaps may be justified (i.e. when applicants are born in a foreign country), but individuals tend to overemphasize such concerns and embed them implicitly in their decision-making (Crandall and Eshleman 2003). Heath and Cheung (2006) show that employers tend to penalize applicants with a migration background who were born, raised, and studied in the UK (second-generation). Likewise, Midtbøen (2014) finds that second generations still face unfair treatment in the Norwegian labour market due to stereotypes employers attach to ethnicity. In these studies, differences in callbacks from employers cannot be attributed to deficient language skills or difficulties in assessing the quality of foreign diplomas. Employers would just discriminate against foreign applicants based on their background, particularly when communication and relational skills are job requirements (Oreopoulos 2011).

Nonetheless, even if bias were the leading source of discrimination, its influence over the screening phase would hinge eventually on how employers manage the hiring process. In this regard, Moss and Tilly (2001) find substantial variation in the management of hiring processes

between firms of different sizes in a study about US employers and their hiring practices. Larger ones were relying on more formal means of testing rather than interviews only, the latter being used more frequently among small firms. The authors also find that the greater the level of formalization of the recruitment process, the higher the probability to engage workers that suffer the brunt of discrimination such as black job seekers. Along the same line, Pedulla (2020) suggests that more structured recruitment processes help standardize the assessment of candidates reducing employers' reliance on stereotypes about some groups of applicants. Also, the author posits that greater accountability and scrutiny of those making screening and hiring decisions make it less likely that these people will rely on their bias. Thus, greater formalization can reduce the role bias plays in employers' decision-making and, eventually, discrimination.

In sum, discrimination may arise because of a lack of information on unobserved characteristics or simply being the result of a bias against some groups, like women and ethnic minorities. If bias triggers discrimination, who is discriminated against may vary depending on the job to be performed and job requirements. These aspects of a job can be linked to employers' expectations of competence and motivation. Nonetheless, formalization of the hiring process might limit the influence of bias, based on gender and immigrant background, on decision-making in the screening phase. Therefore, it is possible to expect that

> ***H.5*** *Employers' differential treatment stems from bias rather than a lack of information*
>
> ***H.6*** *Employers are more likely to call back women than men for jobs that are expected to be women's jobs, but when jobs have no clear gender connotations, employers are more likely to consider men than women.*
>
> ***H.7:*** *Employers emphasizing communication and relational skills in job descriptions are less likely than employers who do not mention these requirements to consider applications from those with an immigrant background than those from native workers.*
>
> ***H.8****: Employers emphasizing motivation in job descriptions are less likely than employers who do not mention these requirements to consider applications from women and those with an immigrant background than men and native workers.*
>
> ***H.9****: Employers using formal hiring procedures are as likely to consider men and women, as well as applicants regardless of their immigrant background.*

2.2.2 Does discrimination depend on what employers offer?

As discrimination may vary across jobs and depending on job requirements that employer set, women and men and ethnic minorities, and majority members may also end up obtaining different working conditions. In this regard, Birkelund et al. (2021) posit that discrimination varies in strength and intensity depending on labor market regulations and associated costs of hiring and firing workers. Particularly, the authors suggest that when dismissal costs of workers are high, discrimination should be stronger. In other words, when employers are more pressured to find the right candidate for their vacant position because of the high costs of firing an employee, they are less likely, for example, to "risk" hiring women over men. This proposition may also imply that, in a given context, employers would be more likely to consider women and ethnic minorities for jobs whose dismissal costs are low rather than those with high costs. In other words, fixed/short-term jobs vis-a-vis long-term contracts.

In this regard, Kalleberg (2000) points out that flexibilization of the labour market and insecurity are generally on the rise, but women and those with an ethnic background represent groups most likely to be hired with temporary contracts, which are more precarious. As per gender, the OECD (2017) confirms this proposition showing that women's participation has been catching up with men, but women are more likely to hold part-time jobs and be contracted under precarious conditions (temporary jobs), which in turn are also paid less. Helbling, Sacchi, and Imdorf (2017) also find that women are more likely than men to hold short-term contracts, which in turn also results in fragmented labour market careers giving rise to a vicious circle of low-quality low-paid jobs that hamper women's future employment prospects. Similar results emerge looking at workers with immigrant backgrounds. EUROSTAT (2021) shows that in European countries workers born outside of the EU represent the group with the largest share of temporary contracts, followed by those born in another EU state than the one where they reside, and finally by natives. Research corroborates these descriptive findings showing that workers with an immigrant background are more vulnerable to short-term and low-paid jobs than native workers (Kogan 2004; Larsen, Rogne, and Birkelund 2018).

These findings resonate with the theory of labour market segmentation, which suggests that the labour market is divided into two segments, which offer different working conditions (Doeringer and Piore 1985). The first segment provides jobs that are better paid and guarantee more stable contractual conditions whereas the second segment is characterized by jobs that are low-paying and more precarious (short/fixed-terms). The theory also suggests low mobility

of workers between the two sectors such that those holding jobs in the second segment would remain entrapped in low-quality and unstable employment (Scherer 2004). As such, employers may contribute to labour market segmentation if those who offer short-term jobs prefer women and immigrant workers to men and natives while those offering long-term jobs subvert this ranking and prefer men and native workers.

Furthermore, the two segments of the labour market vary in terms of the skills that are required: more productive workers with technical skills will tend to hold jobs in the first segment, whereas unskilled workers would be more likely to hold jobs in the second segment (Gordon, Edwards, and Reich 1982). It follows that if employers see some groups as on average more productive than others (Phelps 1972; Arrow 1973), or more competent and with higher motivation and worth (Berger, Cohen, and Zelditch 1972; Correll and Ridgeway 2006), workers categorized as low-productivity or low status would be more likely to hold jobs require lower qualifications than those they hold. In this regard, official statistics hint that women and workers with an immigrant background are more likely to be overqualified for the jobs they hold compared to men and native workers (EUROSTAT 2021b). As such, women and ethnic minorities are more likely to experience job mismatch than men and native workers.

Nonetheless, these statistics do not clarify what role employers play in this skills mismatch divide. Modestino, Shoag, and Ballance (2015) suggest that employers actively look for candidates who are over-skilled for the jobs they offer. Similarly, Verhaest et al. (2018) find through a correspondence study that Belgian employers do not tend to penalize applicants who are a bit more qualified than what would be required, as well as in some instances, being overqualified provides a premium in terms of callbacks. Nonetheless, Campbell and Hahl (2022) suggest that considerations employers make on overqualification hinge on the candidates' gender. The authors show that employers see overqualification among women as a sign of commitment whereas it was considered a sign of job hopping among men and as such negatively. Particularly, the authors find that employers thought men, rather than women, were too good and more likely to leave whenever a better job opportunity would have become available. The same reasoning may apply to candidates with an immigrant background. Employers might think that applicants with an immigrant background would be more likely to accept and keep a low-quality job compared to natives (Frey et al. 1996). As such, employers would be more likely to contact this group of candidates than native workers if their qualifications are just above those required for the job.

However, when the mismatch between applicants' qualifications and those required for the job is severe employers can penalize job applicants (Verhaest et al. 2018). In these instances, employers may see applicants as prone to job hopping as soon as another opportunity of better quality comes around given that they look very capable (Galperin et al. 2020). Or employers may think that since these applicants could not find anything better matching their qualifications, they might not be good workers. Factoring in gender and ethnicity, Pedulla (2020) suggests that experiences of overqualification in employment histories would *reinforce* employers' beliefs and stereotypes about gender and race resulting in a further reduction of callbacks for women and black applicants compared to men and white applicants. Alternatively, the author posits that employers may see overqualification in applicants' employment histories as *irrelevant* for women and black workers but detrimental for men and white workers. The presence of overqualification among black applicants and women would simply confirm employers' beliefs and stereotypes, whereas it would be seen as a negative sign for men and white workers. The author also suggests that there might *not be any differences* by gender or race.

In sum, employers' differential treatment may hinge on job quality, namely contract duration and the match of skills required for the job and offered by candidates. Employers should prefer women and workers with an immigrant background to men and native workers for short-term contracts, and vice versa when long-term contracts are on offer. Also, employers may prefer women and those with an immigrant background to men and native workers when applicants' skills are slightly above those needed for the job. As such

> ***H.10*** *Employers offering short-term jobs call back at higher rates women and workers with an immigrant background than men and native workers, and vice versa if they offer long-term jobs.*
>
> ***H.11*** *Employers are more likely to call back women and workers with an immigrant background compared to men and native workers when applicants' skills are slightly above those needed for the job.*

How employers look at substantial overqualification and whether what they learn hinges on gender and immigrant background are open questions. Nonetheless, it is possible to expect three different scenarios: *a) employers prefer men and native workers to women and those with an immigrant background*, or *b) penalize men and native workers compared to women and*

those with an immigrant background, or *c) assess severe overqualification consistently for all applicants regardless of gender and immigrant background*.

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2.3 Duration dependence and discrimination in context

2.3.1 Do duration dependence and discrimination depend on labour market conditions?

A common takeaway from previous sections on duration dependence and discrimination is that employers' understanding of the information they possess and the beliefs they hold depends on external factors. Beyond what employers see in unemployment duration, how employers use it during screening may rest on the time they have to assess resumes. Similarly, employers generally think men are more competent than women but for jobs characterized as best performed by women, employers may prefer women to men. These propositions suggest that duration dependence and discrimination are highly context-dependent. As such, external conditions are likely to influence employers' beliefs and motives.

In this regard, Lockwood (1991) highlights that local labour market conditions and business cycles contribute to the formation of individual expectations about job seekers who have spent a long time in unemployment. Clark (2003), for example, finds a negative relationship between the unemployment rate in the region of the job seeker and her probability of being currently in unemployment. Similarly, Mooi-Reci and Ganzeboom (2015) assess duration dependence in the Netherlands between 1985–2000. The authors suggest that duration dependence is stronger when job creation is strong and employers must compete to hire workers (tight labour market). Lupi and Ordine (2002), while focusing on the impact of unemployment duration on re-employment wages in Italy, also find a negative effect in areas with a tight labour market and no significant difference where labour markets show weak job creation potential (in a slack).

Some studies also tried to assess whether discrimination varies depending on the conditions of local labour markets using experimental research designs, such as correspondence studies. Baert et al. (2013) send fictitious job applications for positions that are quick to fill (easy to find workers), as well as for those for which it was harder to find a candidate. With this design, the authors posit that they can assess differences in callbacks under different labour market conditions while the labour market overall was not going through an economic downturn. The results show that employers' callback rates for job applicants with different ethnic backgrounds are similar when recruitment is difficult. Employers instead tend to call back ethnic minority candidates less than majority job seekers for those positions that are easier to fill. While gender is not the main focus of their research, Kroft, Lange, and Notowidigdo (2013) also implement a correspondence study across the 100 largest metropolitan areas in the US. Their findings

show that duration dependence gets stronger in tight labour markets, but employers' callback rates do not differ by gender, regardless of the conditions of the labour market (tight or slack).

Empirical evidence thus shows that the strength of duration dependence and discrimination are related to labour market conditions. Particularly, findings on duration dependence suggest that when employers know that jobs are scarce and spending time out of work is a common experience among the local labour force, time in unemployment might not prompt strong expectations about individual productivity (Lupi and Ordine 2002). In slack labour markets with unmet demand for paid labour, employers may not pay a lot of attention to time spent out of work: this would be a common experience among the local labour force. As such, unemployment duration would become a noisy signal in weaker labour markets. Contrarily, in contexts characterized by a tight labour market, employers may wonder why some job seekers with long unemployment duration have not worked recently. Employers would therefore see long-term unemployment negatively and consequently call back at lower rates those with long spells out of work. These predictions conform with screening models given that they conceptualize unemployment as a sign of some unobservable characteristics of job applicants (Mooi-Reci and Ganzeboom 2015).

If, however, unemployment duration is regarded as a measure of productivity decay, as per ranking models, employers would be more likely to call back candidates with longer unemployment duration in a tight labour market than in one with slack (Carlsson, Fumarco, and Rooth 2018). In a tight labour market, there would be generally fewer available applicants per vacancy to rank. Vacancies grow in number whereas the pool of potential candidates shrinks. Thus, those in long-term unemployment are closer to the head of the queue in tight labour markets, which in turn affects the probability that employers would consider their applications. If instead job creation in a labour market is weak and more people are available for each vacancy, the ranking of those in long-term unemployment would worsen and, consequently, the likelihood that employers contact them for an interview.

The use of ranking and screening models and their respective predictions also provide a useful framework to understand potential differences in what employers infer from ethnicity under different labour market conditions (Carlsson, Fumarco, and Rooth 2018). Particularly, within ranking models, ethnic minorities would be more likely to receive a call from employers in strong labour markets than in weak ones because fewer applicants are available for an increasing number of jobs. Within screening models, discrimination should increase under tight

conditions and get weaker when there is slack in labour markets. Similar expectations can also be put forward by substituting ethnicity with gender (Birkelund et al. 2021).

Importantly, screening and ranking models assume no bias against any candidates. If instead bias is the source of differential treatment of applicants, employers would generally prefer, regardless of labour market conditions, those considered high-status applicants vis-a-vis candidates seen as low status. Yet, discrimination might be lower in the tight labour market because more jobs are available while fewer applicants are available to fill them (Moss and Tilly 2001). As in ranking, ethnic minorities and women would be closer to the head of the queue of prospective candidates for any job advertised. In a slack labour market instead, women and ethnic minorities would instead stand lower chances of a callback given that there is a greater number of available men and natives. In this context, employers would place women and ethnic minorities further back in the queue of applicants to be contacted for a job interview.

In sum, two alternative propositions can be put forward for, respectively screening and ranking models. Predictions from ranking models should also be consistent with the status framework such that

> ***H.12a*** *Duration dependence and discrimination are higher in tight labour markets, and vice versa in slack labour markets, as per screening models.*
>
> ***H.12b*** *Duration dependence and discrimination are lower in tight labour markets, and vice versa in slack labour markets, as per ranking models and status framework*

2.3.2 Business cycles and shocks: do they influence duration dependence and discrimination?

While differences in the level of unemployment across labour markets largely depend on structural factors (Bassanini and Duval 2007), labour market conditions may change due to large-scale shocks like the Great Recession (Elsby, Smith, and Wadsworth 2016). In other words, the slack or tightness of the labour market may deviate temporarily from what is conventionally considered the structural rate of unemployment (Ghayad and Dickens 2012). A negative shock like the Great Recession caused a surge in the number of people in unemployment and increase average unemployment duration (Krueger, Cramer, and Cho 2014; Kroft et al. 2014).

Such a change in labour market conditions could also influence how employers see and use unemployment duration. Particularly, the experience of joblessness may become increasingly common for a larger share of the labour force even in places usually characterized by stronger labour markets. Within the ranking model logic, those with longer spells of unemployment would get further behind in employers' ranking. In the context of screening models instead, employers may start to pay less attention to unemployment duration deeming it not as informative as it used to be. Under ranking, duration dependence should therefore increase in the aftermath of a shock and vice versa under screening.

Changes in local labour market conditions might also bear differential implications by gender and ethnicity. In this regard, existing evidence highlights that workers with an immigrant background might be the first to be fired during economic downturns like those provoked by COVID-19 (Fasani and Mazza 2020; OECD 2022). Similarly, Zarrilli and Herni (2021) survey recent evidence on the impact of the COVID-19 outbreak and show that women worldwide were more likely than men to lose their jobs and remain in unemployment. However, it is not as clear whether any potential differential treatment of women and ethnic minorities in hiring processes would become more (less) severe in the aftermath of a negative shock.

Within screening, a shock should increase the heterogeneity of the pool of those in unemployment with regards to gender and ethnicity given that more people are laid off. As such, these characteristics might become less informative during economic downturns and discrimination should weaken eventually. Under ranking instead, women and ethnic minorities would get further down in employers' ranking. Therefore, discrimination should get stronger in the aftermath of an economic downturn.

The third option on discrimination, which is not covered by ranking and screening models, is that discrimination dynamics are not affected by economic downturns. For example, Vuolo, Uggen, and Lageson (2017) look at the impact of the Great Recession on discrimination in the US labour market using an in-person audit study. Given that the crisis started while the authors were collecting data, they could assess employers' response to white and black men applying for low-wage jobs before and during the recession. The authors find that the drop in callbacks was similar for white and black applicants. However, the authors show that callback rates for white applicants during the recession were comparable to those of black job seekers before the crisis. Importantly, black job applicants receive even fewer calls from employers than before the recession.

These findings resonate with Tilly (1998) who suggests that categorization based on gender and race is ingrained in people's minds and organizations like firms contributing to the persistence of existing labour market inequalities. Along these lines, Fernandez (2007) highlights how beliefs about women and work change over time but as part of an intergenerational learning process. Similarly, Heath and Cheung (2006) show that ethnicity remains a salient characteristic for employers even when assessing second-generation applicants who were born, raised, as well as studied in the same country as their prospective employers. Similarly, Quillian et al. (2017) also find that discrimination against black and Latino job seekers did not decrease when comparing employers' callback rates in audit/correspondence studies implemented since 1989.

The evidence thus suggests that beliefs about gender and ethnicity are unlikely to change abruptly in the aftermath of a negative shock affecting a given labour market. As such, differential treatment should remain stable: callback rates should go down proportionally for both women and men and ethnic minorities and majority applicants during economic downturns. More specifically, employers would still be less likely to contact candidates deemed low status compared to those seen as high status in the aftermath of a negative shock affecting the labour market.

Summing up the discussion, screening and ranking models provide opposite predictions regarding the emergence of duration dependence in the aftermath of a shock. *Duration dependence* may (*increase*) *decrease* after a shock hits the economy. As such, the direction of change during economic downturns is an open question. Likewise, *whether employers discriminate more or less in the aftermath of shock*, or *whether discrimination remains stable* in line with expectations from categorical inequality models.

2.4 The relationship between duration dependence and discrimination

Building on evidence and theory from previous sections, this one looks at the relationship between duration dependence and discrimination. Particularly, statistical discrimination and expectation states theory represents the starting point for this discussion. According to the status framework, differential treatment would stem from employers' cognitive bias against candidates deemed low status, like women and ethnic minorities, vis-à-vis their high-status respective counterparts. Instead, within statistical discrimination models, differential consideration of candidates in the initial stages of the hiring process results from employers lacking information on individual productivity. Employers would then sort job applications using candidates' group "membership," which employers can use to infer individual productivity.

One of the potential implications of these two frameworks is that standing lower chances to be considered for an interview also means that those deemed low status or low productivity candidates, depending on the framework, like women and ethnic minorities will have to file more applications to get an interview. These candidates would then remain longer in unemployment (Uhlendorff and Zimmermann 2006; Auer, Bonoli, and Fossati 2015), which in turn might further diminish the probability of being contacted for an interview. Evidence on gender and unemployment duration dependence, mostly on the supply side, shows that increasing time in unemployment bears some long-term unemployment detrimental effects on job prospects for women in the initial stages of their working career in Finland and Germany (Helbling, Sacchi, and Imdorf 2017). Along the same lines, women in the Netherlands seem to experience a short-term negative effect of unemployment on job-finding rates (Luijkx and Wolbers 2009). Men instead seem to endure the most long-term unemployment in the United Kingdom, particularly those with secondary education, while women suffer half as much of the negative effect of one more month of unemployment on job prospects (Gregg 2001). Interestingly, experimental evidence from the US labour market does not point to any significant gender differences in the consequences of unemployment duration on employers' callbacks (Kroft, Lange, and Notowidigdo 2013).

Studies crossing ethnic discrimination and unemployment duration have been focusing more on employers and decision-making in the hiring process. Particularly, Birkelund, Heggebø, and Rogstad (2017) find that Swedish employers are less likely to call back applicants with Pakistani/Muslim names than those with Swedish-sounding ones, but the authors did not find

any ethnic-related differences in the effect of unemployment on employers' callbacks. Similarly, Eriksson and Rooth (2014) did not find any significant differences in the impact of unemployment on call-back rates between ethnic minority applicants with a Middle Eastern background and Swedish candidates. Contrarily, evidence from the US suggests that Afro-American jobseekers receive significantly fewer callbacks from employers compared to their white peers (Pedulla 2018b). While the author finds that Afro-American applicants with extended periods of unemployment do not receive fewer calls than black candidates with shorter unemployment spells, increasing unemployment duration reduces the likelihood of a callback from employers for white job seekers. In sum, the literature that looks at the intersection of gender, ethnicity, and unemployment provides contrasting findings. Nonetheless, it might be possible to better understand and reconcile them by framing how employers use and aggregate these pieces of information that are readily available in resumes.

In the most basic stylized decision-making model, employers would look at each piece of information that is available in a job application and add up inferences made to decide who to call back (Pedulla 2018b). This aggregation model strongly resonates with the statistical discrimination framework, whereby employers value and use additional data to better estimate individual productivity potential. As such, employers' assessment of candidates and the decision to contact someone for an interview could be formalized as a linear function of the information available through résumés. What employers may see as positive characteristics, like being a man and/or native candidate, would each increase the probability that employers call back a candidate. Contrarily, what employers regard as negative, for example, long unemployment duration, would dump the likelihood of a callback. The same logic would also apply when employers intersect gender, immigrant background, and unemployment duration. What employers see as negative signs would lower the probability of a callback and vice versa for what employers consider as positive indicators. Importantly, the assessment of each characteristic, such as unemployment duration, should not be influenced by the applicants' gender and immigrant background. Therefore, there should be no expectation that a specific detail would be more or less detrimental to a subgroup of applicants.

However, it is also possible that not every piece of information about candidates affects the likelihood that an employer contacts a candidate for an interview. Within the status framework, employers would tend to discard additional data on job applicants when they see that information is consistent with their beliefs, particularly those related to characteristics such as gender and ethnicity (Correll and Ridgeway 2006). Employers may thus see unemployment as

a redundant piece of information for those applicants like women and ethnic minorities deemed low status. For these applicants seen as low status, employers would consider long unemployment duration as in line with the competence expectation states they hold. Contrarily, long unemployment duration would be detrimental for those deemed high status: long spells of unemployment would be not congruent with the competence expectations states that employers hold about men and native job seekers.

Within the status framework, ethnicity and gender can be conceptualized as primary frames that individuals rely on to evaluate others (Ridgeway and Kricheli-Katz 2013) and evaluators give a different weight to the same piece of information depending on the status attributed to persons under assessment (Foschi 2000). As such, the perception and understanding of unemployment duration in decision-making become contingent on gender and ethnicity. Gender and ethnicity instead are relied upon to define the status of an applicant. It then follows that the status of an applicant also depends on the cross-categorization of gender and ethnicity. In this regard, Correll and Ridgeway (2006) posit that the aggregation of status characteristics occurs by summation: positive (negative) expectations associated with status characteristics would compound.

Therefore, possessing a set of identities that are deemed low status may further decrease the likelihood of an employer calling back, and vice versa for the high-status bundle (Correll and Ridgeway 2006). Employers, however, would consider (negatively) unemployment duration for candidates with a bundle of high-status characteristics given that long periods out of work would not align with their competence expectations. Employers would instead not consider unemployment duration, or to a very limited extent, for those applicants with a bundle of characteristics associated with low status. For other intersectional candidates, who have a bundle of low and high-status characteristics, employers could make sense of unemployment duration banking on their competence expectations stemming from the characteristics that they see as low-status.

While under the status framework information consistent with the status attributed to a person is discarded, Birkelund, Heggebø, and Rogstad (2017) posit that employers assessing resumes may compound the stereotypes they hold about ethnic minorities and long-term unemployment. Similarly, employers may further penalize women because of their employment histories (Pedulla 2016). Within this framework, employers stigmatize those in unemployment and see them as less reliable and productive (Goffman 1963; Sherman and Karren 2012). As such, unemployment duration is a negative factor that affects the probability of a callback for all

applicants. However, the reduction in calls for interviews associated with long-term unemployment should be larger among groups like women and ethnic minorities than men and majority applicants. This for example is what Pager (2003) finds when assessing the interaction of race and a criminal record in her audit study of the US labour market. For the same reason, such a compounding effect might also be stronger among intersectional applicants like ethnic minority women who are in long-term unemployment.

Therefore, statistical discrimination, status, and stigmatization lead to three sets of alternative propositions on the interaction of gender and ethnicity with unemployment duration. First, within statistical discrimination, it can be expected that employers consider and use unemployment duration in the same manner across groups. Therefore, no difference across groups should be expected in how employers consider unemployment duration and use it to identify candidates for the interview stage. Employers would simply aggregate additively each piece of information to decide who to call back.

Second, according to the status theory instead, the use of additional information like unemployment duration hinges on the status attributed to the applicant. Particularly long unemployment duration would be (in)consistent with low (high) status. As such unemployment duration would be a liability for high-status applicants only, which would reduce the probability that employers would call back. The probability of a job interview would instead be not affected, or just slightly, by unemployment duration when employers see the applicants as low status.

Third, employers may instead compound the stereotypes they hold against ethnic minorities and women and those about persons in long unemployment duration. Given that employers would stigmatize the experience of unemployment, long spells of unemployment should be a liability for all job seekers, but it should be more detrimental for women and ethnic minorities than men and majority applicants.

Pedulla (2018b) defines these three alternative aggregation dynamics as, respectively additive, muted, and amplified congruence, which the author tests utilizing a correspondence study in the US. While the author finds that the muted congruence can help understand findings from his correspondence study in the US labour market, it is not warranted that this might be the case in other contexts (Pedulla 2020). Also, and more fundamentally, the evidence on discrimination at the intersection of gender and ethnicity is mixed (Zschirnt and Ruedin 2016).

Nonetheless, previous chapters explore under what conditions discrimination and duration dependence arise (job type and quality, and labour market performance). As such, previous empirical tests make it possible to test *whether additive, muted, and amplified congruence conform better with employers' decision-making* and to understand the reasons behind the emergence of a specific aggregation pattern. Importantly, sorting out the aggregation patterns that employers follow will help answer the main question of this thesis, which concerns the relationship, or lack thereof, between duration dependence and discrimination.

3 Italy as a case study. Some substantive considerations

Chapter 3 discusses features of the context where this research has been implemented, namely Italy. It motivates why the country has been selected as the sole case study of this thesis. Chapter 3 also provides background information, which motivated design choices guiding the development of the correspondence study (See Chapter 4).

Chapter 3 starts with a summary of the correspondence studies implemented to date in Italy. Section 3.1 shows that this research design has not been widely used in Italy, which represents an advantage for the current study. It also highlights the results from this literature, which can be useful to contextualize those arising from the current research. The Chapter then provides in Section 3.2 a national overview of the status of the labour market, particularly looking at (un)employment rates and participation in the labour force. It zooms in on the situation of young Italian graduates, as well as focuses on what employers look for in the sectors and jobs that the current study has targeted.

The following Sections, namely 3.3 and 3.4, discuss respectively gender in the Italian labour market and the condition of those with an immigrant background, particularly those with Romanian origins, which is the largest group in Italy. Beyond discussing labour market outcomes and differences, these two sections delve into expectations and beliefs employers hold and how these are interlinked with the jobs the current study has targeted.

Chapter 3 then closes with a discussion in Section 3.5 on the divide between Italian macro-regions, looking at trends in labour market outcomes, gender inequalities, and the condition of those with Romanian origins.

3.1 Correspondence studies in Italy

Before this data collection, just a few correspondence studies have been implemented in the Italian context. Studies that relied on this research design looked at both the Italian rental and labour market. With regards to the rental market, Baldini and Federici (2011) designed an online correspondence study to assess the level of discrimination against people with Arab and Eastern European-sounding surnames in the three largest Italian cities. As per the labour market, Patacchini, Ragusa, and Zenou (2015) used a correspondence study to assess discrimination against LGBT people based on their affiliation with LGBT-related organizations. Similarly, some studies aimed at disentangling discrimination, based on ethnicity, in hiring processes. Allasino et al. (2004) realized the first-ever audit study in Italy, which looked at discrimination against Moroccans in low-skilled jobs in main urban cities. Their contribution to this field is quite relevant. The study looked at discrimination at distinct stages of the hiring process, from screening to the job offer. The authors find that discrimination rates between Italian and Moroccans, which were matched in all their characteristics other than nationality, decreased as applicants made it through the stages of the hiring process.

Recently, Busetta, Campolo, and Panarello (2018) designed and implemented an online correspondence study to isolate discrimination against first- and second-generation job applicants, including European and non-European applicants. The study used the same approach as Allasino et al. (2004), namely a paired match design. Resumes in this study were constructed to make applicants look the same in all aspects except for their immigration background, including Romanian origins. This study provides interesting estimates of what the authors suggest is taste-based discrimination. Also, their findings point to differential treatment in favor of men versus women regardless of their immigration background. Finally, Busetta, Campolo, and Panarello (2020) used another correspondence study, with the same paired-match design to assess the interaction of an ethnic background and being overweight on employers' likelihood to invite job applicants to an interview.

This limited number of correspondence studies in Italy is important as it makes employers receiving fictitious applications less likely to suspect that they are part of an experiment. At the same time, having benchmarks on ethnic discrimination (Busetta, Campolo, and Panarello 2018) can also help understand the findings of the current research in the Italian context. Importantly, the current study can expand the existing research on the Italian labour market, which falls short of looking at the interaction of labour market histories and discrimination.

Correspondence studies implemented so far in Italy focus on estimating between-group differences in callback rates. They do not look at mechanisms behind employers' decision-making process beyond controlling for the type of job and job location(Busetta, Campolo, and Panarello 2018; 2020). Also, the current research addresses design issues of past correspondence studies implemented in Italy, including the role of unobserved characteristics (Heckman 1998) and job search externalities (See Chapter 4) that plague paired-match designs and bias their estimates (Phillips 2019).

3.2 Unemployment and the labour market of young graduates

A bird-eye view of the Italian labour market tells that in the past decades the country has been experiencing slow economic growth, considerable risk of unemployment for its labour force, as well as job insecurity due to the increased use of temporary contracts (OECD 2018). Most studies on unemployment duration, particularly correspondence studies, focused on labour markets with generally low levels of unemployment while exploiting internal differences between local labour markets (Kroft, Lange, and Notowidigdo 2013). While Bentolila, Garcia-Perez, and Jansen (2017), look at Spain, which also experiences a very high level of unemployment, the authors design an observational study and consequently study duration dependence from the employees' perspective. The existing literature has yet to look at employers' use of unemployment duration in a context like Italy, thus making it an interesting case study to complement previous findings.

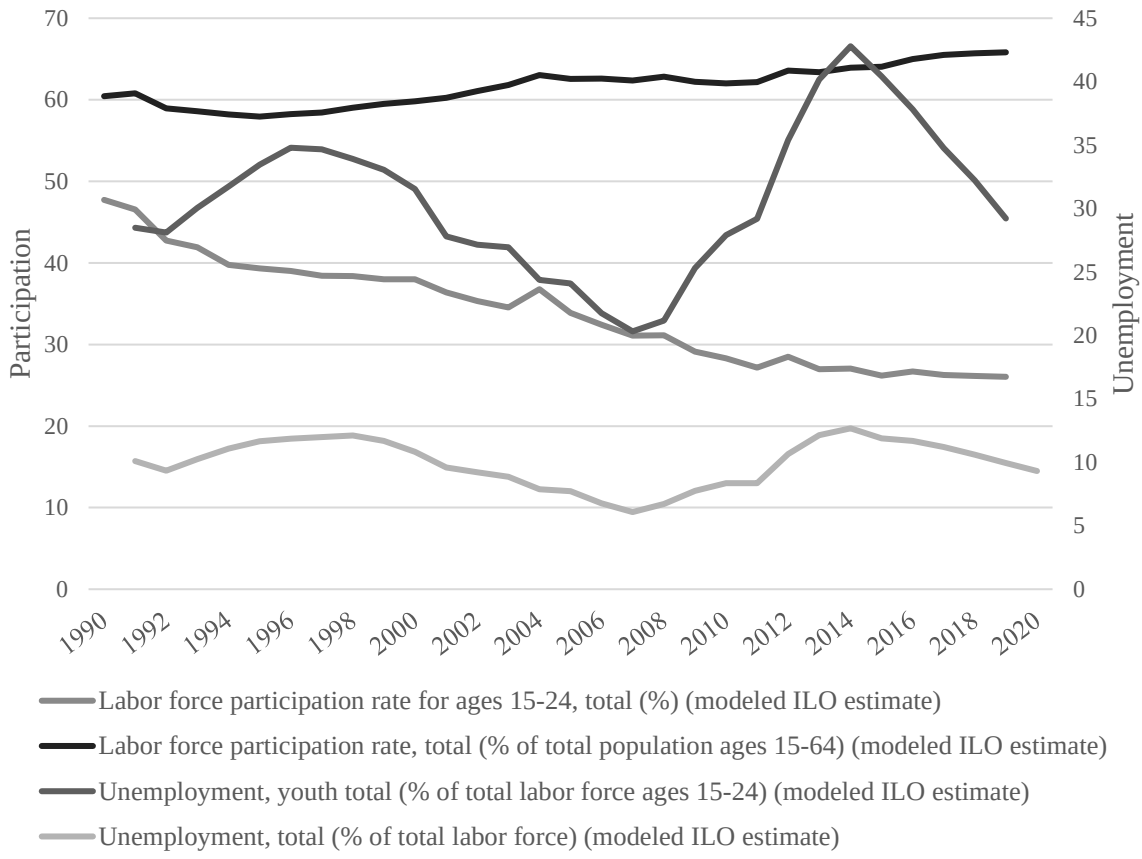
With regards to unemployment, Figure 3.2.1 shows that the share of those looking for a job declined from 2000 till the start of the Great Recession, after which it went up to 20% in 2014[2]. Importantly, among the pool of job seekers not in employment in 2013, 56.4% were in long-term unemployment, and the average time before finding a job was estimated at 21 months (Crepaldi, Pesce, and Samek Lodovici 2014). In the years following 2014, the size of the group in long-term unemployment and the average duration went down, respectively about 40% and 17 months (Mandrone et al. 2016). Average unemployment duration differs substantially between age groups, and it was substantially longer among new labour market entrants (Crepaldi, Pesce, and Samek Lodovici 2014). Thus, it is instructive to look at labor force participation rates and unemployment among young people.

Figure 3.2.1 shows worrisome declining trends in the labor force participation of young people (15-24). After the Great Recession, the share of young people in long-term unemployment went up dramatically (Adda and Triggari 2016) along with the percentage of young people who were not in education, employment, or training (ISTAT 2016). While the Great Recession contributed to the surge in unemployment and drop in participation rates, Centra and Ricci (2017) note how these phenomena depend on structural factors such as skills mismatch and changing landscape of the Italian labour market. Similarly, Brzinsky-Fay (2007) finds through sequence analysis that Italy has one of the longest school-to-work transitions in Europe

[2] Figure 3.2.1 does include data after the COVID-19 outbreak, which was characterized by a drop in labour force participation and consequent decrease in the unemployment rate (ISTAT 2020c).

pointing to the lack of coordination between education and labour market institutions. Thus, youth unemployment is an endemic feature of the Italian labour market (ISTAT 2018b).

Figure 3.2-1 Trends in unemployment rates and labour force participation, total and 15-24



Source: ILO Labour market data, World Bank data repository

While statistics on unemployment, participation, and duration often refer to those in the age bracket of 15-24, Italian graduates have also been experiencing an increased risk of unemployment (Brunetti, Cirillo, and Ferri 2020). Italian graduates also take longer (about 3 years) than their European peers to land a stable job after leaving university at about 25 years old (Pastore, Quintano, and Rocca 2021). Beyond structural factors, how employers and job seekers try to find each other might contribute to the length and complexity of the Italian school-to-work transition. When it comes to finding new hires most Italian employers, especially those with 1-10 workers, still rely heavily on informal networks and those using job portals are usually mid/large-size firms and to a lesser extent, small firms (Mandrone et al. 2016). Similarly, in 2017, 90% of all job searchers relied on informal networks, even if the majority used multiple channels such as the internet, especially among those in long-term unemployment (ISTAT 2018b).

While the use of informal networks is widespread, web search seems to be increasingly gaining importance among young applicants. ISTAT (2018b) reports that individuals with a degree were more likely to have found their job through formal applications than any other means, particularly through online job portals. Importantly, the use of these channels in the Italian context is also associated with a better match between job seekers and employers (Meliciani and Radicchia 2016). Instead, the use of networks among job seekers can result in the segregation of job opportunities (Calvó-Armengol 2004; Calvó-Armengol and Jackson 2004), as well as these informal channels tend to reproduce existing inequalities in job allocation (Moss and Tilly 2001). Studying employers' hiring decisions through web portals, therefore, focuses on a specific segment of the Italian labour market, particularly graduates. Yet, the segment is growing. As such, this study could provide evidence of the potential of this job search channel to help reduce inequalities in access to jobs and improve the quality of matching.

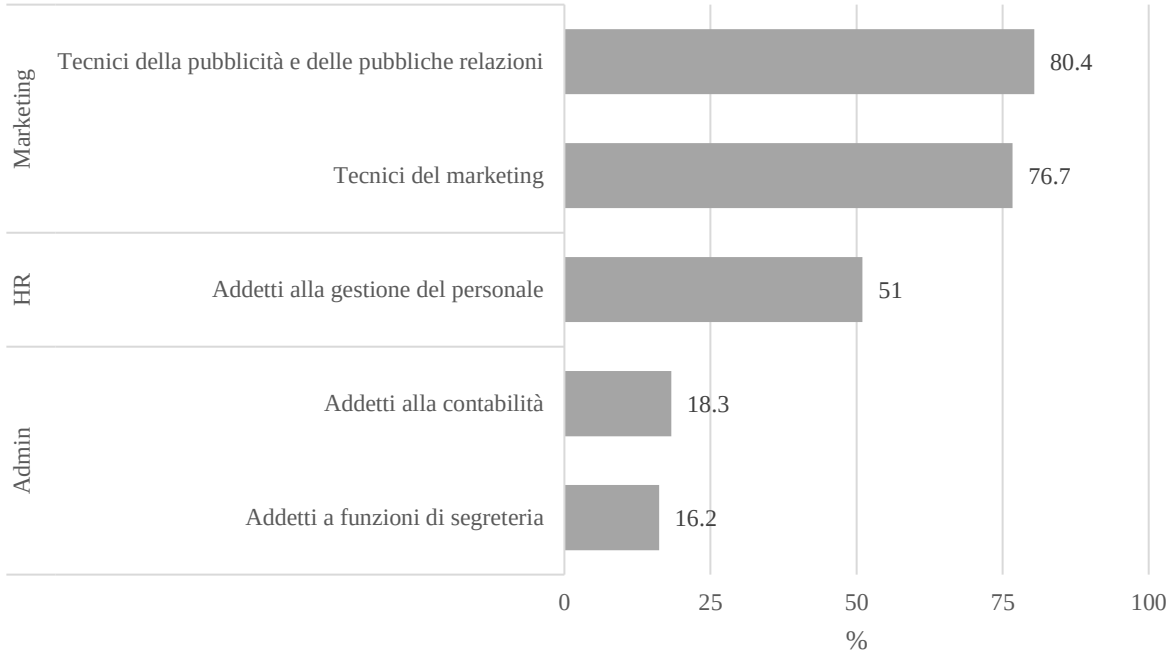
For example, online portals currently provide access to a wide array of jobs, particularly those in great demand. UNIONCAMERE (2018) highlights that a large share of new jobs has been and will be created in some key clusters, including Human Resources (HR), Administration, and Marketing. UNIONCAMERE also reports that jobs in these clusters are projected to increase further between 2018-2022. It follows that jobs in these clusters are easy to find online and could provide gainful employment for young graduates. Nonetheless, not all of them, as reported by employers, require a BA. Figure 3.2.2, which uses data from the Excelsior project[3], shows that about 80% of jobs created in the marketing cluster require tertiary education. This percentage goes down to 50% for potential new hires in HR and between about 18% and 26% for administrative jobs, respectively accountants and executive assistants. It thus seems that on one hand, applicants with a BA may have an edge over applicants not as qualified in the administrative and HR cluster, while the marketing sector increasingly targets graduates only. On the other hand, Italian graduates searching for jobs in the administrative and HR clusters are likely to be overqualified, which resembles the current situation they face (Brunetti, Cirillo, and Ferri 2020).

From a research perspective, the literature debates whether getting a job that is not at the right level of qualification and skills can be either a stepping stone or detrimental to individual professional growth (Scherer 2004; Verhaest et al. 2018). In this regard, it is interesting to note

[3] The representative sample includes 35,000 employers providing information on more than 550.000 enterprises (Franceschetti, Guarascio, and Mereu 2019)

that there is a generalized understanding among the Italian public, that if unemployed, young job seekers should be accepting anything that comes their way, otherwise they should not be receiving unemployment benefits and support (Cardone, Deidda, and Marocco 2019). However, Italian employers may (not) look at overqualification from a different perspective.

Figure 3.2-2 Employers requiring at least a Bachelor for the job they offer, by cluster and per job



Source: "Banca dati professioni", UNIONCAMERE, Excelsior project, 2020

Given that this study uses fictitious candidates who are equally qualified but apply for jobs that differ in their educational requirements, this thesis can help understand within-group inequalities in labour market outcomes. In this regard, the current study can contribute to research on inequalities in the graduate labour market, which has highlighted a sharp increase in wage inequality that mainly stems from within-degree subject differences in pay (Lindley and McIntosh 2015). This thesis could instead disentangle some factors behind within-degree differences in job findings rates, as well as within-degree inequalities compared to the quality of the opportunities that graduates could access.

3.3 Gender in the Italian labour market

Gender inequalities in the Italian labour market have been quite persistent and hard to tackle (Cirillo, Fana, and Guarascio 2017). Men still earn more than women, as well as they are more likely than women to be employed, with the gap being one of the widest among OECD countries (OECD 2018). Yet, the situation has been improving in terms of labour market participation as shown in Figure 3.3.1 Such a slow but continued increase in women's participation, as well as in employment rates, has also been followed by a reduction in the unemployment gap between men and women. However, the (un)employment gap between men and women shrunk mainly due to the increased rate of joblessness among men in the aftermath of the crisis and it started to widen again once growth restarted after 2014 (Canal and Gualtieri 2018). Women are still more likely to hold part-time and low-quality jobs and be overeducated for the task they perform while their probability to land a permanent job is lower than men (Crepaldi, Pesce, and Samek Lodovici 2014).

Figure 3.3-1 Trends in unemployment rates and labour force participation, men, and women

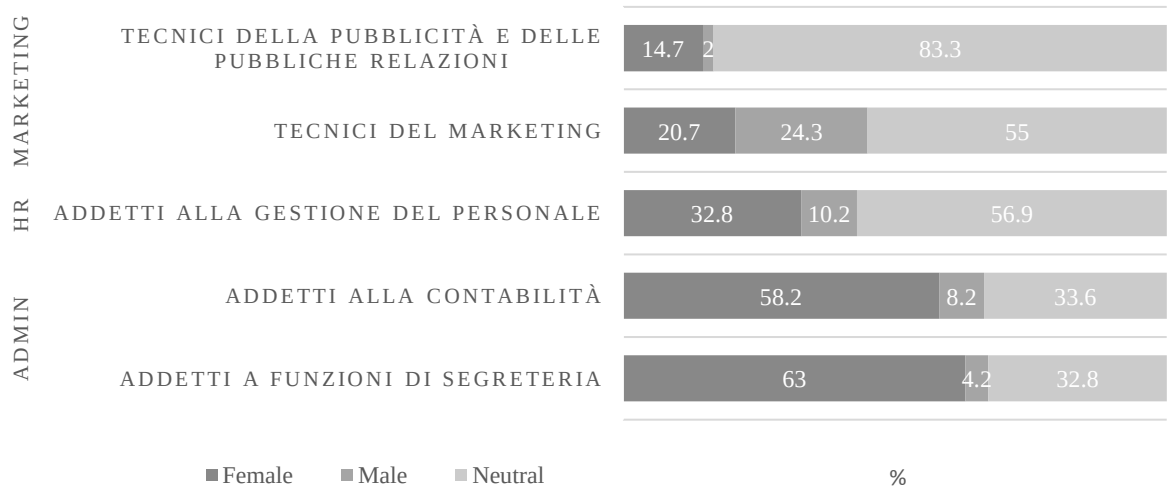
Source: labour market data, national estimates, ISTAT

Differences in the number of hours worked and quality of jobs, along with gaps in labour force participation, trace back to structural gender differences that characterize Italian society, particularly the role of women in families. For example, Curci and Mariani (2013) show that the gender gap in labor force participation is the widest among those who report they have not

been working due to family-related motivations. In line with this finding, Amici and Stefani (2013) show that women spend more minutes than men during the day carrying out chores and taking care of family members. Reinforcing this point, Barbieri et al. (2020) find participation and employment gaps among women between those who are in households including children, and those in units without. By adding an age gradient, which is relevant to the current research, Scialdone and di Padova (2020) show that men are more likely than women to be not in education, employment, or training during the school years (aged 15-24), but the opposite is true among those, like young graduates, entering the labour market (25-29 and 30-34).

The gendered nature of the Italian labour market also emerges when looking at employers' expectations about who is the right candidate for their needs. Figure 3.3.2 uses data from the Excelsior project, which asked Italian employers whether women, men, or both were the most suitable candidates for the vacancy that they will need to fill. Figure 3.3.2 provides a breakdown of employers' responses for jobs in sectors with high job creation potential, namely Marketing, HR, and Administration. Importantly, Figure 3.3.2 reflects employers' gender beliefs and provides some information on motives that could help perpetuate gender segregation in the labour market.

Figure 3.3-2 Percentage of employers wanting a woman, a man, or being neutral, by sector and per job



Source: "Banca dati professioni", UNIONCAMERE, Excelsior project, 2020

First, employers' views differ between sectors with the marketing cluster being the one where employers hold neutral views about the gender of the best-suited candidates. Administration is the most skewed towards women being the best candidate to fill in a potential vacancy. HR is

somewhere in between with 57% percent reporting neutral views and the remaining respondents preferring female workers in 32.8% of cases and men in 10.2%. The second point emerging from Figure 3.3.2 is the within-job cluster heterogeneity in marketing. For example, within marketing, there is a larger percentage of employers who express gender preferences for the position of marketing specialist compared to jobs related to public relations and advertising. Contrarily, about two-thirds of employers in administration either looking for executive assistants or accountants think women are the best place to do these jobs. Finally, the key takeaway from Figure 3.3.2 is that focusing on these three job clusters would help factor in differences in employers' expectations and beliefs about the gender of their ideal candidate. As detailed in Chapter 2, such competence expectations influence whether employers are likely to call back a man or a woman for a job interview.

3.4 Migrant workers and new generations of Italians

As gender inequalities persist, the Italian labour market is also far from being inclusive for workers with foreign origins (OECD 2018). Nonetheless, the integration of foreigners into the Italian society and labour market is of foremost importance given the sizeable and increasing number of people moving to and residing in Italy (Pugliese 2006). Foreign nationals have within-group employment rates higher than Italians, but workers coming from abroad experience higher unemployment rates (Crepaldi, Pesce, and Samek Lodovici 2014). The unemployment rate for those of foreign origins was about 14.2% in 2017, which is approximately 5 percentage points higher than the OECD average (Direzione Generale dell'Immigrazione e delle Politiche di Integrazione 2019). This should not come as a surprise in a country where unemployment is widespread and quite common among its labour force.

Romanians represent the largest cluster of all foreigners in the country (Colucci 2019) with a gender-balanced composition (Pugliese 2006). This group moved to Italy at the end of the '80s and beginning of the '90s and increasingly so over the 2000s (Cingolani 2009). Employment rates among Romanian men and Women are respectively 75% and about 54%, as well as women register lower levels of labour force participation than men (Contu et al. 2022). Romanians are mainly employed in the service sector, followed by industry, and women tend to find employment in the care sector whereas men are more likely to engage in the construction sector (IDOS 2022). Nonetheless, between 2010 and 2020 there has been an overall 40% increase among Romanians in employment rates for skilled professions, which has been even more pronounced for qualified back office jobs (76%) (IDOS 2022).

In terms of qualification, Cohal (2014) reports that about 80% of Romanians residing in Italy attained compulsory education, 10% a high school diploma, and another 10% tertiary education. Importantly, Romanians, compared to any other group, report the highest number of students across all levels of the Italian education system (Santagati and Ongini 2016; IDOS 2019). At the tertiary level, there are about 10,000 students with Romanian origins enrolled in Italian universities (IDOS 2022) and about 90% of the Romanian Italians who graduated from Italian universities move to Italy before acquiring their secondary education (AlmaLaurea 2022). This implies that it is possible to find young Romanians who have attained their education in Italy, particularly at the tertiary level[4] (Cohal 2014).

[4] Based on Ustat-Miur data, Romanians represented the 12.6% of the foreign nationals currently pursuing a BA in Italy. Again, they were the largest group of foreign nationals.

Importantly, such a long-term presence of Romanians in Italy has brought about a large share of people who were born in Italy to parents of Romanian origins, that is second generations (Colucci 2019). Second generations, such as Romanian Italians, are increasingly attaining tertiary education and following occupational pathways that resemble those of Italian graduates (AlmaLaurea 2022). Romanian-Italians, compared to other second generations with parents of different nationalities, better master the Italian language and show higher rates of companionship with groups of Italians only (ISTAT 2020b). In other words, they tend to experience lower social segregation. This matters since employers may be concerned about the quality of education attained in third countries and the language skills of foreign nationals (Oreopoulos 2011; Zschirnt and Ruedin 2016). For example, Pieroni et al. (2022) find that immigrants with lower levels of proficiency in the Italian language stand a 20-30% lower chance of employment than those who master the language. With regards to labour market outcomes, available data from EUROSTAT (2016) show a one-percentage point gap in employment rates between second generations and Italians with a native background in the age group 25-54. However, second generations tend to have higher employment rates than first generations (those who were born abroad and moved to Italy). Thus, from a substantive perspective, second-generation Italians with a Romanian background offer a relevant and plausible target to study discrimination and to inform discussions on the integration of second generations in the Italian labour market.

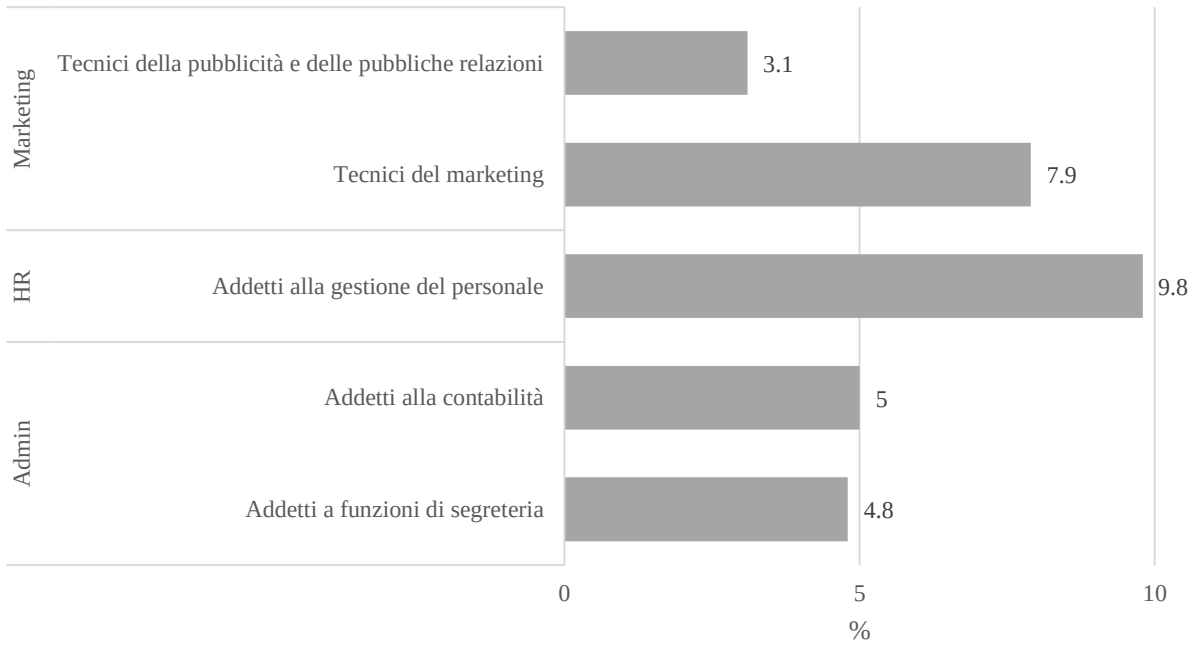
Employers across different job clusters may show a different propensity to hire such profiles. While this type of data is not available, the Excelsior project inquired Italian employers about their expectations to onboard immigrant workers for the jobs they expect to create. Even if the question does not directly concern second generations, it could be considered a loose proxy of openness to consider profiles such as those of candidates with Romanian origins. Like gender, Figure 3.4.1 breaks down these data for job clusters identified as having high job creation potential and the respective sub-professions. Overall, the figure tells that employers have low expectations across the job clusters. A look at the clusters shows that employers in HR are those with the highest expectation of employing someone with an immigrant background (about 10%). In the Administrative cluster, employers seem less likely than those in HR to consider such a profile as just 5% among them, across sub-professions, would expect to get a foreign national on board.

Marketing is instead heterogeneous across sub-professions. Employers looking for someone to work on public relations are the least likely across clusters (in expectation) to hire an immigrant

worker. Employers needing marketing specialists instead are more open to this possibility representing the second highest rate across professions (7.9%). Such a difference might be driven by the type of tasks to be performed and the skills required. For instance, marketing specialists are more analytical types of jobs whereas those dealing with public relations require more relational and communication skills. For the latter, employers may thus prefer an Italian native who they can rest assured master language and writing, as mentioned in previous paragraphs.

Besides broad expectations about hiring immigrants, employers might hold expectations and beliefs about Romanians, which can be as important in influencing employers' decision to consider them suitable candidates. In this regard, Cingolani (2009) brings to bear the representation shared among the Italian public, which depicts Romanians as security threats. Similarly, Eurobarometer data on the opinions Italians have regarding foreigners who reside in their country show that 74% of respondents hold negative views about the contribution of immigrants (Valbruzzi 2018). Particularly, Italians think that the rising number of foreigners is associated with (perceived) increased criminality and 58% reported that they see immigration as damaging to the employment prospects of Italians.

Figure 3.4-1 Percentage of employers expecting to hire an immigrant worker, by sector and per job



Source: Banca dati professioni, UNIONCAMERE, progetto Excelsior, 2020

Nonetheless, Cingolani (2009) reports that Italians may also see Romanians as culturally proximate and hard-working, supporting the opinion that they are easier to integrate. Within this discourse, the author also stresses the importance of the representation of Romanian women as wives and mothers, which stems from their concentration in the care sector. Employers may thus lean towards one of these two narratives when dealing with those of Romanian origins, which again makes the study of this group quite relevant to inform discussion on the integration of the new Italians.

3.5 Within-country differences

Italy represents an interesting case study given that the country manifests sharp differences between regions in aspects that are key to the current research. Importantly, labour market outcomes and functioning of the labour market vary between the North, Center, and South of the country (Lupi and Ordine 2002). Such differences have proved to be persistent over time and economic catch-up has never really happened, nor it is in sight (Vecchi 2017). For example, after the Great Recession, unemployment went up in regions already registering higher rates pre-crisis, particularly those in the South (OECD 2020). Such rise in unemployment and decrease in employment rates was markedly concentrated in a few regions of the South including Sicily and Campania compared to others like Abruzzo, Molise, and Basilicata, which experienced trends like those seen in the North (ANPAL 2019). These regions also show the highest rates of inactivity, that is people who are not working, nor actively looking for a job. While the net change in employment turn positive in the North and Center between 2008 and 2018, it was still negative in the South in 2018 (Svimez 2019).

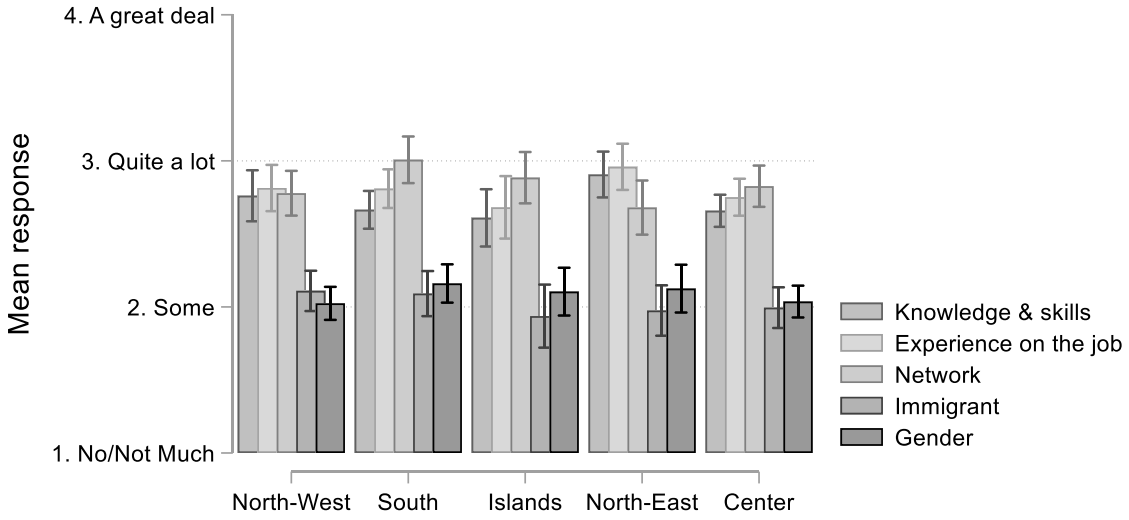
Unemployment rates in the South are also higher among young people and increasing post-crisis compared to their peers in the other regions (Adda and Triggari 2016). Similarly, the rate of young people not in education, employment, or training (NEET) stands at 28% compared to 17% in the Center and 14% in the North (ISTAT 2016). This means that the NEET rate in the South is about double of the other Italian macro-regions. Such territorial differences also influence job search behavior. ANPAL (2019) highlights that job seekers across regions rely heavily on individual networks to find work while also using other complementary channels. Nonetheless, the number of channels and actions taken to find a job decreases as regional unemployment rates go up. Unemployment duration differs across regions with a marked increase in the years of the Great Recession at 15 months in the North and 27 in the South (Crepaldi, Pesce, and Samek Lodovici 2014).

To explain the situation of the labour market, research focusing on the Italian divide posits that macro-regions differ in their underlying social institutions, norms, and beliefs (Felice 2015; Bigoni et al. 2018). What is apparent looking at regional labour market statistics and outcomes, for instance, is the gendered nature of these differences. Cirillo, Fana, and Guarascio (2017) show that the gap in participation between men and women in the South, compared to the North and the Center, is still substantial today even if it shrunk by 20 percentage points since 1992. However, Brunetti, Cirillo, and Ricci (2018) highlight the compositional nature of this catch-

up. The reduction in the gender gap in participation was driven by a reduction in men's employment given that men were overrepresented in the sectors most affected by the crisis, which in turn were more likely to be in the North than in the South (Svimez 2019). Importantly, gaps in participation rates between macro-regions are also strongly related to the greater amount of time women living in the South spend on chores and with children (Amici and Stefani 2013).

Macro-regions also differ in their distribution of those with Romanian origins. While this group represents the majority of those with an immigrant background across almost all regions, they live in greater numbers in the Northeast, North, and Center while the lowest concentration can be found in Campania and Calabria (South) (ISTAT 2018a). Differences in magnitude across a geographical location may matter as Valbruzzi (2018) shows that places with a smaller population of immigrant background are also those where Italians tend to overestimate the number of inhabitants with an immigrant background. The distance between perception and reality is larger in the South than in the North, which suggests that there might be differences in terms of differential treatment across regions with (more) fewer residents with a Romanian background. In this regard, Figure 3.5.1 shows which factors, according to Italians, exert greater influence on employers' decisions to hire someone. Respondents had to report, based on a 4-point Likert scale going from not at all (1) to a great deal (4), to what extent

Figure 3.5-1 Mean response among Italians on factors shaping hiring decisions, by region



Source: European Social Survey 2018 – Round 9[5], Italy

[5] ESS sample is nationally and regionally representative. It includes 2600 respondents residing in 170 towns with a gender and age distribution that mirrors that of the national population, as well as the same education attainment.

knowledge, individual network, experience on the job, as well as gender and immigrant background drove employers' hiring decisions. Importantly, Figure 3.5.1 provides the regional breakdown of respondents' answers using the geographical grouping given by ESS, which includes North-East/West, the South, and the Center, as well as the Islands (Sardinia and Sicily). While these data focus on the ultimate hiring decision (job offer), they can still provide some interesting indications for the current study about generalized perceptions of what may drive employers' decision-making.

Overall, Italians think that knowledge, and experience on the job and network matter much more, and by far, than characteristics such as immigrant background and gender. Italians still think that employers consider gender and immigrant background when making hiring decisions but just to some extent. Also, there is regional variation in the ranking of the three leading factors. However, there is just slight variation across regions both in terms of gender and immigrant background with the former being on average considered more important than the latter (even if with overlapping confidence intervals).

Results from correspondence studies implemented in Italy are presented in Section 3.1. however, suggest that the view of Italian respondents is optimistic. While these previous studies focus on isolating differential treatment based on ethnicity and gender, the current design can also help understand the "weight" that employers give in the screening phase to gender and immigrant background along with individual skills and qualifications. Particularly, how employers across Italian macro-regions look at and aggregate all these pieces of information to identify candidates to be invited for a job interview. As such, the current study can tell what matters the most in practice for employers among those items shown in Figure 3.5.1. and how employers' practices may contribute to perpetrating labour market inequalities within and across Italian macro-regions.

4 Research design and operationalization

The study of employers and how they help shape labour market inequalities can take various forms. Researchers have relied on both qualitative and quantitative approaches to understand employers' choices and behaviors. Interviews and ethnographic studies have been leveraged to understand what matters to employers (Bills 1990; Holzer 1996; Moss and Tilly 2001; Bonoli and Hinrichs 2010), as well as how the design of hiring processes is skewed in favor of applicants with high-status backgrounds (Rivera 2015). More recently, the experimental methodology has been systematically utilized to isolate discrimination in employers' decision-making, particularly in the screening phase (Pager 2003; Bertrand and Mullainathan 2004) and to understand employers' motives (Van Belle et al. 2017).

Correspondence studies represent one of these experimental designs that researchers have been relying on to assess differential treatment in the labour market (Pedulla 2018a). A correspondence study entails that the researcher inquiries directly to employers by responding to real job vacancies available in the labour market (Gaddis 2018). Employers are not aware they are part of a study since the researcher assesses employers' decision-making through their responses to fictitious résumés sent to existing job advertisements (Zschirnt 2016). Researchers create résumés that are similar if not equivalent in all aspects, while modifying systematically one or a few key characteristic(s), like gender, ethnicity, and unemployment duration, which are listed in résumés of these fictitious profiles. Employers' calls to fictitious applicants for an interview are then recorded and the researcher can measure differences in callback rates based on those characteristics that vary between resumes. This design allows the researcher to attribute differences in callbacks to those characteristics that vary systematically between résumés. As such, a correspondence study makes it possible to isolate discrimination (if any) stemming from employers' decision-making. In the context of this thesis, a correspondence study allows us to infer whether employers leverage unemployment duration, gender, and immigrant background as discussed and hypothesized in Chapter 2.

Nonetheless, other research designs, potentially, could have been used to address the research questions of the current project. Also, there are methodological issues that if not addressed in the design stage can bias estimates obtained from the data collected through a correspondence study (Neumark 2012; Phillips 2019). Therefore, it is fundamental to substantiate the choice of a correspondence study by assessing its comparative advantage compared to alternative

designs. Also, consider the ethical implications of this design[6] and discuss how methodological issues have been addressed in the current research.

In this regard, Chapter 4 builds on the previous one and details the rationale behind the choice of the research design of this thesis, as well as how it has been structured and implemented. In the first Section (4.1), Chapter 4 explains why a correspondence study is the right design to address the research questions of this thesis. Section 4.2 then delves into the ethics of correspondence studies. As mentioned previously, employers do not know they are active research participants. Thus, Section 4.2 aims to show that the relevance and benefits of this study, as well as "do no harm" considerations, render the engagement of employers safe and inexpensive.

Importantly, isolating differential treatment in correspondence studies rests on the use and share realistic and relevant profiles (Carlsson, Fumarco, and Rooth 2014). Failing to use fictitious profiles that could represent real types of employers found in their labour markets can severely bias estimates and hamper the assessment of discrimination in hiring processes (Heckman 1998). Thus, the third (4.3) and the fourth (4.4) sections discuss design choices by making links with features of the Italian context. Particularly, Section 4.3 discusses how the data collection was organized and how résumés were structured. The following Section (4.4) discusses how unemployment duration, gender, and immigrant background were signaled in resumes and how they were allocated to fictitious profiles. The section also presents the random allocation of other characteristics like soft skills and characteristics of the employment history, including the number of jobs, and the size of firms, among others.

[6] The Ethics Committee at the European University Institute assessed the project description and design of the experiment concluding on 14 November 2018 that both complies with the rules, norms, and values of the "EUI-Code of Ethics in Academic Research." The formal approval from the committee along with the data protection review can be found in Annex H.

4.1 Why a correspondence study?

The use of correspondence studies in social sciences has been growing over the past decades. This methodology was used initially in the '60s with the rise of the civil rights movement to assess and measure discrimination. It has then become prominent in the field of labour market discrimination across several geographic locations (Zschirnt and Ruedin 2016; Verhaest et al. 2018). Such increasing interest in this methodology is due to its potential to reveal whether employers de facto treat differently applicants when instead the law mandates equal treatment and equal access to opportunities (Neumark 2016). This feature also characterizes other approaches like factorial survey experiments (vignettes[7]) and laboratory experiments given that they provide the researcher with control over the environment and information that is provided to respondents. However, unlike factorial surveys and laboratory experiments, a correspondence study captures what employers do in the screening process for a real job vacancy (Protsch and Solga 2015).

In this regard, Pager and Quillian (2005) show that when employers know they are under scrutiny their answers differ from the decisions and choices taken for existing job vacancies. Similarly, after running a correspondence study in the Swedish labour market, Rooth (2007) contacted employers who received fictitious résumés during the implementation of the study. Employers were asked to take the Implicit Association Test (IAT), which provides a measure of implicit performance stereotypes. The author then shows that results from the IAT are just weekly correlated to employers' explicit statements about ethnic minorities and majority applicants. In a correspondence study instead, employers are not aware of being studied while taking decisions on existing vacancies. This aspect is an advantage compared to the lab and factorial survey experiments in the context of the current research questions.

Importantly, lab and factorial survey experiments may rely on undergraduate students, which would not tell much about employers' decision-making in the labour market. To counter this limitation, researchers have used web-based factorial survey experiments to make employers' engagement less costly, but the response rate remains extremely low around 10%-15% of those contacted (Di Stasio 2014; Van Belle et al. 2017). It follows that taking employers to the lab would be even harder due to the amount of time they would need to invest to participate in the

[7] "Experimental vignette methodology studies consist of presenting participants with carefully constructed and realistic scenarios to assess dependent variables including intentions, attitudes, and behaviors, thereby enhancing experimental realism and also allowing researchers to manipulate and control independent variables" (Aguinis and Bradley 2014).

experiment (Gërxhani 2017). A correspondence study instead does not require additional engagement from employers. Fictitious résumés that the researcher sends are part of a pool of applicants that need to be screened anyway to identify suitable profiles for existing vacancies (Gaddis 2018). Also, the use of online job portals makes it easy to engage employers at no cost while allowing the researcher to reach a larger *N* across several locations (Kroft, Lange, and Notowidigdo 2013).

Alternatively, researchers could bring the lab into organizational settings to study how employers make decisions in their "natural" environment. For instance, Baldassarri (2015) run a lab in the field in Uganda with producers' organizations to study mechanisms that would lead to cooperation. While this arrangement would allow studying employers in their environment, employers would still know they are under scrutiny. This aspect makes a lab-in-the-field experiment not suitable for the research questions of the current thesis. Overall, it also makes correspondence studies a superior alternative to web-based factorial surveys given that employers reached make decisions for existing job vacancies rather than being presented with a hypothetical hiring process.

Beyond experiments, interviews constitute an additional means to understand whether and how employers use unemployment duration, gender, and immigrant background to sort candidates. For instance, Bonoli and Hinrichs (2010) interviewed employers in several EU countries to grasp the meaning employers attach to long-term unemployment. This design has been highly informative to understand employers' motives to put forward hypotheses and to stimulate further research on the topic. Similarly, Moss and Tilly (2001) conducted a large study of US urban labour markets, including interviews, to understand how employers saw and used race in their hiring decisions and organization of work. Similarly, interviews combined with participant observation like Rivera (2015) can help understand how employers' status-related considerations are ingrained in the hiring process.

However, these qualitative approaches would fail to quantify the (relative) "weight" employers give to gender, immigrant background, and unemployment duration, as well as their intersection in the screening phase of the hiring process. Also, interviews on topics such as discrimination may be severely influenced by social desirability bias due to the sensitive nature of the topic (Moss and Tilly 2001). Using a well-designed correspondence study can instead isolate the consequences of employers' biases on the outcome of the screening phase (Neumark 2010; Carlsson, Fumarco, and Rooth 2014). Finally, from a methodological standpoint, a correspondence study would help circumvent issues related to unobserved heterogeneity by

ruling out the selection and compositional effects, which usually plague observational studies (Kroft, Lange, and Notowidigdo 2013).

In sum, a correspondence design offers several advantages over other approaches in the context of this research project. Unlike interviews, (web-based) factorial survey experiments, and lab (in the field) experiments, a correspondence study assesses the decision to call back a candidate in the screening phase of an existing job vacancy. Given that employers do not know about the research, a correspondence study eliminates the risk of the Hawthorne effect. Employers may change their behavior and decision-making simply because they know they are part of an experiment. Correspondence studies can also quantify duration dependence and discrimination, overcoming unobserved heterogeneity, whereas interviews can help better understand what employers may think. Factorial surveys show low response rates, which creates a pool of selected respondents. Instead, a correspondence study can reach a large *N* of employers across several locations and in different sectors using online job portals, as well as employers cannot self-select in the study given that they do not know by design they are taking part in a study.

4.2 Ethics in correspondence studies

While the previous section highlights the merits of correspondence studies, this design raises ethical concerns for the research community. These concerns deserve to be discussed to uphold the standards of good research. Also, addressing ethical concerns bear implications for the design of the current correspondent study. De facto, a correspondence study is a covert research design given that employers do not know they are active participants in an experiment. Correspondence studies are carried out without the informed consent of the participants and include a deceptive element since employers receive fictitious resumes in response to real vacancies. Therefore, the power of correspondence studies to detect unbiased behavior in the field lies on complicated ethical grounds.

Nonetheless, the case for not collecting explicit consent is strong in correspondence studies implemented in the labour market. Differential treatment and discrimination are usually covert and not easily observable phenomena, as well as employers do not openly declare to undertake them. For this reason, employers cannot be informed of their participation in correspondence studies (Blommaert, Coenders, and Tubergen 2014). As discussed in the previous section, informing employers about the research and its purpose is likely to bias and invalidate results (Pager and Quillian 2005; Rooth 2007). Having employers sign an informed consent means that they know resumes are not real and that how they screen them is under scrutiny. Were these arrangements to be operationalized, correspondence studies would lose their comparative advantage over factorial surveys or labs-in-the-field. It is also worth emphasizing that when meticulously designed, correspondence studies offer a clean assessment of recruitment practices and employers' compliance with non-discriminatory legal provisions (Bovenkerk 1992). Taking such a perspective makes employers' time and the moral costs, incurred by researchers who implement a correspondence study, a small bearable price (Riach and Rich 2004).

The use of correspondence studies also finds support in legal frameworks such as the "EU Code of Ethics for Socio-Economic Research." The code recognizes the need to carry out covert research without informed consent, explicitly referring to field experiments in the labour market that aim to isolate discrimination in hiring processes (Dench, Huws, and Iphofen 2004). In the US, the legislation mentions that certain research goals can only be pursued without the informed consent of the participants (Gelinas, Wertheimer, and Miller 2016). In other words, the moral costs of deception should not represent an impediment to the use of the

correspondence study given the larger benefits in addressing a social issue (Riach and Rich 2004). Further, the current correspondence study is concerned with understanding whether, at the aggregate level, employers are likely to use time in unemployment duration, gender, and immigrant background as sorting criteria. It does not aim to single out individual employers. Such focus on the aggregate level ensures the anonymity of uniformed participants; that no harm is inflicted on employers and no risk is imposed onto their welfare, nor on their rights. These research principles are pivotal criteria to have an IRB waiving the informed consent and are highly likely to be met and respected when implementing a correspondence study (Pager 2007).

Previous research using correspondence studies has sometimes opted for post-hoc consent to some (Midtbøen 2014) or all employers (Liebkind, Larja, and Brylka 2016) contacted during the experiment, which means employers were informed about the experiment several months after the end of the study. Asking for post-hoc consent would not affect the pool of applicants given that the vacancy would no longer be available. Nonetheless, post-hoc consent may still backfire imposing significant risk on personnel carrying out selection once the nature of the study (and the study itself) is known to the firm (Pager 2007). Further, informing participants post-hoc could influence future employers' hiring behavior, which would have not happened if they were not informed at all. Importantly, the Institutional Review Board (IRB) at the University of Chicago approved a correspondence study on how employers use unemployment duration (Kroft, Lange, and Notowidigdo 2013), which is also investigated in this research project. However, the IRB constrained researchers from contacting firms that participated in the experiment at any time, either during or after the experiment. Therefore, in line with these provisions, the current research does not seek pre- and post-hoc employers' consent.

As mentioned previously, the study does not seek to single out individual employers. Therefore, during data collection no personal, nor sensitive information was registered (i.e. firm name, address, phone, or owners' data), which guarantees that employers in this study remain anonymous and that it is impossible to identify *directly* firms in the final dataset. The data collection just entailed the gathering of details from the job ad to study the language employers use and the requirements of the vacancy, namely job requirements, type of contract, and salary. Further, when employers contacted a fictitious applicant, the content of the message was immediately transcribed offline. Importantly, employers' email addresses and phone numbers from these messages were not stored in the final dataset. In sum, the final dataset is completely anonymized and there is no possibility of *directly* identifying any firm.

Additionally, the public use version of the final dataset also omits the city of the vacancy as it reports just the macro-region. Similarly, the dataset just reports the month rather than the time and the day of the application. These fixes make it extremely hard if not completely impossible to identify *indirectly* employers. Data have been stored offline and encrypted following the same procedure for the backup, as well as no data transfer to third parties has taken place. Finally, the analysis has been done offline ensuring that the PC is not connected to the internet. In sum, data collection, storage, and management have minimized any potential risks, or harm, to employers, their privacy, and anonymity.

As employers spend time screening resumes, the current project has also minimized the time employers use to look at fictitious resumes. To uphold this principle, each employer who has taken part in the data collection has just been contacted once. Employers who posted several job ads during the time of the data collection received only a batch of resumes for the first job they advertised. Employers have been immediately re-contacted to decline interviews in case of a positive response: when employers called back, left a voice message, or an email asking for an interview, employers have received a reply, by phone or email, turning down the offer. All these fixes aimed to ensure that risks and loss of time for employers were kept at a minimum.

4.3 Operationalization of the correspondence study

The data subjects of the current study are Italian employers posting vacancies on online job portals. Between September 2019 and May 2020, 4,079 resumes were sent in response to 1,041[8] employers/vacancies. Vacancies were found via online job portals focusing on 11 of the most populous cities in Italy: 5 cities in the North, namely Bologna, Genova, Milan, Turin, and Verona[9]; 2 cities in the central region (Florence and Rome), as well as other 4 cities in the Southern region (Bari, Catania, Naples, and Palermo). A pilot was also run in July 2019 to test procedures and safety of the arrangements taken to contact employers. About 212 resumes were sent to 53 employers. Particularly, the pilot allowed to test the use of different job portals, carry out a quality check to identify and remove bugs in the production of resumes, as well as in the process of selecting vacancies and sharing profiles with employers. Ultimately, the pilot provided a means to test the ease of matching responses from employers to fictitious resumes. No serious issues were identified, but data from the pilot are not considered in the analysis of the current project[10].

Urban areas were selected as the sole focus of the data collection due to the increasing concentration of the labour force in these zones and their ability to create jobs. Similarly, data collection focused on the private[11] service sector, which is currently one of the fastest growing sectors worldwide and has a key role to play in employment creation (ILO. 2015). Studying the service sector is therefore relevant as it provides an understanding of hiring decision dynamics for jobs that are and will be in demand. Also, its employment creation potential guaranteed that a large *N* of employers could be reached.

[8] The total number of resumes sent is uneven because 19 employers received batches with just one resume rather than four; 11 employers received batches with just two resumes; 6 employers received batches with just three resumes. Job ads were either removed or were no longer available before all four resumes could be sent out. Analysis has been carried out without these employers and their exclusion does not affect estimates. As such, these employers were retained in the final sample.

[9] Verona is not among the 10 largest cities in Italy. Venice was initially selected to collect data in North-East region of Italy. Nonetheless, after the pilot run in July 2019 it was decided to include Verona and drop Venice from the data collection. Both cities are in the same region, but Verona is in one of the greatest regional job clusters of the Italian labour market. Importantly, it also represents an area where a large share of immigrant workers resides and actively participate in the labour market.

[10] Analysis has also been carried out including these data from July 2019, which did not affect results presented in the following chapters.

[11] The public sector was not considered in this study because applications for public jobs usually require additional documents (e.g. IDs, school certificates etc.). These documents would have to be forged. Such practice, however, could be costly for employers (screening time), as well as for the researcher since it raises the risk of detection and the legal consequences.

Within the service sector, resumes were sent to employers posting vacancies for entry-mid-level jobs in Human Resources (HR), Administration, and Marketing. Within these sectors, resumes were sent in response to job ads related to 6 occupations, namely HR specialist or generalist; marketing or social media manager; an accountant or administrative assistant/secretary. While these occupations vary in content and functions, they can all be categorized as desk jobs. Beyond substantive considerations on employers' expectations and gendered framing of these jobs, which were previously presented, this occupational category was targeted because job vacancies were quite standardized in structure and content. Such a feature made it easier to create fictitious resumes that could be relevant for employers and develop a standard routine for their generation.

Also, the choice of desk jobs stems from considerations related to the importance of personal appearance in employers' decision-making (Patacchini, Ragusa, and Zenou 2015). Including a picture, while not a mandatory requirement, remains a practice in the Italian labour market, particularly for those jobs that require daily direct contact with people external to the organization. Given that this study focuses on desk jobs, which do not require major contact with externals, resumes did not include a picture. A picture was considered unnecessary also based on informal conversations with personal contacts who work as recruiters at 4 different companies. These informants were consulted before the start of the data collection. Furthermore, evidence also shows that discrimination is higher in customer service jobs, which entail direct contact with others (Nunley et al. 2015). Thus, focusing on desk office jobs might provide more conservative estimates.

Vacancies for these 6 professional profiles were mainly found through two job portals, namely Indeed.com and Bakeca.it. Jobs were sampled daily using a set of criteria to ensure standardization in the types of vacancies selected, as well as to standardize the job search routine, which was automatized using Python. First, employers had to be within a 25-km radius of one of the 11 cities included in the study. Research has shown that greater commuting distance from the workplace can dissuade employers to call an applicant for an interview (Baert 2015; Phillips 2015). For the same reason, resumes always had a personal address that corresponded to the city where the job was located. Second, jobs selected were recently published and not older than a week[12], which guaranteed that the selection process was

[12] Less than 1% of all applications were sent on the 4th-6th since the job ad was published.

ongoing. Third, the minimum requirements listed in the job vacancy were in line with the fictitious profiles to be sent.

To guarantee a quality match between the job advertised and resumes, all fictitious profiles had a set of fixed characteristics. This set of common characteristics was developed to ensure that all profiles shared the same background and skills, as well as to satisfy minimum requirements that were commonly found in ads on web portals and to maximize the probability of a callback. Particularly, in terms of educational attainment, professional experience, IT, and language skills. Therefore, each fictitious profile included the following fixed details: a business-oriented high school diploma (called "Ragioneria", in the Italian educational system), a BA in Economics and Business, a certificate of English proficiency, as well as computer competencies in the use of the Microsoft Office package (Word, Excel, etc.).

While education level was fixed, the institution where applicants attained their qualifications was randomly assigned. For each of the 11 cities of this study, the name of all high schools offering a diploma of “Ragioneria” and universities with a BA in economics was collected. By design, the Diploma of Ragioneria was always acquired from an institute randomly drawn among those in the city where the profile was born (see Section 4.4 on the allocation of the city of birth). The city of BA instead could vary with a 50% chance of being acquired in the same city of birth, and a 50% chance to be earned in a university located in another city covered by the study. AlmaLaurea data show that almost all Italian High school students acquired their diplomas in the same city of birth. Thus, the design of education of the fictitious profiles aimed to mirror, to the maximum extent possible, that of real graduates while maintaining random variation in the assignment of the location where the BA was obtained.

Importantly, all profiles were 27-28 years old. The age profile mirrors that of the average real Italian graduate in the process of acquiring a more stable job after having earned a BA at around the age of 24/25 (Pastore, Quintano, and Rocca 2021). Also, the age of BA graduation of the fictitious profiles was set at 24/25 years old. This decision made it possible for all applicants to have acquired 3 years of on-the-job experience, in line with the average profile mentioned above. Setting the age of graduation at 24/25 also allowed the design to hold constant years of experience while varying randomly unemployment duration[13]. Eriksson and Rooth (2014) also use a similar design to ensure all applicants had comparable labour market experience. The

[13] See Annex B, which provides an overview of the structure of the employment history and dates of graduation.

current design has replicated such a design to rule out potential differences in perceived productivity among fictitious profiles.

Having profiles of the same age, as an alternative design, implies that the allocation of unemployment duration of different lengths results in shorter labour market experience among those with longer spells of unemployment. That is, on-the-job experience is correlated by design to time out of work. It follows that it would have been impossible to disentangle whether employers called back candidates at different rates because of their long unemployment duration or shorter labour market experience. In the current design instead, candidates who are 24 are always allocated longer unemployment spells than those who are 25. Age is thus correlated with unemployment duration. Nonetheless, a year should not make an enormous difference in employers' decision to call back. In this regard, several ads in this study just had an explicit age cap for applicants set at 30 years old. Importantly, in this design number of years of experience and unemployment are not related at all. As such, it is possible to isolate the effect of unemployment duration on employers' callbacks ensuring that no perceived difference stems from the length of work experience. Finally, age was not specifically mentioned in the resume. It could be inferred only by looking at the date of birth, which minimizes any potential confounding effects of age on the callback rate.

When a vacancy was deemed suitable, based on the criteria above, 4 fictitious profiles[14] were generated using a computer programme written by Lahey and Beasley (2009). This has been edited to fit the requirements of the current study. The computer programme populated empty templates (see Annex A) with information that is usually found in resumes, including fixed characteristics listed above along with other details regarding professional experience and sociodemographic characteristics (see Section 4.4). Once the computer programme created four profiles, these were sent over a day with a spacing of a few hours between each application.

Response to any of the four resumes, or its lack thereof, represents the dependent variable of the current study. Responses were either received in the forms of calls or emails both stating a direct invitation to participate in an interview. Unanswered calls were often followed by an email. If this was not the case, the employer was re-contacted to trace back the call. Importantly, calls and emails seeking clarification or additional details were not coded as positive employers' responses but kept for records. Given that resumes could vary in name and

[14] This follows the practice of previous correspondence studies, including Bertrand and Mullainathan (2004), Nunley et al. (2016), and Patacchini, Ragusa, and Zenou (2015), which also sent batches including 4 CV to the same vacancy.

surname (see Section 4.3), a total of 72 surname-name email accounts were generated to collect written employers' responses. Each surname that could be randomly allocated to a fictitious candidate was also associated systematically with the same phone number[15] (10 numbers for 10 surnames in total). The computer programme was designed to avoid that resumes in the same batch had the same surname and, consequently, the same phone number.

[15] For instance, phone number *b* is always assigned to surname *a*. Therefore, when an employer from city *x* contacted candidate with surname *a* using phone *b* was possible to match uniquely the employer from city *x* to candidate with surname *a*.

4.4 Ensuring random variation in fictitious resumes

The fictitious profiles sent to employers were designed to be equivalent in terms of their age, education, and professional experience. Resumes were then matched with jobs whose minimum requirements were in line with the qualifications of fictitious resumes. As such, differences in employers' responses cannot be attributed to these characteristics that are common across all resumes. Nonetheless, if, for example, a characteristic like gender varies systematically in all these fictitious resumes, which are otherwise equivalent, any differences in callbacks can be attributed uniquely to employers' considerations about gender. This cue represents a standard design to detect discrimination (Correll and Benard 2006).

As the current study aims to understand how employers see and use unemployment duration, gender, and immigrant background in the screening phase of the hiring process, the standard design just described has been adapted. In the current design, more than one characteristic may represent a source of differential treatment as hypothesized in Chapter 2. Therefore, these characteristics were randomized both among profiles in the same batch and between vacancies. It follows that gender, immigrant background, and unemployment duration are uncorrelated by design. Also, using a random allocation of treatment variables among the same batch lowers efficiency, but it takes care of job search externalities, which can bias results (Phillips 2019).

When the composition of the batch of resumes is fixed, for example, a batch always includes two resumes with 12 months of unemployment and two resumes with two months, the likelihood of a callback for the individual i with amount x of time out of work structurally depends on the "quality" of the other profiles. Particularly, the probability of a call depends on the quantity of time x spent in unemployment by the other candidates in the same batch. The effect of time in unemployment would thus be a mix of spillover and differential treatment from employers, as well as these types of paired designs underestimate discrimination by as much as 19% (Phillips 2019).

Furthermore, randomization, within- and between-vacancies, of individual details like gender, immigrant background, and time in unemployment can both recover an unbiased effect of these characteristics and reduce the risk of detection by employers as compared to paired designs (Lahey and Beasley 2018). In paired designs, the researcher sends the same profiles (at least two) to all employers and these profiles usually differ in one characteristic. For example, one profile is always a man, and the other is always that of a woman. This strategy allows for the comparison of callback rates based on gender as the only varying characteristic in fictitious

resumes. As mentioned above, this design may confound differential treatment with spillovers, as well as increase the risk employers realize that profiles are the same. These considerations motivated the choice of within batch and between employer randomization of treatments. It also made it safer to send four resumes to the same employers given that profiles randomly vary in several characteristics at once.

A computer programme, based on Lahey and Beasley (2009) and edited to fit the purpose of this thesis, provided a routine to ensure that randomization was carried out systematically. Primarily, the computer programme allocated randomly four styles (i.e., font, colors) to the four profiles to be sent to employers. This was done to ensure that resumes could visually look different to employers and minimize the risk of detection of the field experiment. As the second step, the computer programme was developed to determine whether the applicant was going to be Italian with or without an immigrant background. The immigrant background was signaled by utilizing first names and surnames[16]. For the current study, Romanian names and surnames were used to signal an immigrant background.

However, given that employers may have concerns about the language and communication skills of profiles with an immigrant background (Oreopoulos 2011), resumes included information about citizenship among the sociodemographic information provided in the header. Profiles with Romanian first names and surnames were thus given both Italian and Romanian citizenship. Those with an Italian name and surname had only Italian citizenship. Importantly, all profiles, regardless of their first names and surnames, were born in Italy. They also acquired all their education in the Italian school system as detailed in the previous Section (4.3). Thus, profiles with an immigrant background are second-generation Italians as they were born in Italy to foreign parents, namely from Romania (first generation).

The computer programme was designed to pick a Romanian background with a 25% chance. This probability was chosen to guarantee the plausibility of the batch composition. It may be still very unlikely in the Italian context to receive for the same vacancy four profiles all with Romanian origins and an Italian BA. Nonetheless, setting the probability at 25% still meant that a batch could be allocated about two resumes from Romanian-Italian applicants. Also, it guaranteed a large enough *N* of applicants with an immigrant background. After the computer programme picked the immigrant background of the applicant or lack thereof, it chose the

[16] The selection of the surnames builds on the work of Enzo Caffarelli who has used administrative data to study the origin of Italian surnames and the distribution of foreign sounding surnames across Italy.

gender of the applicant. Gender is signaled using common first names that can be uniquely associated with men or women. Yet, these names depend on the immigrant background of the applicant. For example, if the profile were allocated an immigrant background, the programme would give a first name and a surname that are Romanian sounding, and vice versa. Importantly, the first name would be that of a woman or a man with a 50% probability for both the group with and without an immigrant background.

Along with the four Romanian-sounding first names, two for women and two for men, a total of eight Italian names, four for men and four for women, were used in the experiment. Also, there was no replacement in the computer programme such that each first name could appear more than once in the same batch. This means that in a batch, which includes four resumes, a certain name (i.e. Andrea) could be used more than once (i.e. in two out of four resumes). The gender composition of any batch, therefore, was completely random, including batches with women or men only or a mix of men and women. Importantly, once the computer programme picks the gender of the applicant, the language of resumes was tailored accordingly by the computer programme. This arrangement was necessary given the gendered nature of the Italian language where names and adjectives align with the gender of the subject (i.e. subject names of occupations like addett*o* or addett*a* – adjectives to describe oneself like estroverso or estroversa).

Like gender and immigrant background, unemployment duration was randomly allocated, among profiles in each batch and between vacancies. Unemployment duration was signaled using the dates of the most recent job experience held by the profile. Therefore, the time elapsed since the last job could be 0 months (currently working); a profile could instead receive a short unemployment spell (2 or 6 months) or a long one (14 or 22 months). These thresholds were selected based on findings from other correspondence studies. Particularly, previous studies suggest that short spells may not harm the applicant (Oberholzer-Gee 2008), whereas the chances to get a callback tend to become grim after the 6th month in unemployment (Ghayad 2013; Kroft, Lange, and Notowidigdo 2013; Krueger, Cramer, and Cho 2014). Therefore, having a very short-unemployment spell, like 2 months, and being able to assess what happens to callbacks after the 6th month can be instructive to compare the findings of the current study with existing ones.

While gender, immigrant background, and unemployment duration represent the focus of the study other characteristics regularly available in resumes were randomized within and between vacancies. This study relies on a factorial approach that Valentina Di Stasio and Lancee (2020)

also use in their multi-country correspondence study on labour market discrimination. Resumes are designed like vignettes in factorial surveys and sent to real job openings instead of being administered to a convenience sample or to employers who know they are part of a study. Table 4.4.1 provides an overview of these additional details. Starting from the left of the Table, each fictitious profile was allocated randomly to a city of birth among the 11 cities covered by the current study. Once the city of birth was allocated, the computer programme selected, as explained in Section 4.3, the name of the high school attended and the city and the name of the institute where the BA in economics was acquired.

The profile could then get either one job experience or two with a 50% chance. Descriptions of the job experiences were standardized both in terms of content and length, measured as the number of characters. These were job specific and taken from real resumes available online. Beyond professional experience, all profiles have as first job experience either an internship or an unemployment spell, allocated with a 50% chance by the computer programme. Importantly, all the firms mentioned in the employment history were in the same city of the

Table 4.4-1 Factors and levels randomization, sociodemographic characteristics - work experience.

Area of birth	*City of BA*	*Employment history (# jobs)*	*First internship*	*Firm size most recent job*	*IT*	*Training*
North	Same as Diploma	One experience	Yes	1-9	Job specific software	Ongoing
Center	Different from Diploma's	Two experiences	6 months out of work	10-49	No information	No information
South		-	-	>=50		

job ad vacancy was available. Names of firms were collected online and categorized based on the number of employees (1-9, 10-49, and >=50). For each entry in the employment history, a name from this city-firm database was randomly picked with an equal probability of being of a firm with 1-9, 10-49, and >=50 employees, as well as with no possibility of duplicates. A specific firm could only be allocated to one resume in a batch to reduce the risk of detection by employers. Finally, the fictitious applicant could have ongoing training in the resume, as well as it could have jobs specific computer software assigned.

Resumes also included a statement on the applicant's willingness to work and adapt to working conditions, as well as an ongoing volunteering engagement. These aspects were added to signal candidates' motivation. The literature suggests that aspects like motivation are usually

unobserved and employers can use unemployment duration to get clues about it (Van Belle et al. 2017). As such, having details on aspects such as motivation in resumes can help explain whether the difference in callbacks could stem from a lack of information or bias. While not job-specific, volunteering should provide a more tangible measure of individuals' commitment given that those engaged in volunteering have the willingness to devote their free time to a cause. A statement instead might be something that anybody can add to their resumes and employers may just see it as "cheap talk." Both the statement and volunteering will be used to test the hypothesis that employers who stress motivation in job ads respond more (*H.4a*) or less (*H.4b*) frequently to applicants in long-term unemployment who provide signs about their motivation compared to candidates with the same unemployment duration but no information about individual motivation. Finally, Table 4.4.2 shows the results of the randomization of all

Table 4.4-2 Correlation matrix: varying characteristics among fictitious profiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
(1) City of birth	1												
(2) Woman	-0.02	1											
(3) IT-RM	-0.01	0.02	1										
(4) Motivation	-0	-0.01	0.02	1									
(5) Skills Dev	0.01	0.01	-0.02	-0.02	1								
(6) Tech skills	-0.01	-0	-0	-0.02	0.01	1							
(7) Volunteer	-0.03	0	-0.02	0.03	0.01	0.02	1						
(8) First job	0.01	0.022	0.01	0.02	-0.01	0	-0	1					
(9) Unemp duration	0.02	0.02	-0.01	-0.03	0.01	0.01	-0	0	1				
(10) Two jobs	-0	0	-0.01	0.02	-0.01	0	0.01	0.02	-0.04	1			
(11) Firm size	-0.01	0.01	0.01	0	-0.01	-0.01	-0.01	0	0.02	-0.02	1		
(12) Order sent	-0.02	0.02	0	-0.01	0	0	-0.04	0	0	-0.01	-0.01	1	
(13) CV Style	-0.01	0.02	0.02	0.02	-0.03	-0.01	-0.02	0.03	0.02	-0.02	-0	0.03	1

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

varying characteristics among the 4,079 resumes sent to employers as part of this study. The table reports the pairwise correlation between variables showing the extent that one depends on the other. Estimates in Table 4.4.2 highlight clearly that there is no significant correlation between any of the variables allocated to the fictitious profiles. Also, the size of all estimates is zero. Randomization within- and between-resume, therefore, was successfully carried out throughout the implementation of the correspondence study.

5 Data and Methods

Having described how data collection was designed and implemented, Chapter 5 shifts the focus on data and their analysis. The Chapter is organized around two main Sections. The first one describes data collected through the correspondence study. This descriptive analysis looks initially at how applications for available jobs were filed, as well as how callbacks are distributed across periods, sectors, and Italian macro-regions. Section 5.1 then focuses on describing the employers that have been included in this study, particularly the size of their firms to understand whether the sample of this study is representative of the population of Italian firms. Section 5.1 also uses data collected from job descriptions to present what employers look for in a candidate and offer in terms of pay and contract type, among others.

Chapter 5 then discusses in the second section the empirical strategy to analyze data. Section 5.2. is organized around four sub-sections to mirror the structure of Chapter 2, which presents the theory and hypothesis in four sections. Sub-sections will deal respectively with duration dependence, discrimination, the influence of labour market conditions on these two phenomena, and intersectionality. Thus, each of the four sub-sections of Section 5.2 present how data are analyzed to test the hypotheses formulated in the respective section of Chapter 2.

5.1 The employers of this study: who they are, what they offer, and what they want

As discussed in the operationalization of the correspondence study, fictitious resumes were sent in response to employers/online job ads, advertised online between September 2019 and June 2020. Resumes were shared with employers in major urban Italian cities in the North, South, and Center of the country, before and after the COVID-19 outbreak in response to online job ads.

Most online vacancies were found through the job portal Indeed.org (85%) while about 14% on Bakeka and 1% through other job portals like Monster. Fictitious profiles were, on average, sent in response to these ads after 18hrs that the job ad was published online. The application process entailed in about 43.5% of the vacancies just sending a resume and a cover letter either through email or through the job portal. For one-third of the applications (30.4%), a form on individual work experience had to be filled out along with a resume and a cover letter. A similar application was also filled for other 22% of the jobs found to provide information on work experience and education, whereas about 4% of the applications' socio-demographics had to be shared in a form. Importantly, all information provided in these forms could be found in resumes. No additional data had to be shared.

The responses received, to these job applications, via phone or email, constitute the dependent variable of the current study. Table 5.1.1 reports the total callback rate and the number of resumes sent, as well as the breakdown of these aggregate figures by region, period and labour market sector of the employers posting the job ad. The total callback rate, which is the percentage of employers who made an explicit request for an interview, stands at about 11% of the applications sent[17]. In absolute terms, 459 resumes received a positive response out of 4,079 resumes sent. In other words, 22.5% of all employers reached during the data collection responded to, at least, one resume.

Table 5.1.1 also shows no major differences in response rates between job clusters, namely Administrative, Human Resources, and Marketing. Nonetheless, job clusters vary sharply in the total number of applications sent and received. About 67% of fictitious resumes were sent in response to administrative assistant and accountant job ads. Slightly more than a quarter of

[17] Such response rate mirrors those of previous correspondence studies in the field of hiring discrimination.

fictitious profiles were generated instead to target vacancies in the Marketing job cluster (26.5%) while about 6.3% of all fictitious profiles were sent in response to job offers in HR.

Table 5.1-1 Mean callback rates, total and by sector, region, and period

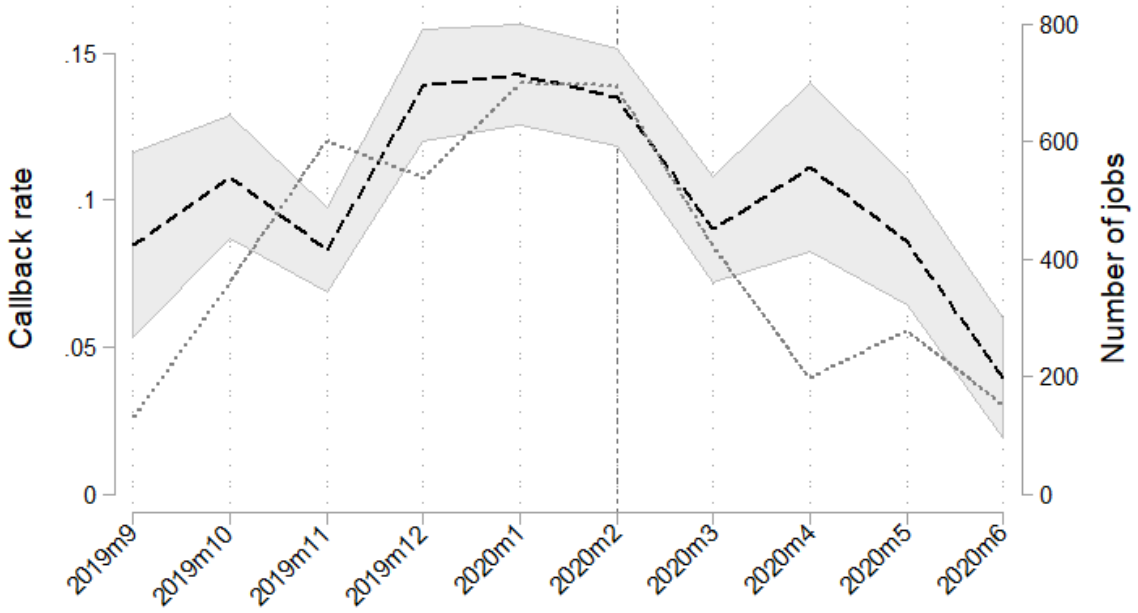
	N	*%*	*(Mean) callback*	*SD*
Sectors				
Admin	2,740	67.17%	0.11	0.32
HR	258	6.33%	0.10	0.31
Marketing	1,081	26.50%	0.11	0.32
Region				
South	828	20.30%	0.13	0.34
Center	1,152	28.24%	0.09	0.29
North	2,099	51.46%	0.12	0.32
Covid				
Before	3,028	74.23%	0.12	0.33
After	1,051	25.77%	0.09	0.28
Total	4,079	100%	0.11	0.32

Callback rates differ between macro-regions ranging from 9% in the Center of Italy to 12% in the South, with the North of the country in between where employers responded to 11% of the applications sent in the area. About half (51.5%) of the job ads in the dataset were advertised by employers in the North of Italy. A third of the applications responded to vacancies created in the Centre of Italy (28.2%), while fewer applications were sent to employers in the Centre of Italy (20.3%) and South. The breakdown does not come as a surprise. It reflects the respective job creation potential across Italy, which can be exploited in the analysis to compare employers' decision-making under different labour market conditions (Allasino, Venturini, and Zincone 2004).

The bottom of Table 5.1.1 then reports a 3-point percentage gap in responses received to fictitious profiles sent before and after the COVID-19 outbreak. Before the lockdown imposed by Italian authorities in March 2020, 12% of resumes received positive feedback while the call-back rate dropped to 9% after strict measures were put in place. Most fictitious resumes were sent in response to jobs found in the 6 months before the start of the pandemic (74.2%). About 25.8% of fictitious profiles were instead sent to vacancies generated after the start of the lockdown. Figure 5.1.1 also shows how the response rate (black-dashed line) and response rate

(light grey-dotted line) fluctuated over the data collection period and dropped drastically after the Italian Government enacted the lockdown measures (vertical-dotted line).

Figure 5.1-1 Callback rate and number of vacancies over time of the data collection (months)



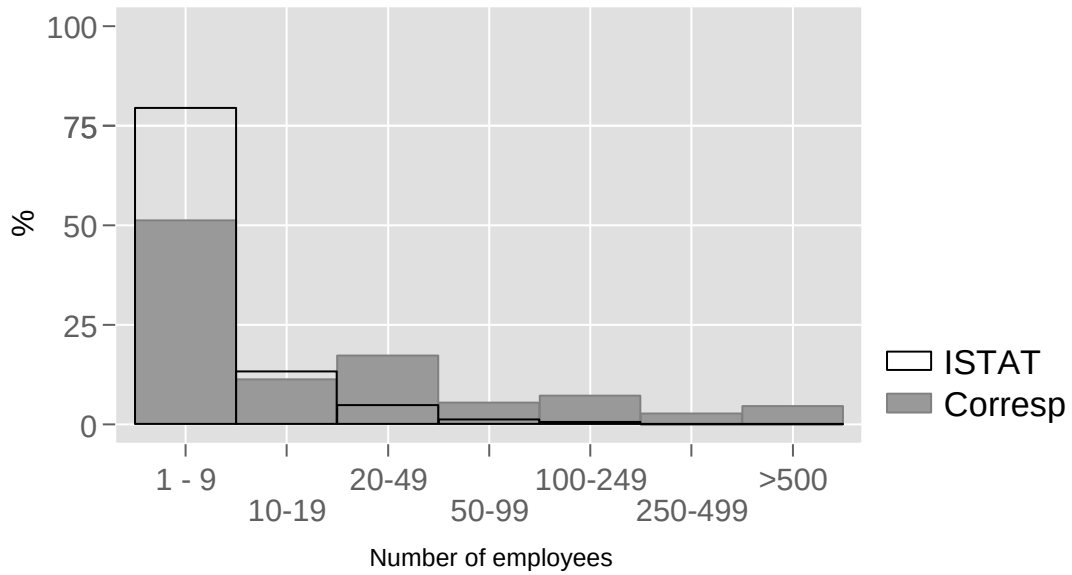
It was mentioned in Section 3.3 that employers using formal means such as online job portals still represent a minority in the Italian job market (Ferri, Ricci, and Sacchi 2018). Particularly, smaller enterprises tend to rely more often on their networks and referrals. Larger ones instead are more likely to rely on formal and structured hiring processes. Therefore, the implication of the current study, which relies on formal means of job search, is that the type of enterprises reached might differ from those using informal means to find prospective employees. In this regard, it can be instructive to compare the profile of enterprises reached in this correspondence study with that of the overall Italian market.

The Italian National Institute of Statistics (ISTAT) carries out a census of Italian Enterprises. It collected data from a representative sample of 24% of Italian enterprises, which generates 84.4% of value-added and contracts 91.3% of Italian employees (ISTAT 2020a). Figure 5.1.2 overlays data from the 2019 enterprise census and those from the current correspondence study. Enterprises are categorized based on the number of employees they have. Data on the number of employees for employers reached in the current study were collected relying on information

that is publicly available online[18]. This information could be found for about 73% of the sample. Therefore, plotted data and percentages refer to the sample of employers with information on the number of employees.

With this caveat in mind, Figure 5.1.2 shows that the correspondence study "under sampled" enterprises employing 1-9 workers. Data from ISTAT (2020a) highlight that 79% of the enterprises in the Italian labour market employ 1-9 workers whereas 51% of the enterprises that received fictitious profiles are of the same dimension. The other side of the coin, emerging from Figure 5.1.2, is the "oversampling" of larger enterprises (20 employees and above) in this correspondence study compared to the national distribution. While the sample of the correspondence study is skewed toward larger enterprises, it can still be informative about smaller entities, which constitute half of the entities reached. Nonetheless, the difference between the sample and national distribution will be important in the discussion of the findings and their generalization.

Figure 5.1-2 Firm size: comparing ISTAT and correspondence study



Source: ISTAT, Censimento permanente delle imprese 2019

Furthermore, having data on the size of enterprises, proxied by the number of employees, matters as it provides some additional information about employers and their hiring practices. Moss and Tilly (2001) highlight that the larger a firm, the more structured the hiring processes are, including HR people screening resumes rather than the owner of the enterprise or some

[18] The main source of data on number of employees come from the Dun & Bradstreet Data Cloud (D&B), which brings together profiles of enterprises globally. When information could not be found on D&B, information on the number of employees was collected on the LinkedIn profile of the enterprise.

employees with no HR background. Thus, it is important to assess differences in size between enterprises within the sample of the correspondence study.

Table 5.1.2 provides the total number of cases with non-missing information on the number of employees working at the employers who were reached in the current studies. This number is also disaggregated by job cluster, region, and period along with the percentage of cases with non-missing information. Finally, Table 5.1.2 provides information about the distribution of the variable number of employees. As per job clusters, data on the number of employees is available for almost 90% of employers posting jobs to fill HR-related vacancies. The percentage goes down to 71.5% and 74.2% for admin and marketing job ads, respectively. Interestingly, employers posting admin-related jobs tend to be smaller on average than those searching for employees working in HR and marketing. Enterprises looking for marketing persons were the largest on average in terms of the number of employees. Those looking for hiring someone working in HR stood in between.

While the mean number of employees suggests that employers own large enterprises, the median shows that 50% of the employers in Admin and Marketing-related jobs are small enterprises with 8 or fewer employees. Employers in HR tend to be small-medium instead.

Table 5.1-2 Number of employees, Total and by Sector, Region, and Period

	N	*%*	*Mean*	*SD*	*Median*
Sector					
Admin	1,960	71.53	82.12	340.37	8
HR	229	88.76	135.63	261.68	19
Marketing	803	74.28	247.34	1,313.79	8
Region					
South	565	68.24	69.52	379.07	6
Center	830	72.05	93.27	568.45	7
North	1,597	76.08	171.54	898.18	13
Covid					
Before	2,290	75.63	105.00	466.00	10
After	702	66.79	214.00	1,275	7
Total	2,992	73.35	130.56	741.02	9

Looking at non-missing cases by Region in Table 5.1.2, the number of employees could be found for about 68% of the employers in the South, 72% in the Center, and 76% in the North. Similarly, the average number of employees and the median are increasing from South to North.

That is, enterprises in the sample tend to be small among employers contacted in the South and larger in the Center. Employers contacted in the North tend to be larger than in the other two regions. Finally, Table 5.1.2 highlights some differences in the type of enterprises reached before and after the COVID-19 outbreak. First, there is information on the number of employers for 75% of the enterprises reached before the pandemic while this percentage goes down to about 67% among employers contacted after the outbreak. Also, on average, enterprises that were reached in the pre-COVID-19 period were smaller than those reached after March 2020. Nonetheless, the median of the number of employees suggests that 50% of the employers in both pre-and post-start of the pandemic are small.

To get a better understanding of the employers in this study, the information shared in job ads can be quite useful too. Details provided in vacancy announcements give details about employers and their firms and what the requirements of the job are. These details have been coded as part of the application process and key characteristics are summarized in Tables 5.1.3 and 5.1.4 coded as binary indicators. Tables thus show whether employers (did not) mention some details in the job ad. Table 5.1.3 provides the share of employers that provide information on their companies and the tasks to be carried out as part of the job. The Table also brings together binary indicators on whether employers need candidates on board as soon as possible, as well as whether employers look for a person full-time and if employers disclose the salary as part of the ad. Finally, the equal opportunity indicator refers to the inclusion of an equal opportunity statement in the description of the vacancy.

Table 5.1.3 shows that just 39% of the employers who receive a batch of resumes shared some details about their enterprises. That is, 61% of the employers did not share as part of the ad their economic sector, what they do, or any other detail about their history or approach to business. Most of the job ads mentioned what prospective employees were supposed to do (81%) and 86% of the vacancies were not to be urgently filled. Very few employers posted an expected salary for the job offered (16%) and likewise a statement about equal opportunity legislation (13%). Finally, 69% of the vacancies mentioned the contract employers were willing to offer (temporary vs long-term) and 71% were looking for someone full-time.

Table 5.1-3 Information employers provide in job ads

Statistics	Company description	Tasks	Urgent hiring	Contract Offered	Full- vs Part-time	Salary	Equal Opportunity
Share	0.39	0.81	0.14	0.69	0.71	0.16	0.13
SD	0.49	0.39	0.35	0.46	0.45	0.36	0.34

Table 5.1.4 gathers binary indicators on the presence of key requirements, including previous work experience, education attainment, and knowledge of English. In 80% of the job vacancies, employers mentioned requirements in terms of previous work experience whereas education featured as a requirement in about half of the jobs. This means that in 20% and 47% there was no mention of requirements on, respectively, work experience and education. Further, English was a requirement in slightly more than a third of job ads (37%).

Table 5.1-4 Information on requirements in job ads

Statistics	Experience required	Minimum Education	Foreign Language
Share	0.80	0.53	0.37
SD	0.40	0.50	0.48

For those employers who had information on work experience, education and the contract offered, it has been possible to collect some additional details on what they were looking for. The pie charts in Figure 5.1.3 provide a breakdown of these additional details. Looking at experience, the pie chart shows that about two-fifth of all employers needed 1 year of experience or below. Those requiring between one and two years of education represent 15% of the total, which is the same percentage of employers who wanted someone with experience but failed to specify the number of years in the job ad. Finally, just a tenth of the employers required someone with two/three years of work experience.

With regards to education, in a fifth of the job ads, employers set the minimum educational attainment at the high school level or below. One-third of the employers listed having a BA but as optional or preferred in 14% of the job ads or as the required minimum in about 19% of

the vacancies. Also, in 1% of the descriptions, employers mentioned a master's degree as preferable. As per contracts that employers offered, about half were temporary, 4% were to be determined after the interview based on the experience of the candidate whereas 18% were for long-term jobs and 30% did not specify the type of contract.

Figure 5.1-3 Breakdown of information on requirements in job ads and language

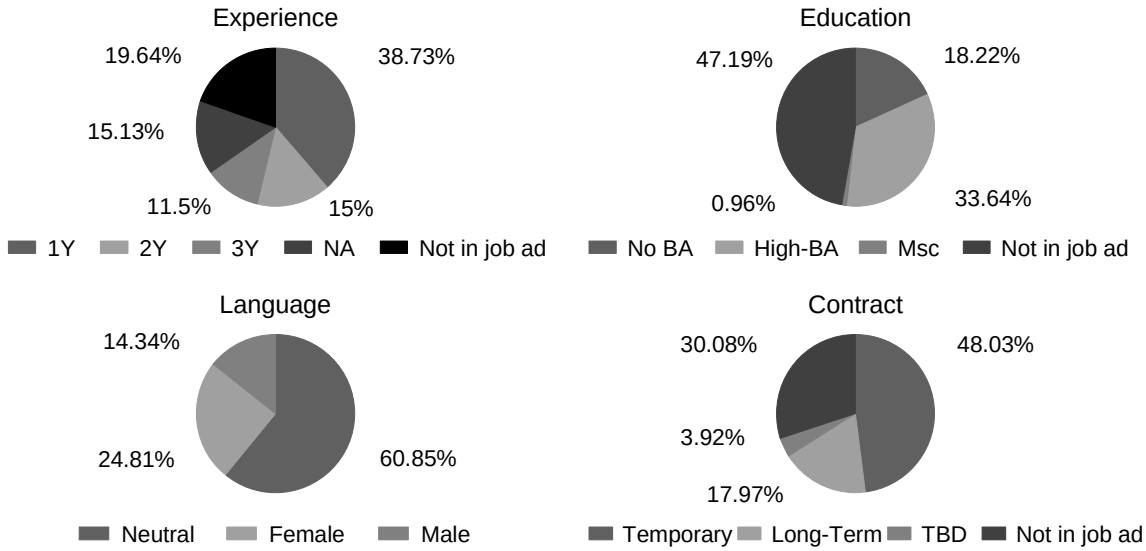


Figure 5.1.3 also includes a variable that categorizes employers based on the language in the job ad. More specifically, whether employers used gender-neutral language, only masculine nouns, and adjectives, or only feminine nouns and adjectives. The breakdown in Figure 5.1.3 shows that 61% of the job ads used gender-neutral language while describing tasks to be performed and conditions of employment. About one-fourth of the vacancies used a female-oriented language and about 14% masculine language. The hiring percentage of ads using only feminine nouns and adjectives probably stems from the proportion of admin job ads (i.e. secretary, personal assistant, etc.), which are stereotypically associated with women.

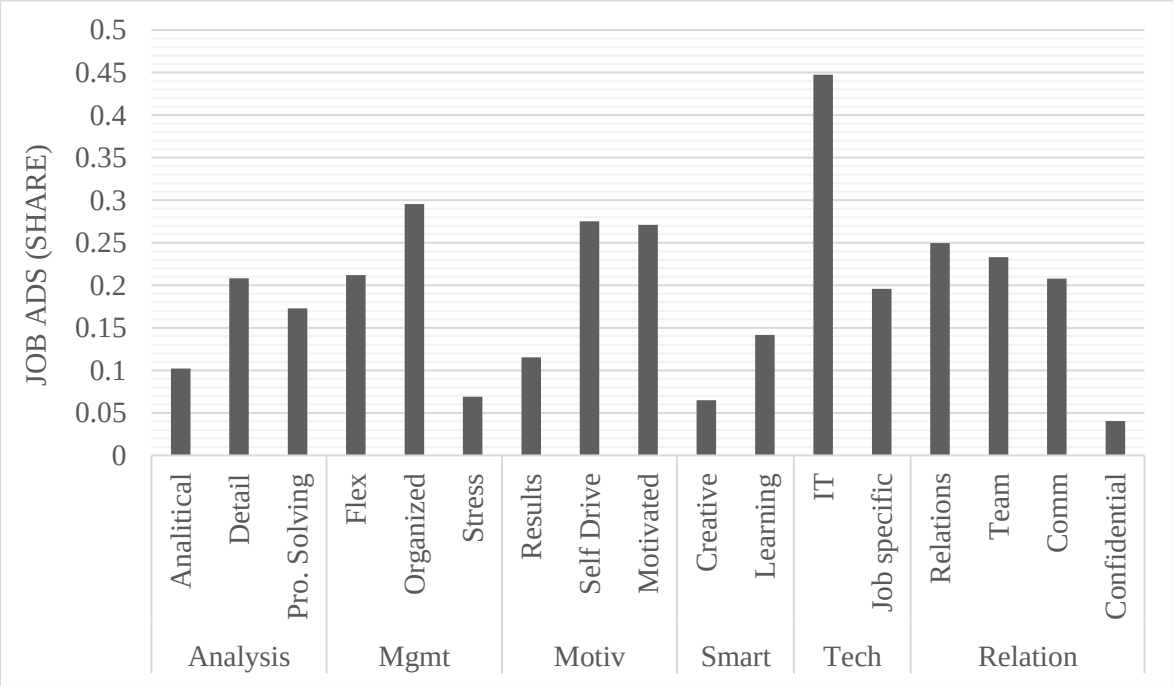
The last aspect that employers mention in their job ads referred to skills, both soft and hard, needed to perform the job. Particularly, employers mentioned in the job ads several different soft skills. This is in line with the increasing importance of soft skills, or non-cognitive skills, for both education and labour market attainment (Heckman and Carneiro 2003; Brunello and Schlotter 2011; Kautz et al. 2014). However, Moss and Tilly (2001) highlight the increasing attention to these so-called skills as problematic given the subjective nature of defining and measuring these skills. Thus, Figure 5.1.4 reports soft and hard skills that were mentioned in the job ads of this study. Skills are grouped by competence area, namely analytical, managerial

(mgmt), motivation-related (motiv), individual potential (smart), as well as technical Skills (including IT and job-specific requirements), and relational skills (relation).

The figure shows that the item most mentioned in job ads relates to the use of computers and software (45%). This is not surprising given that the jobs targeted are routinely carried out with the use of computers. Nonetheless, employers still find it important to mention it among the requirements for the job while they listed in 20% of cases job-specific requirements. The organizational skills of the prospective employees were also needed in a third of the job descriptions. Within the managerial competence area, a fifth of the ads was looking for someone able to adjust (Flex) while stress management was mentioned in about 7% of the listings. Surprisingly, the analytical competence area (except for attention to detail) and individual potential (Smart) were not so prominent in the listings of the current study.

Skills in the relation competence area along with those related to motivation were mentioned more frequently by employers. Motivation (self-drive and motivation) and relational skills (building relations, teamwork, and communication) were also found in about a fourth of the job ads. Being results-oriented and confidential were instead mentioned respectively, just in 7% and 4% of the ads. Overall, it seems that employers in the sample list more often attitudinal aspects of their prospective employees rather than technical ones. Such greater emphasis may increase the risk of interjecting individual subjectivity in the hiring process and consequently discrimination.

Figure 5.1-4 Soft and hard skills employers mentioned in job ads, by competence area



5.2 Empirical strategy

This section provides an overview of the empirical strategy that the study relies on to understand employers' decision-making and differences in what they consider important and who, eventually, they decide to call back. Aside from descriptive statistics and disaggregation of callback rates by gender, immigrant background, and unemployment duration (See Section 5.1), multivariate regressions can shed light on the relationship between callbacks and key variables of interest. A linear probability model is used throughout the analysis as the baseline model to test hypotheses developed in Chapter 2.

The choice of a linear probability model is in line with the design choice to randomize treatments (gender, immigrant background, and unemployment duration). The data analysis of paired design usually retains only those cases where there is a response from employers, thus estimating net discrimination (Riach and Rich 2004). The standard practice with designs that are not paired is to retain all employers/observations and estimate average marginal effects using a linear probability model (Neumark 2018). Using this approach, the analysis reports the number of jobs that applicants from a certain group should apply for before getting an interview (Bertrand and Mullainathan 2004). This is more in line with the current design, which seeks to assess overall discrimination in the labour market, as well as the relationship between discrimination and duration dependence. As such, employers' non-response to any of the resumes they receive is as relevant as positive callbacks, which makes the linear probability model best suited for this type of analysis.

The outcome of this study, namely $Job\ Call_{ie}$ for CV_i was coded alongside vacancy characteristics published by $Employer_e$ and other characteristics included in CV_{ie}. $Job\ Call_{ie}$ takes a value of 1 if $Employer_e$ called back CV_{ie} to schedule an interview or 0 otherwise. Data are hierarchical given that CV_{ie} is nested within $Employer_e$. The current section is organized into 5 sub-sections. Each sub-section groups hypotheses and how to test them mirroring the organization of Chapter 2.

5.2.1 Identifying duration dependence

The analysis starts by testing hypotheses formulated in Section 2.1, namely that employers call back at higher rates candidates with short unemployment spells compared to applicants with long ones (*H.1*). Model (1) is the first step to test *H.1*,

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \varepsilon_{ie} \quad (1)$$

where i indexes the individual profile, e refers to the Employer. Thus, Un_{ie} represents unemployment duration allocated to each fictitious profile shared with employers contacted as part of this study. Given that employers receive 4 fictitious resumes, Model (1) uses cluster-robust standard errors ε_{ie}, which helps address issues of heteroscedasticity generated by the nested structure of the data (Auspurg and Hinz 2015).

Model (1) can also be expanded to integrate a set of control variables, including a vector X_{ie} capturing cosmetic features allocated randomly to resumes (i.e. font, style) along with vector H_{ie} encompassing sociodemographic characteristics (gender and immigrant background) and characteristics of the (employment) history of the profile, particularly the Italian macro-region of birth, whether it had one or two jobs, an internship, or a period of unemployment at the beginning of the career and whether the profile worked for a big company (more than 50 employees)

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + X_{ie} + H_{ie} + \varepsilon_{ie} \quad (2)$$

Particularly, to control for potential differences in the assessment of unemployment duration between employers in the three Italian macro-regions, the variable Reg_e is added to Model (2), as well as one to capture employers contacted before and after the COVID-19 outbreak. $Covid_e$controls for differences over time as the data collection spanned across 2019 and 2020 for 10 months. The Government of Italy implemented a complete lockdown on March 8. As a result, the data can be split into two periods: 7 months before the emergency and 3 after the start of the outbreak. Finally, Model (3) also includes a categorical variable to control differences in callbacks between employers in Administration, HR, and Marketing $Sect_e$

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + X_{ie} + H_{ie} + \varepsilon_{ie} \quad (3)$$

where Reg_e takes the value of 0 if the employer e is in the South, 1 if s/he resides in the Centre, and 2 if the employer e operates in the North of Italy. $Covid_e$also takes the value of 0 if the employer e has posted a job ad in the months before the declaration of the lockdown by the Italian Government or is equal to 1 if the employer e posted the job after it.

While Model (3) factors in differences in response rate between employers located in different regions and reached at a different point in time of the data collection, it assumes implicitly that employers are consistent in their judgment of the resumes they receive. That is, they dedicate the same attention and time, for example, to each of the resumes they receive. Given that each employer has assessed four fictitious profiles, it is possible to evaluate this implicit assumption. The data have, therefore, a hierarchical structure. This design feature allows us to separate what employers learn from profiles' characteristics, such as gender and immigrant background, from idiosyncratic differences in employers' judgments of these details. This can be achieved by adding a random intercept to Model (4) along with vectors X_{ie} and H_{ie}

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + X_{ie} + H_{ie} + \mu_e + \varepsilon_{ie} \quad (4)$$

where μ_e is an employer-specific error component, which summed with β_0, provides a measure of the variance in employers' decision to call back applicants in their batch. The random intercept provides an estimate of employers' social understanding of unemployment duration while modeling any inconsistencies in the assessment of the four different profiles.

The next step of the analysis is a comparison of employers who look urgently to hire someone with those who are not as rushed to fill an existing vacancy. In other words, whether differences in callbacks between applicants with longer and shorter unemployment duration get larger when employers have less time to screen resumes (*H.2*). The Model builds on (4), but it estimated once for employers who seek someone urgently and another time for employers who are not in a rush to find an employee, formally

$$Job\ Call_{ier} = \beta_{0r} + \beta_1 Un_{ier} + \gamma_1 Reg_{er} + \gamma_2 Covid_{er} + \gamma_3 Sect_{er} + X_{ier} + H_{ier} + \mu_{er} + \varepsilon_{ier} \quad (5)$$

where r indexes whether employer e faces urgency using the variable Urg_e, which takes the value of 1 if employers state in the job ad that they look for someone who can start the assignment immediately, and 0 otherwise.

Having dealt with whether and how employers use unemployment duration, the analysis focuses on what employers infer from unemployment duration. In this regard, Section 2.2 highlights how some employers might be more (less) likely to call back applicants in long-term unemployment. More specifically, employers listing motivation as a job requirement should be less likely to call back applicants in long-term unemployment than those employers who do not (*H.3*). This proposition can be tested by adding to Model (4) an interaction term between a variable measuring whether employers mention commitment/motivation in job ads Cmt_e with Un_{ie}

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Un_{ie} * Cmt_e + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + \gamma_4 Cmt_e + X_{ie} + S_{ie} + H_{ie} + \mu_e + \varepsilon_{ie} \quad (6)$$

where Cmt_e is equal to 1 when employers list commitment/motivation as a job requirement, and 0 otherwise.

Finally, using Models (6), it is also possible to test whether employers mentioning motivation are more (*H.4a*), or less (*H.4b*), likely to call back those in long-term unemployment when they get information on this job requirement. Information provided by fictitious applicants on this job requirement is captured in the current design through two proxy variables to flag whether s/he

1. Was willing to travel, relocate, and work flexible hours $Motiv_{ie}$;
2. Was engaged in volunteering activities $Volu_{ie}$

Any of these variables takes a value of 1 if the profile provides additional information, otherwise s_{ie} is equal to 0 when the profile does not include any additional information. Two models are estimated including a three-way interaction term. The first with $Motiv_{ie}$, the second with $Volu_{ie}$. Which are interacted with $Cmt_e$and Un_{ie}

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Motiv_{ie} + \beta_3 Motiv_{ie} * Cmt_e + \beta_4 Un_{ie} * Cmt_e + \beta_5 Un_{ie} * Motiv_{ie} + \beta_6 Un_{ie} * Motiv_{ie} * Cmt_e + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + \gamma_4 Cmt_e + X_{ie} + H_{ie} + \mu_e + \varepsilon_{ie} \quad (7a)$$

and

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Volu_{ie} + \beta_3 Volu_{ie} * Cmt_e + \beta_4 Un_{ie} * Cmt_e + \beta_5 Un_{ie} * Volu_{ie} + \beta_6 Un_{ie} * Volu_{ie} * Cmt_e + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + \gamma_4 Cmt_e + X_{ie} + H_{ie} + \mu_e + \varepsilon_{ie} \quad (7b)$$

The estimates of β_6 in Models (7a) – (7b) can tell whether there are any differential returns to details on motivation among those in long-term unemployment when employers (do not) emphasize commitment to work.

5.2.2 Isolating and understanding discrimination

This part of the analysis tests hypotheses formulated in Section 2.2. It starts by looking at whether employers discriminate based on gender and immigrant background because of a lack of information about applicants or bias (*H.5*). To test *H.5*, the analysis estimates a random effect model, which includes Gen_{ie}. The variable takes a value of 0 if the profile is a man and 1 if it is a woman. Likewise, IB_{ie} is equal to 1 if the applicant has Romanian origins, and 0 otherwise. Model (8) includes sector, the macro-region, and period (COVID-19) fixed effects along a vector X_{ie} capturing cosmetic features allocated randomly to resumes (i.e. font, style). Further, Model (8) integrates a vector H_{ie} to capture features of the employment histories of fictitious profiles, including the Italian macro-region of birth, whether it had one or two jobs, an internship, or a period of unemployment at the beginning of the career and whether the profile worked for a big company (more than 50 employees). Lastly, Model (8) adds a vector S_{ie}, which includes motivation and volunteering along with whether the profile is engaged in professional development and if s/he mentions job-specific computer programmes in the resume.

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Gen_{ie} + \beta_3 IB_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_e + X_{ie} + H_{ie} + S_{ie} + \mu_e + \varepsilon_{ie} \quad (8)$$

Fictitious profiles were designed to have the same length of professional experience and level of education to ensure that differences in callbacks cannot be attributed to observable differences in resumes. Importantly, Romanian-Italian profiles were born by design in Italy and have completed all their studies in the same country such that there is no ground for employers to be concerned over the quality of qualifications or language proficiency. If Model (8) isolates differences in employers' callbacks, results provide the first piece of evidence in favor of bias rather than lack of information as the cause of discrimination (*H.5*).

While fictitious profiles are equivalent in the observables, as well as proxies for unobservable characteristics were included, employers may still perceive that groups differ systematically with regards to characteristics that cannot be readily observed from resumes (Heckman 1998). Employers would then use gender and immigrant background to get a hint about these unobservable aspects that cannot be found in resumes. As such, even if the correspondence study isolates differences by gender and immigrant background, the origin of these differences might still be missing information.

Models so far assume, implicitly, that the distribution of unobservable characteristics, more precisely the variance, is equal between men and women, as well as Italians and Romanian-Italians. However, Neumark (2012) shows that in correspondence studies, if employers perceive higher (lower) variance among resumes from ethnic minorities, that is greater (smaller) heterogeneity, such difference leads to (overestimation) underestimation of discrimination. Thus, design choices about profiles might introduce bias, and in the worst-case scenario, estimates might just be the product of how profiles have been structured (Baert 2015).

Neumark (2012) models this issue by relaxing the assumption that the variance of unobservable characteristics of two groups is the same, which can help recover unbiased estimates (Baert 2015). This approach separates the mean difference in callback rates between groups, which could be attributed to employers' bias, from any perceived difference (effect) through the variance of unobservable characteristics (group heterogeneity in unobserved characteristics). The identification of the model requires random variation in productivity-related characteristics and equal returns from them across groups, an assumption that can be tested using estimates from a heteroskedastic probit model[19] (Carlsson, Fumarco, and Rooth 2014).

This model allows the variance of the error term ε_{ie} to differ in one model between men and women and another model between Italians and Romanian-Italians. The model requires two steps. First, it computes the difference in callbacks between groups, and results are compared to those from a simple probit model, which assumes equivalence of group variance. These estimates will still include the effect that can be attributed to the between-group difference in the variance. Therefore, in the second step, it is possible to decouple the mean difference in callbacks between groups from the effect through the variance. As such, the between-group difference is an unbiased estimate of employers' differential treatment of women vs men and Italian vs Romanian- Italians. This procedure can also be seen as a formal test of statistical discrimination (Baert 2015) and testing the assumption of equal group variance can tell whether the origin of employers' discrimination is bias or information (*H.5*). This approach also checks indirectly whether the design of fictitious profiles was sound.

[19] Linear probability models are heteroskedastic by default, which is not a concern given that the use of cluster robust standard errors solve the issue. However, with a linear probability model the null hypothesis of equal group variance will always be rejected with a binary dependent variable. Particularly, with a linear probability model as the predicted probably of Y increases, residuals increase as well such that the variance always get larger with higher values of the estimated Y. Thus, while linear probability models and probit return similar average marginal effects, testing this null hypothesis requires the specification of nonlinear probability model.

After having dealt with the source of discrimination, the analysis looks at whether employers are more likely to contact women than men depending on the gendered expectations of the job to be performed (*H6*). This study applied to jobs in Administration, HR, and Marketing, which can be used as proxies of the gendered nature of jobs. Section 3.3 has shown that employers in Admin jobs overwhelmingly think that women are the best for this type of candidate, followed by those in HR (about 33%). Marketing instead can be seen as a neutral sector based on employers' responses. The analysis thus segments Model (8) by the sector of the employer $Sect_e$ and estimate three regressions. This approach tests *H6*, namely whether employers expecting women to be the best candidates for the job (Admin and HR) tend to prefer them over men, as well as whether they prefer men when gendered expectations are not as strong (Marketing).

$$Job\ Call_{ies} = \beta_{0s} + \beta_1 Gen_{ies} + \beta_2 IB_{ies} + \gamma_1 Reg_{es} + \gamma_2 Covid_{es} + X_{ies} + S_{ies} + H_{ies} + \mu_{es} + \varepsilon_{ies} \tag{10}$$

where s indexes the sector of the employer e. Another means to test *H.6* is to look at the language that employers use to describe the ideal candidate in the job description. Job ads were coded to capture whether employers described the ideal candidate using gendered or neutral language[20] and the analysis uses the variable $Lang_e$ to disaggregate Model (10) by the language used in the job ad, formally

$$Job\ Call_{iel} = \beta_{0l} + \beta_1 Gen_{iel} + \beta_2 IB_{iel} + \gamma_1 Reg_{el} + \gamma_2 Covid_{el} + \gamma_3 Sect_{el} + X_{iel} + S_{iel} + H_{iel} + \mu_{el} + \varepsilon_{iel} \tag{11}$$

where l indexes whether the employer e uses gendered language in the job ad, either male (0) or female-oriented (1), or gender-neutral language (2). Three models are therefore computed.

The analysis then aims to test *H7*, namely whether employers who emphasize communication and relational skills in job ads are more likely to call back native workers than applicants with an immigrant background compared to employers who do not mention these aspects in job descriptions. Information on job requirements on communication and relational skills was collected from job ads and is captured $SoftRL_e$. Model (12) therefore first disaggregates a random effect model using the variable $SoftRL_e$

$$Job\ Call_{ies} = \beta_{0s} + \beta_1 Gen_{ies} + \beta_2 IB_{ies} + \gamma_1 Reg_{es} + \gamma_2 Covid_{es} + \gamma_3 Sect_{es} + \gamma_4 Lang_{es} + S_{ies} + H_{ies} + \mu_{es} + \varepsilon_{ies} \tag{12}$$

[20] Annex L provides examples of job ads for each level of gendered language, namely female- and male-oriented, and neutral

where s indexes whether the employer e (does) not highlight the importance of communication and relational skills in the job ad. Two models are estimated: one for employers mentioning these requirements and another for those who do not.

Like communication and relational skills, employers in this data collection often mentioned motivation as a job requirement. These employers are, supposedly, less likely than those who do not mention such requirements in the job ad to call back women and applicants with an immigrant background compared to men and native workers (*H.8*). Again, job ads were coded to capture this requirement, or its lack thereof, to generate the variable Cmt_e. Like model (11) – (12), a set of two regressions is estimated by Cmt_e

$$Job\ Call_{iem} = \beta_{0m} + \beta_1 Gen_{iem} + \beta_2 IB_{iem} + \gamma_1 Reg_{em} + \gamma_2 Covid_{em} + \gamma_3 Sect_{em} + \gamma_4 Lang_{em} + \gamma_5 Soft_{em} + S_{iem} + H_{iem} + \mu_{em} + \varepsilon_{iem} \quad (13)$$

Finally, the same approach is then used to grasp whether employers using formal hiring procedures are as likely to consider men and women, as well as applicants regardless of their ethnicity (*H.9*). Formalization of the hiring process is proxied by the number of employees employed by the firm (1-9, 10-19, 20-49, >=50). This categorization is captured by the variable $Size_e$, which leads to estimating three separate regressions

$$Job\ Call_{ies} = \beta_{0s} + \beta_1 Gen_{ies} + \beta_2 IB_{ies} + \gamma_1 Reg_{es} + \gamma_2 Covid_{es} + \gamma_3 Sect_{es} + \gamma_4 Lang_{es} + \gamma_5 Soft_{es} + \gamma_6 Cmt_{es} + X_{ies} + S_{ies} + H_{ies} + \mu_{es} + \varepsilon_{ies} \quad (14)$$

where s indexes the size of the firm.

The last part of the analysis focuses on testing hypotheses formulated in Section 2.2.2, which looks at whether discrimination varies as a function of job quality. Using information from the job ad, information has been collected from the job ad on whether the contract offered was temporary or permanent ($Contr_e$). Using this variable, it is possible to test whether employers offering short-term jobs call back at higher rates women and workers with an immigrant background than men and native workers, and vice versa if they offer long-term jobs (*H.10*). This entails estimating two models that group employers depending on the type of contract as follows

$$Job\ Call_{iec} = \beta_{0c} + \beta_1 Gen_{iec} + \beta_2 IB_{iec} + \gamma_1 Reg_{ec} + \gamma_2 Covid_{ec} + \gamma_3 Sect_{ec} + \gamma_4 Lang_{ec} + \gamma_5 Soft_{ec} + \gamma_6 Cmt_{ec} + \gamma_7 Size_{ec} + X_{iec} + S_{iec} + H_{iec} + \mu_{ec} + \varepsilon_{iec} \quad (15)$$

where c is the index for employers offering either a temporary job or a permanent contract such that $Contr_e$ respectively takes either a value of 0 or 1.

The second measure of job quality is $Overqual_e$, which categorizes employers based on the qualifications they require for the job, namely a high-school diploma or lower (0), either a diploma or a Bachelor (1), or Bachelor only (2). This variable captures overqualification as well as whether overqualification is severe (0), just slight (1), or qualifications match (2). Importantly it helps assess whether employers prefer women and those with an immigrant background to men and native workers when overqualification is just slight (*H.11*). Also, it can help answer the question of whether employers are less or more, or as likely to call women and workers with an immigrant background compared to men and native applicants when overqualification is substantially above those needed for the job. The comparison between employers can be done again by segmenting a random effect model $Overqual_e$.

$$Job\ Call_{ieo} = \beta_{0o} + \beta_1 Gen_{ieo} + \beta_2 IB_{ieo} + \gamma_1 Reg_{eo} + \gamma_2 Covid_{eo} + \gamma_3 Sect_{eo} + \gamma_4 Lang_{eo} + \gamma_5 Soft_{eo} + \gamma_6 Cmt_{eo} + \gamma_7 Size_{eo} + \gamma_7 Contr_{eo} + X_{ieo} + S_{ieo} + H_{ieo} + \mu_{eo} + \varepsilon_{ieo} \quad (16)$$

5.2.3 Assessing the influence of labour market conditions on duration dependence and discrimination

Previous Models control for differences in response rates between employers in different regions and across time. Nonetheless, they cannot show whether duration dependence and discrimination vary under different labour market conditions. Particularly whether both would be higher when the labour market is tight and lower when it is slack, in line with screening models (*H.12a*), or the opposite as per ranking models (*H.12b*). To test these propositions on duration dependence and discrimination across different labour markets, the analysis segments a random effect model by Italian macro-regions.

$$Job\ Call_{ier} = \beta_{0r} + \beta_1 Un_{ier} + \beta_2 Gen_{ier} + \beta_3 IB_{ier} + \gamma_1 Covid_{er} + \gamma_3 Sect_{er} + X_{ier} + S_{ier} + H_{ier} + E_{er} + \mu_{er} + \varepsilon_{ier} \quad (17)$$

where r indexes the region of the employer e. Thus, three equations are estimated: one for the North, one for the Centre, and one for the South of Italy. Also, the three-by-region models retain a random error μ_{er} capturing idiosyncratic differences in decision-making between employers in the same region. Models include a vector E_e with employers' characteristics, namely gendered language, firm size, whether the ad included a requirement on motivation and relational skills, the type of contract offered, and whether the job matched the qualifications of the applicant.

The analysis relies on the same approach to compare callback rates by unemployment duration, gender, and immigrant background before and after the impositions of the lockdown in Italy. during economic downturns. The comparison can help understand whether duration dependence decreases, or increase, as well as whether discrimination goes up, or down, or remain stable after the imposition of COVID-19-related restrictions. Thus, two models have been estimated: one for employers targeted pre-COVID-19 and the second for employers contacted after the outbreak.

$$Job\ Call_{iec} = \beta_{0c} + \beta_1 Un_{iec} + \beta_2 Gen_{iec} + \beta_3 IB_{iec} + \gamma_1 Reg_{ec} + X_{iec} + S_{iec} + H_{iec} + E_{er} + \mu_{ec} + \varepsilon_{iec} \quad (18)$$

where c indexes the period in which employer e received the fictitious profile i, that is before or after the declaration of the state of emergency.

5.2.4 Assessing the relationship between duration dependence and discrimination

The final part of the analysis focuses on how employers aggregate what they gather from unemployment duration, gender, and immigrant background. This assessment can tell whether and how employers' understanding of characteristics, like unemployment duration, may depend on concomitant aspects of the applicant such as gender and immigrant background. First, the analysis looks at any differential returns to increasing unemployment duration between women and men and Italian vis-a-vis Romanian- Italians, or lack thereof. This can be done by estimating two models The first one includes an interaction term between gender $Gen_{ie}$and time in unemployment duration Un_{ie},

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Gen_{ie} + \beta_3 IB_{ie} + \beta_4 Un_{ie} * Gen_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_{ie} + S_{ie} + X_{ie} + H_{ie} + E_{er} + \mu_e + \varepsilon_{ie} \quad (19)$$

while the second one interacts with unemployment duration Un_{ie} and immigrant background IB_{ie}

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Gen_{ie} + \beta_3 IB_{ie} + \beta_4 Un_{ie} * IB_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_{ie} + S_{ie} + X_{ie} + H_{ie} + E_{er} + \mu_e + \varepsilon_{ie} \quad (20)$$

The analysis then looks at callback rates for intersectional applicants by including an interaction term between gender Gen_{ie} and immigrant background IB_{ie}

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Gen_{ie} + \beta_3 IB_{ie} + \beta_4 Gen_{ie} * IB_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_{ie} + S_{ie} + X_{ie} + H_{ie} + E_{er} + \mu_e + \varepsilon_{ie}$$

(21)

Finally, (6) can be augmented by adding a three-way interaction term that brings together both status characteristics, $Gen_{ie}$and IB_{ie}, along with Un_{ie} as follows

$$Job\ Call_{ie} = \beta_0 + \beta_1 Un_{ie} + \beta_2 Gen_{ie} + \beta_3 IB_{ie} + \beta_4 IB_{ie} * Un_{ie} + \beta_5 Gen_{ie} * Un_{ie} + \beta_6 Gen_{ie} * IB_{ie} + \beta_7 Gen_{ie} * IB_{ie} * Un_{ie} + \gamma_1 Reg_e + \gamma_2 Covid_e + \gamma_3 Sect_{ie} + S_{ie} + X_{ie} + H_{ie} + E_{er} + \mu_e + \varepsilon_{ie}$$

(22)

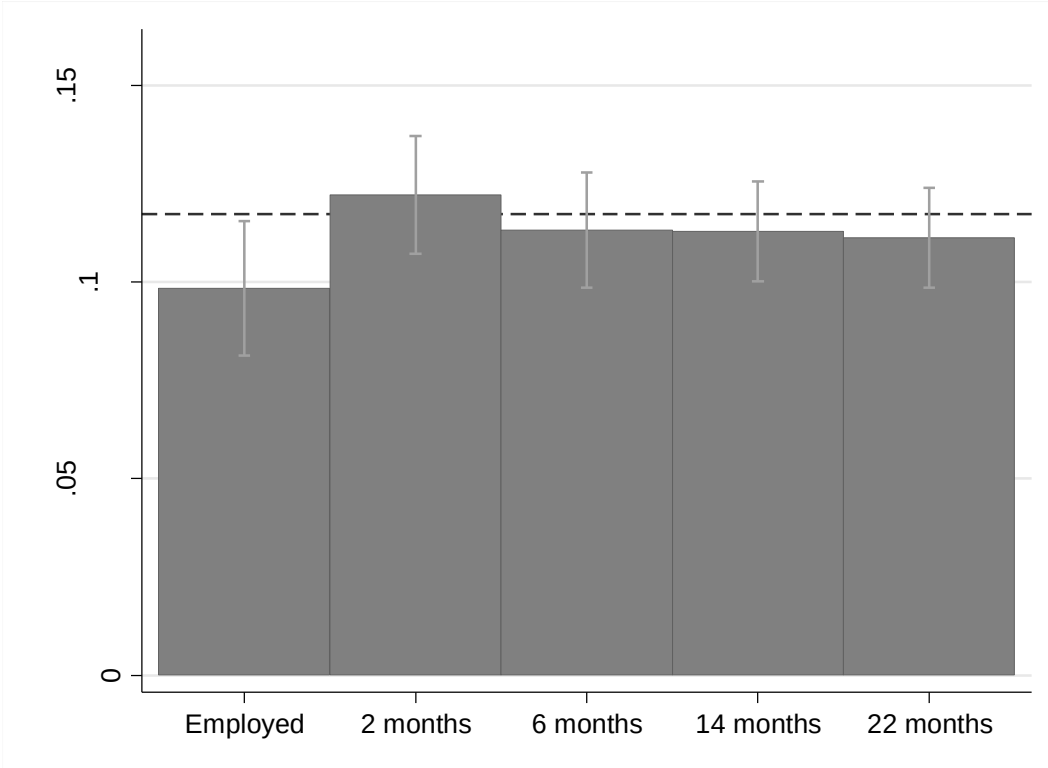
Estimates of β_7 will provide evidence about the aggregation logic that employers follow when assessing unemployment duration, gender, and immigrant background. Particularly whether additive, muted, and amplified congruence conforms better with employers' decision-making.

6 Results

6.1 Descriptive findings

Before delving into the multivariate analysis, it is instructive to assess callback rates and disaggregate them by key independent variables of the current research project, namely unemployment duration, gender, and immigrant background. Figure 6.1.1 shows the average callback rate over the unemployment duration. Figure 6.1.1 also plots the total callback rate for this study, which stands at 11.2% (black dashed line). The graph indicates that employers seem to call back at similar rates applicants with short (2/6 months) and long (14-22 months). Differences between unemployment durations do not look substantive as confidence intervals overlap, which suggests that the likelihood of employers calling back does not go down as unemployment duration lengthens.

Figure 6.1-1 Response rate by the *number of months in unemployment*



Turning now to gender and immigrant background, Figure 6.1.2 reports stark differences in callback rates between gender and origins. The right panel shows that employers are more likely to contact women than men. Women's callback rate is also higher than the sample average, whereas men are below the average benchmark. Estimates in the left panel show that employers tend to respond more frequently on average to Italians than Romanian-Italians. At

this point, it is important to recall that differences in callback rates cannot be attributed to qualifications, work experience, or uncertainty around language. These characteristics are equivalent across profiles. Additionally, Romanian-Italians were born, raised, and studied in Italy. Importantly, callback rates for Italians and Women are higher than the total callback rate of the study while they are lower for Romanian- Italian and men. This suggests that gender and immigrant background represent driving factors in employers' decision (not) to call back otherwise comparable applicants.

Figure 6.1-2 Response rate by gender and immigrant background

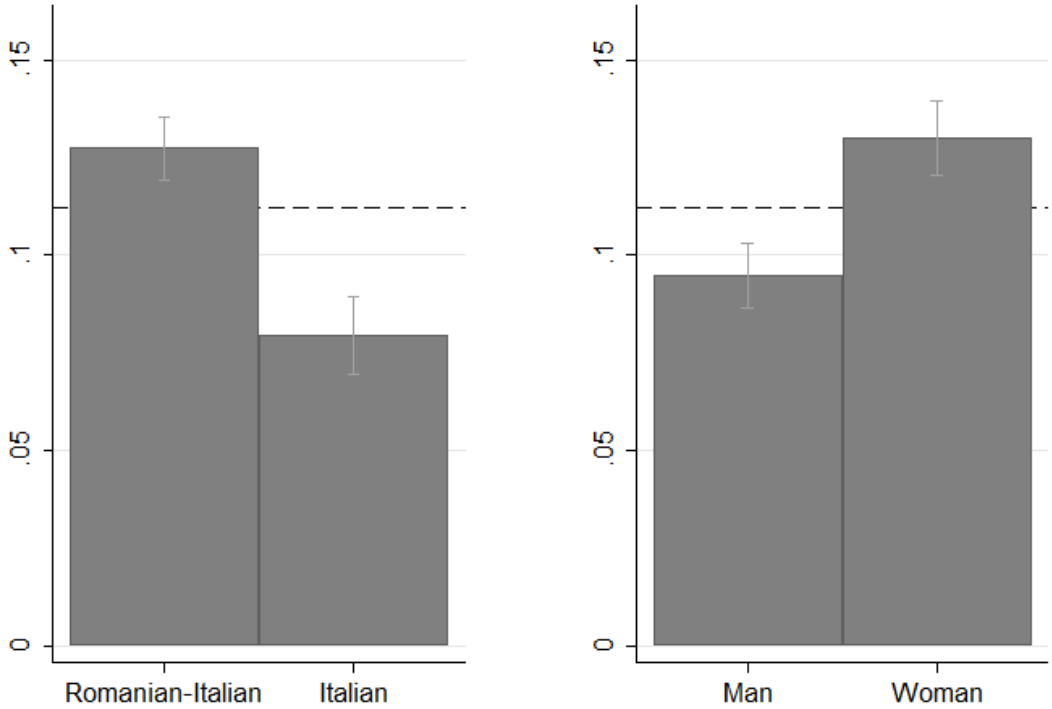


Figure 6.1.3 instead crosses gender and immigrant background and shows callback rates for intersectional fictitious profiles. The graph highlights that employers are most likely on average to contact Italian women with no immigrant background while they are least likely to contact Romanian-Italian men. The latter are also less likely to be invited by employers for an interview than Italian men with no immigrant background. Employers instead are on average keener to call Romanian-Italian women than Romanian-Italian men, but confidence intervals overlap. Romanian-Italian women are instead less likely on average than Italian men with no immigrant background to be called by employers, but the gap is not significant.

Overall, Figure 6.1.3 suggests that Italian men with no immigrant background represent employers' "average." The figure also shows that the gender callback gap shrinks close to zero when looking at Romanian-Italian men and women, whereas the difference between Italian

men and women is significant and substantial (five percentage points). The other takeaway from Figure 6.1.3 is that employers prefer, consistently with the previous figure, Italians to Romanian-Italians. Taking these findings together suggests that immigrant background seems to weigh more than gender in employers' decision-making. Also, whether employers consider gender depends on the immigrant background of the applicant.

Figure 6.1-3 Response rate by intersectional status groups

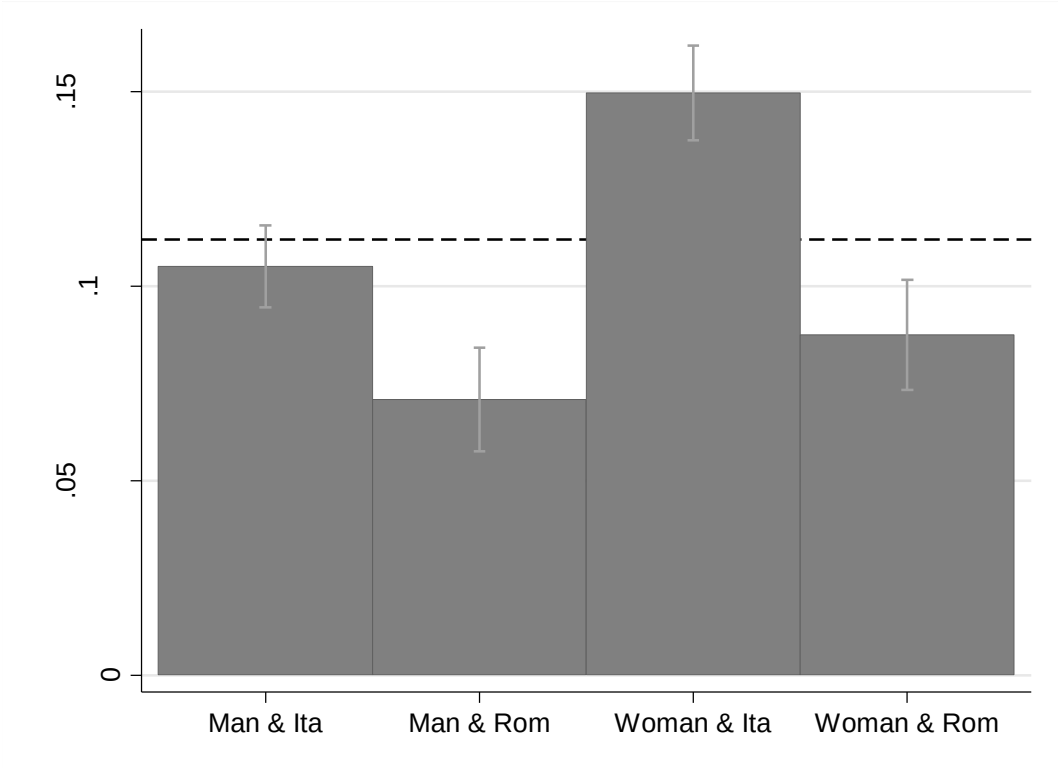
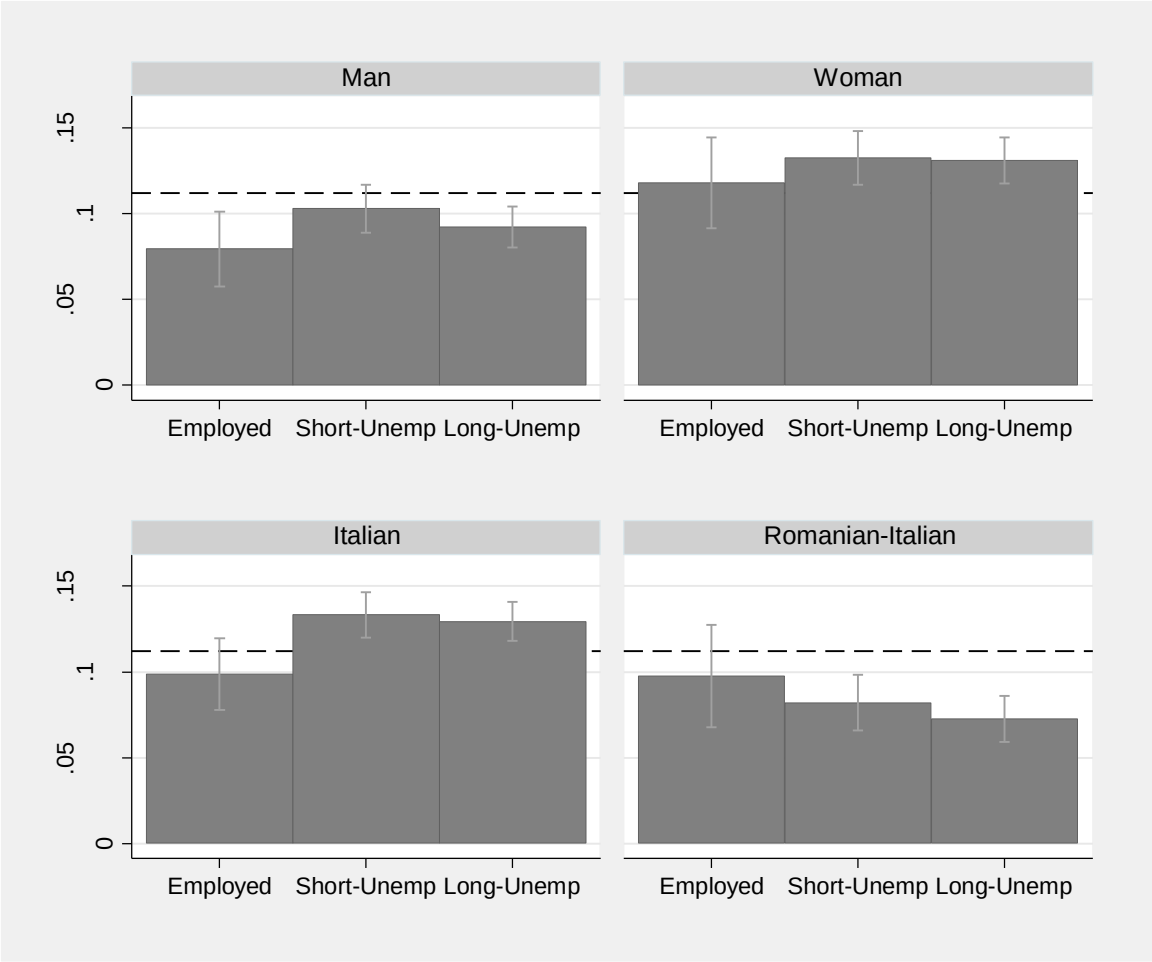


Figure 6.1.4 provides response rates, in the bottom panel, for Italians and Romanian-Italians over unemployment duration. The top panel instead reports average callback rates for women and men over the unemployment duration. The top panel shows a similar pattern among women and men: those currently working receive fewer calls than those in short-term unemployment, and likewise those in long-term unemployment. There does not seem to be an interaction. The same pattern holds among Italians whereas, among Romanian-Italians, callback rates decrease over unemployment duration. While differences in callback rates over unemployment are not statistically significant among Romanian-Italians, it is instructive to compare those with and without an immigrant background with the same duration. Italians and Romanian-Italians with a job are contacted at the same rates. However, there is a callback gap of about 5 percentage points between Italian and Romanian-Italians in short-term unemployment. The gap widens when profiles with and without an immigrant background are in long-term unemployment.

Thus, employers seem to consider positively unemployment duration if accrued by Italians. It becomes a liability for Romanian-Italians, which suggests that how employers consider immigrant background could contribute to making unemployment duration scarring and detrimental.

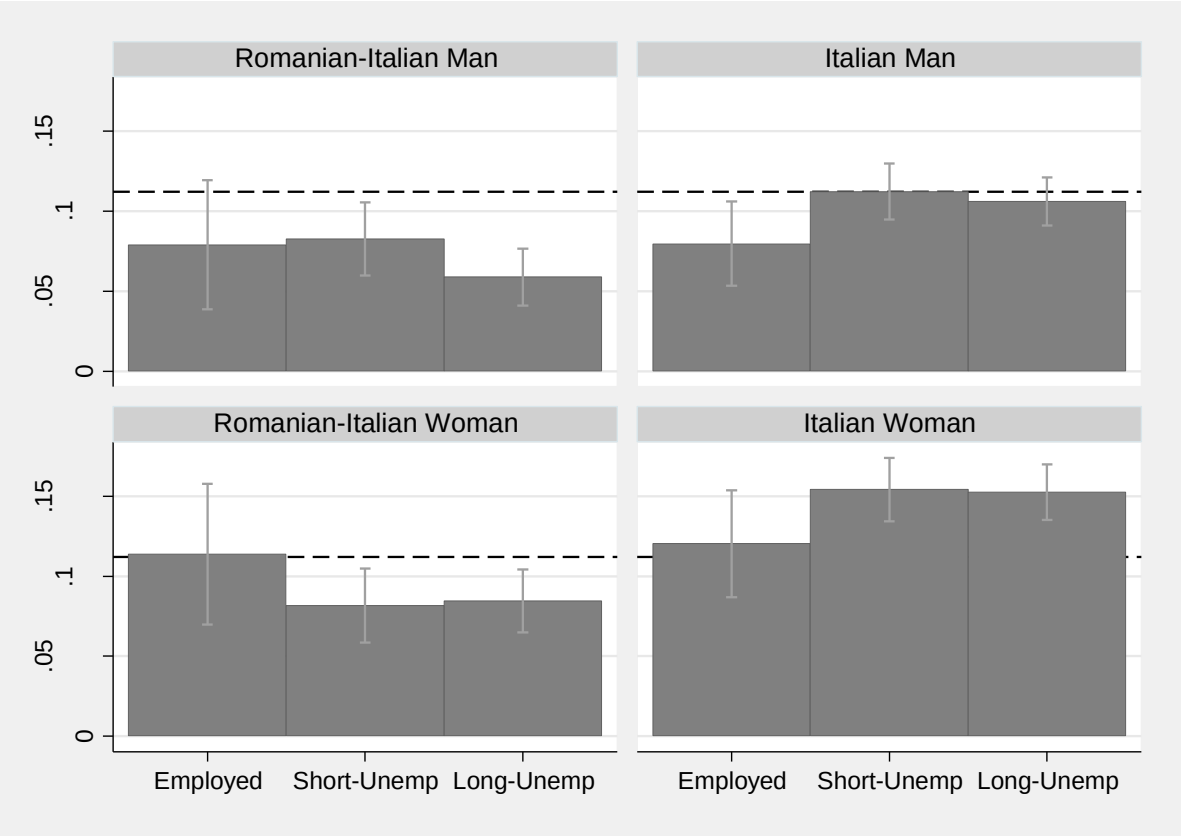
Figure 6.1-4 Response rates over unemployment duration, by gender (upper panel) and immigrant background (lower panel)



Finally, it is possible to explore differences in callback rates for intersectional profiles by crossing gender, immigrant background, and unemployment duration. The top panel in Figure 6.1.5 shows callback rates for Italian men on the left and Romanian-Italian men on the right over unemployment duration. The same comparison is presented for women in the lower panel. The Figure confirms the patterns in employers' callback rates highlighted in the previous graph: increasing callback rates on average for Italian (wo)men as unemployment duration lengthens, and vice versa among Romanian-Italian (wo)men. Also, employers seem to respond differently, on average to short-term unemployment between Romanian-Italian women and men. Intersecting groups provides a nuanced picture of differential callback rates. However,

Figure 6.1.5 shows that employers rely on the immigrant background as a key factor to sort applicants, and what they learn from gender and unemployment hinges on it.

Figure 6.1-5 Response rates by unemployment duration, per immigrant origin and gender



While Figures 6.1.1-5 describe differences in callback rates based on the characteristics that were randomly allocated to fictitious profiles, hypotheses formulated in Chapter 2 also aim to test differences in callback rates between employers. Besides recording callbacks from employers, the data collection also gathered information on employers and the jobs they offered using job ads, as detailed in Section 5.1. The employers reached through the correspondence study differ in the amount of information they shared in job ads, as well as with regards to how they describe their ideal candidates.

These differences are described in Figure 6.1.6 and Figure 6.17. Particularly, Figure 6.1.6 compares employers based on information they shared, in the job ad, on their companies, and the contractual conditions they offer. Figure 6.1.7 instead compares employers using job requirements that employers listed in the job description, particularly the skills they were looking for (Figure 6.1.7). The two Figures group employers in clusters, which were obtained using Latent Class Analysis (Muthén 2008). This type of analysis assumes that a population comprises a set of clusters of individuals sharing some common traits. Importantly, these

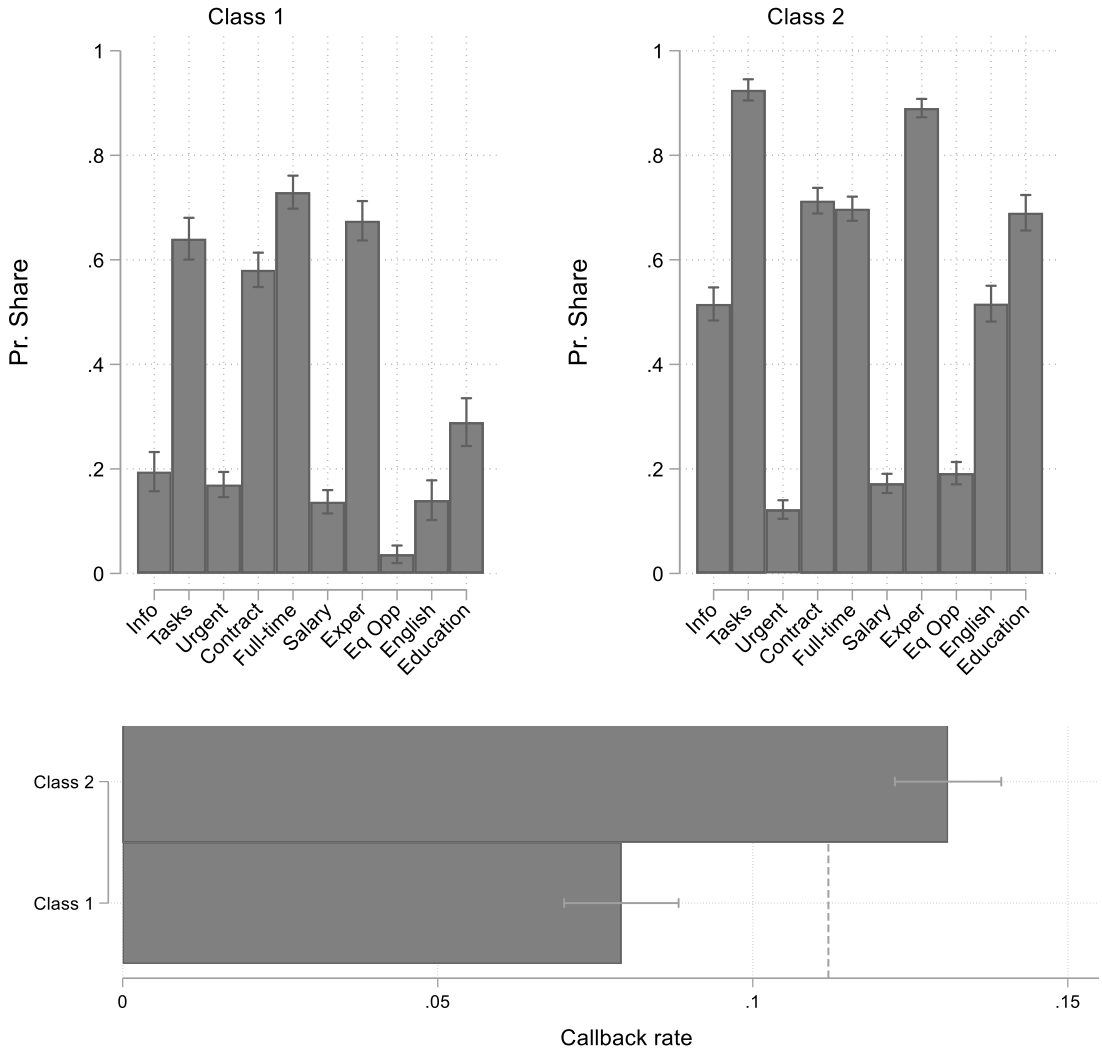
clusters can be identified using explicit data and information that individuals provide on the unobserved common traits (Collins and Lanza 2010).

For example, Figure 6.1.6 shows the results of latent class analysis based on a set of binary indicators, including whether the employer described their company in the job ad (1); whether s/he described the tasks to be performed on the job (2); if it was an urgent hire (3); if the contract was temporary (4); full-time (5); if the salary was mentioned (6); as well as if the employer had details in terms of requirements related to experience (7), education (8), English (9) and if the employer mentioned a statement of equal opportunities (10). All indicators can be conceptualized, for example, as the propensity of employers to share information and/or the ability to use job ads to narrow down the pool of prospective candidates.

In practice, the latent class analysis generated two clusters of employers using these 10 binary indicators. The two clusters represent the solution with the best fit with 36% and 64% of employers allocated, respectively to Class 1 and Class 2. Figure 6.1.6 shows that employers in Class 2 were more likely to have published job ads including information on the tasks to be performed on the job, along with details on the type of contract offered. Employers in Class 2 also shared more often details about job requirements in terms of the number of years of experience required, education attainment, and foreign language (English). Importantly, employers in the second cluster were far more likely to provide information about their companies. Instead, employers in Class 1 were slightly more likely to be urgently looking for someone to hire while they were as likely to share information on salaries and less likely to include statements on equal opportunities.

While these clusters are not a taxonomy, they are still helpful descriptive devices. Classes 1 and 2 seem to point to substantive differences in employers' provision of information to a prospective candidate. The third panel at the bottom of Figure 6.1.6 shows that differences between clusters of employers, based on the amount of information shared, are associated with differences in callbacks. Particularly, the group of employers sharing less information (Class 1) is far less likely than the group sharing more data with candidates (Class 2) to call back fictitious profiles. Also, the response rate of Class 1, the "less information", is far below the mean response rate of the study whereas the response rate of Class 2, the "more information" is higher than the mean benchmark. The difference suggests that there might be underlying differences in how employers screen candidates.

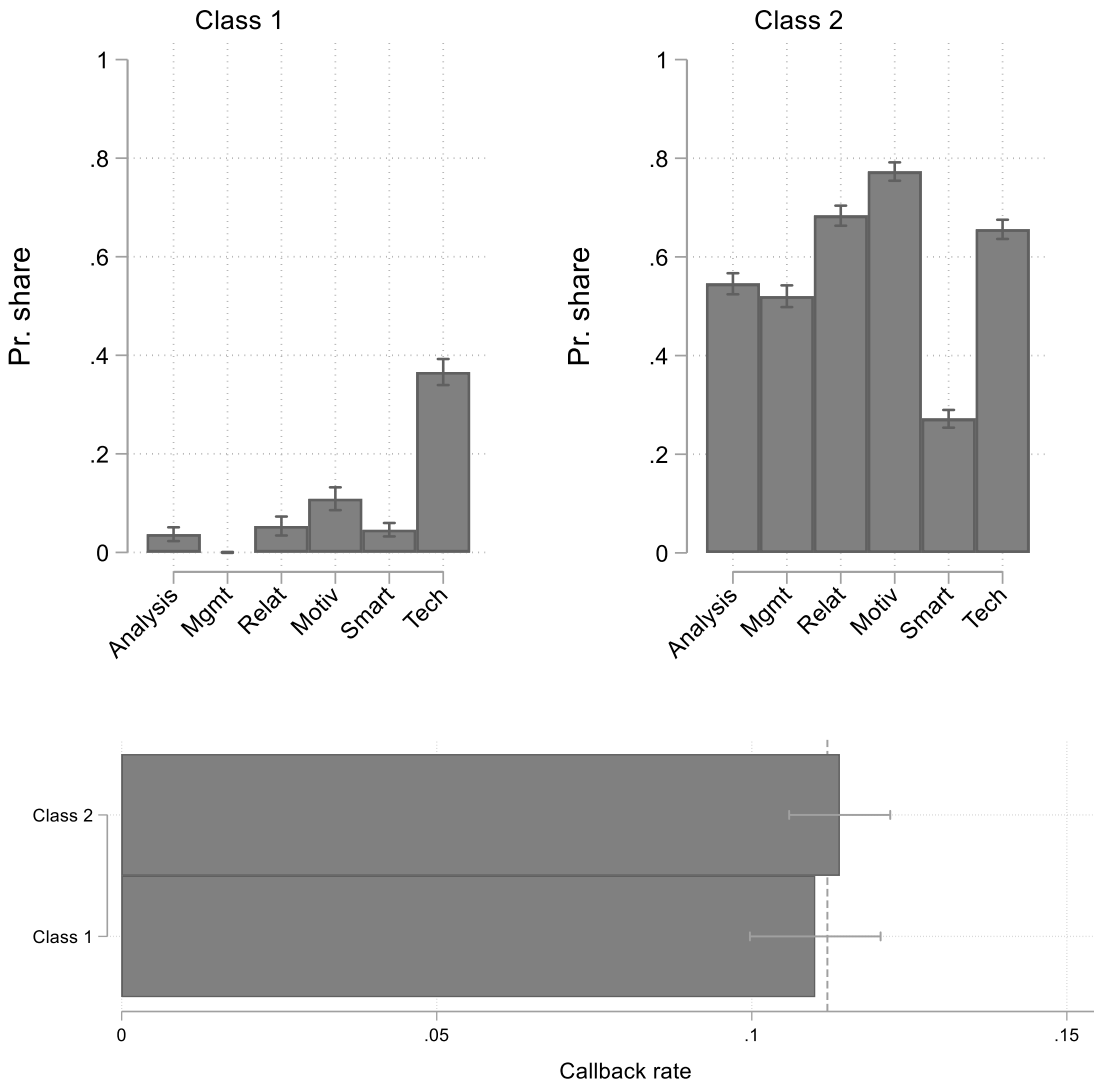
Figure 6.1-6 Item response "job description" and mean callback rates by latent class



The same analytical approach is used in Figure 6.1.7. Employers have been clustered based on whether they mentioned, in the description of their ideal candidate, analytical skills (1), management-related skills (2), relational skills (3), or motivation (4), whether the candidate needed to be creative and ready to learn (5), as well as whether the ad mentioned job-specific skills or IT (6). Similarly, to Figure 6.1.6, a two-class solution provided the best fit. The analysis, presented in Figure 6.1.7, highlights that one group of employers, Class 1 (37%), was very likely to mention technical-related skills only. Employers in Class 2 (63%) instead were more likely to describe the ideal candidate they were looking for using a mix of skills along with the technical ones. Figure 6.1.7 shows that there seems to be no difference in terms of callback rates between these two clusters, regardless of differences in the approach adopted to describe the ideal candidates. Nonetheless, the high share of employers interested in soft skills

highlights the relevance of these aspects among employers, which however are difficult to elicit from written applications.

Figure 6.1-7 Item response "skills" and mean callback rates by latent class



6.2 Duration dependence and employers' decision-making

6.2.1 (How) do employers use unemployment duration in the screening phase of the hiring process?

Descriptive findings from the previous section suggest that employers do not seem to care about unemployment duration. A quick assessment of callback rates over time out of work tells that fictitious profiles with different and increasing current unemployment spells received similar callback rates. Nonetheless, multivariate analysis can help better understand whether this finding holds once additional information that was provided as part of the fictitious resumes is controlled for.

The first model (1) includes unemployment duration only because it aims to test whether *employers are more likely to consider applications from those in short-term unemployment than from candidates with a job or in long-term unemployment* (*H.1*). Unemployment duration is categorized over three levels and takes a value of 0 if the candidate is currently employed, 1 if it was unemployed for 2 or 6 months, and 3 if it was in unemployment for longer (12 and above). Estimates of unemployment duration on callbacks are provided in Table 6.2.1.1 for Models (1) – (4). Results for Models 1-3 confirm the two descriptive findings from Section 6.1. Employers are not less likely to call back those in long-term unemployment compared to fictitious profiles in short-term unemployment. Importantly, estimates are close to zero when comparing short- vs long-term unemployment. Also, the size of the effect of unemployment duration on callbacks does not vary substantially across models as additional controls are included in the model, nor do they become more precise (i.e., standard errors are not affected). Results, therefore, do not lend support *H.1*.

When a random effect is added in Model (4), the difference between those currently employed and those in short-term unemployment becomes larger and significant ($p < 0.05$). After accounting for idiosyncratic differences in the way employers assess their batch, the model suggests that employers tend to prefer profiles who are in short-term unemployment to those who currently hold a job. In other words, employers generally prefer those in short-time unemployment to candidates who have a job. Nonetheless, estimates also hint that employers are not consistent in the way they make this comparison when assessing their batch of four resumes.

While duration dependence does not emerge, the result might be contingent on the time employers can dedicate to the screening. In this regard, *H.2* posits that if employers face urgency, the difference in callbacks between applicants in short-term unemployment vis-à-vis

Table 6.2.1-1 Unemployment duration on callbacks, linear coefficients displayed –OLS with clustered employer standard errors Models (1)-(3) and Random Effect Model (4)

	(1)	(2)	(3)	(4)
Employed	-0.019	-0.019	-0.021	-0.029*
	(0.015)	(0.015)	(0.015)	(0.012)
Long-term	-0.006	-0.006	-0.006	-0.006
	(0.010)	(0.010)	(0.010)	(0.009)
CV Style	-	YES	YES	YES
Sociodem.	-	YES	YES	YES
Emp. Hist	-	YES	YES	YES
Area FE	-	-	YES	YES
Time FE	-	-	YES	YES
Sector FE	-	-	YES	YES
Random Effect	-	-	-	YES
sigma_u				0.210
sigma_e				0.235
ICC				0.445
Adj R2	0.000	0.010	0.015	
N	4079	4079	4079	4079

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

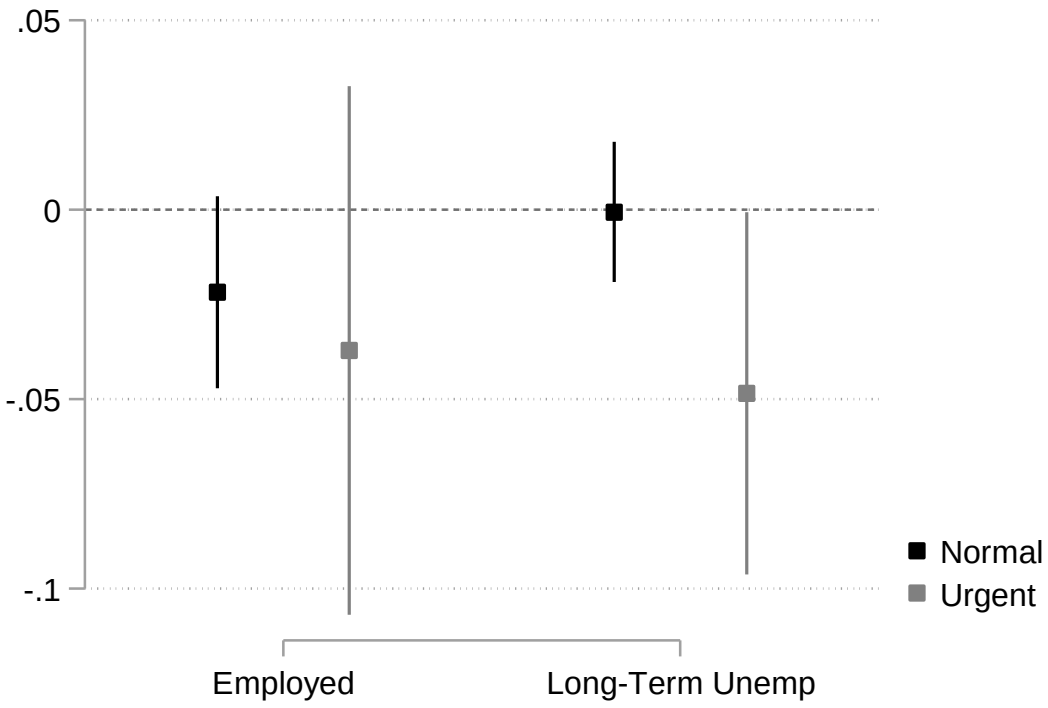
Note: regression tables and estimates for Models 2-4 are available in Annex G. Model (1) does not include any control variables. Model (2) adds CV style variables: font, style, and the order in which the employers received the 4 resumes. Model (2) also includes details of the employment histories (Emp. Hist), particularly the Italian macro-region of birth, whether it had one or two jobs, an internship, or a period of unemployment at the beginning of the career and whether the profile worked for a big company (more than 50 employees). Finally, model (2) includes Gender and Immigrant background (Sociodem). Model (3) adds on top of the controls in Model (2), the macro area of the employer (Area FE), the period (Time FE), and the Sector of the employer (Sector FE). Models 1-3 are estimated using an Ordinary Least Square (OLS) with robust cluster standard errors at the employer level whereas Model (4) is a random effect model.

those in long-term unemployment is larger than when employers are not as time constrained. Model (5) tests this hypothesis by estimating Model (4) twice: once for employers who need to hire someone immediately, as stated in the job ad, and once for employers who do not include urgency in the job ad. The average marginal effects for these two models are shown in Figure

6.2.1.1 using short-term unemployment as the base category.

The Figure shows that employers make no difference between applicants in short and long-term unemployment when the hiring is not urgent. This result replicates findings from Models (1) – (4), which are against the general expectation on unemployment duration under *H.1*. However, employers are less likely to call back an applicant in long-term unemployment than one in short-term when there is urgency, whereas the difference is not statistically significant for employers who are not in a rush to hire someone. This result lends support to *H.2* and suggests that how employers use unemployment duration depends on the time they have for the screening of resumes. Interestingly, the point estimate is similar between those in employment and those in long-term unemployment under urgency. Those in long-term unemployment do not seem to get more calls than applicants with a job when employers face urgency even if they would be able to start the job immediately as they do not have an ongoing job contract.

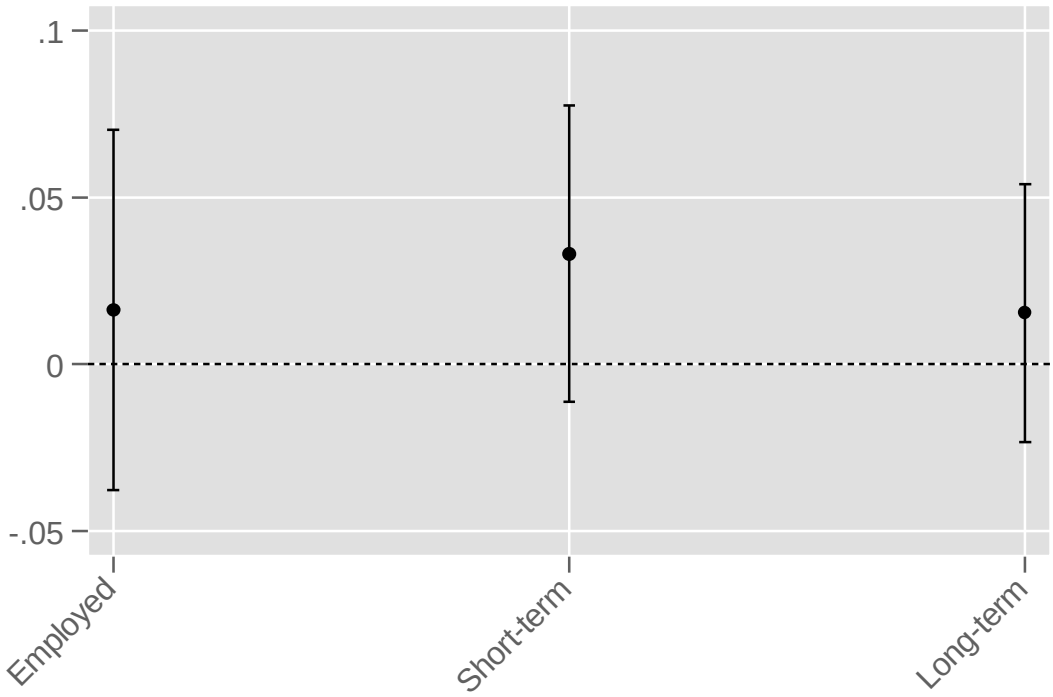
Figure 6.2.1-1 Average marginal effects: Unemployment duration on callbacks, by urgency



6.2.2 What do employers infer from unemployment duration?

The next step of the analysis investigates the motives that make unemployment duration meaningful for employers. Particularly, it tests whether *employers who set motivation and commitment to work as a job requirement are less likely to call back applicants in long-term unemployment than employers who do not set motivation as necessary (H.3)*. Model (6) interacts unemployment duration and whether employers mentioned motivation in their job ads. Figure 6.2.2.1 plots average marginal effects, which represent the difference in the likelihood of a callback between employers who mention motivation in the job and those who do not (base category) over the unemployment duration. On average employers listing motivation are more likely to call back applicants in long-term unemployment compared to employers not listing it, but differences are not statistically significant. Employers who mention motivation as a job requirement are therefore not more averse than their peers who do not emphasize this aspect to applicants with long unemployment duration. As such, results do not lend support to *H.3*. Thus, results seem to indicate that employers do not see unemployment duration as a sign of lower motivation.

Figure 6.2.2-1 Average marginal effects: motivation on callback, over unemployment duration



Nonetheless, differences may still emerge in how employers who emphasize these job requirements use information from resumes. Particularly, whether *employers who mention motivation in the job are more (H.4a), or less (H.4b) likely to call back applicants in long-term*

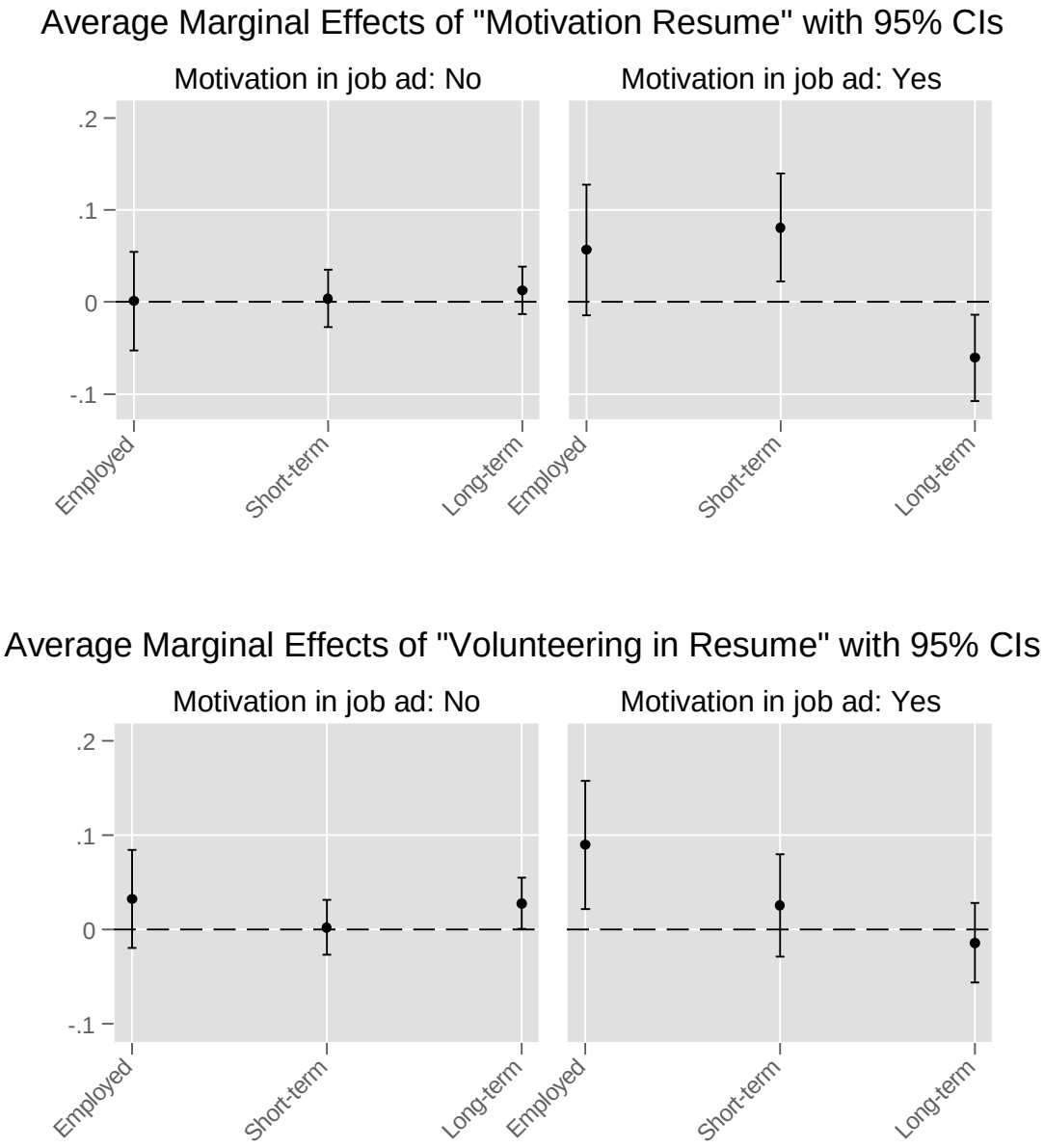
unemployment who provide details on their motivation compared to applicants with the same duration but no information. Model (7a) adds a three-way interaction term between unemployment duration, whether the profile includes a statement about the motivation for the job and whether the job ad mentions motivation as a requirement. Similarly, Model (7b) includes a three-way interaction term, but with volunteering rather than a statement on motivation as an additional measure of individual commitment.

The average marginal effects from these two models are shown in Figure 6.2.2.2. The upper panel reports the average marginal effects of having a statement regarding individual motivation for the job on the probability of a callback. Applicants with no statement on motivation for the jobs are the base category. The average marginal effects are estimated for each level of unemployment duration for employers who mention motivation in the job ad and those who do not. Likewise, the bottom panel of Figure 6.2.2.2 reports the average marginal effects of a statement on volunteering in the resume over unemployment duration by a group of employers. Starting with the upper panel and looking at employers who mentioned motivation in the job ad, estimates show that these employers are less likely to call back applicants in long-term unemployment who include a statement about their motivation compared to applicants, with the same unemployment duration, who do not include such statement. Importantly, the effect is large and significant lending support for *H.4b*.

Instead, among employers who do not emphasize motivation, the effect of having a statement about motivation on the likelihood of a callback is zero for applicants with long-term unemployment. It is also interesting to see that employers who emphasize motivation and find a statement on individual motivation in the resumes of applicants in short-term unemployment are more likely to call them back compared to applicants with the same duration and no statement on individual motivation. As such, employers who emphasize motivation respond differently to applicants who provide information about this aspect depending on the length of their unemployment spells.

The bottom panel of Figure 6.2.2.2 discloses instead the average marginal effects of volunteering over unemployment duration for employers mentioning motivation and for those who do not. Looking at employers who mention motivation in the job ad, the average response to volunteering decreases as the unemployment duration gets longer. There is a jump in callbacks for candidates who are currently employed when they mention volunteering, with a significant average marginal effect. If instead applicants are in short-term unemployment, the effect of volunteering among employers who mention motivation is still positive on

Figure 6.2.2-2 Average Marginal Effects of Motivation and Volunteering (mentioned in resumes) on callbacks over unemployment duration



average but not significant. The effect of volunteering for applicants in long-term unemployment is also not significant among this group of employers but on the average negative. This is interesting given that employers who do not mention motivation are significantly more likely to call back applicants in long-term unemployment with ongoing volunteering compared to applicants with the same duration and no volunteering. In sum, employers mentioning motivation do not on average call back fewer times those in long-term unemployment than employers who do not list motivation in job ads (against *H.3*). However, the combination of employers asking for motivation and getting signs of it from those in long-term unemployment diminishes the probability of a call back in line with *H4.b*. Thus, signs of

motivation do not boost their probability of a call back from employers stating motivation, which was formulated as an alternative hypothesis in Section 2.1.2 (*H.4a*).

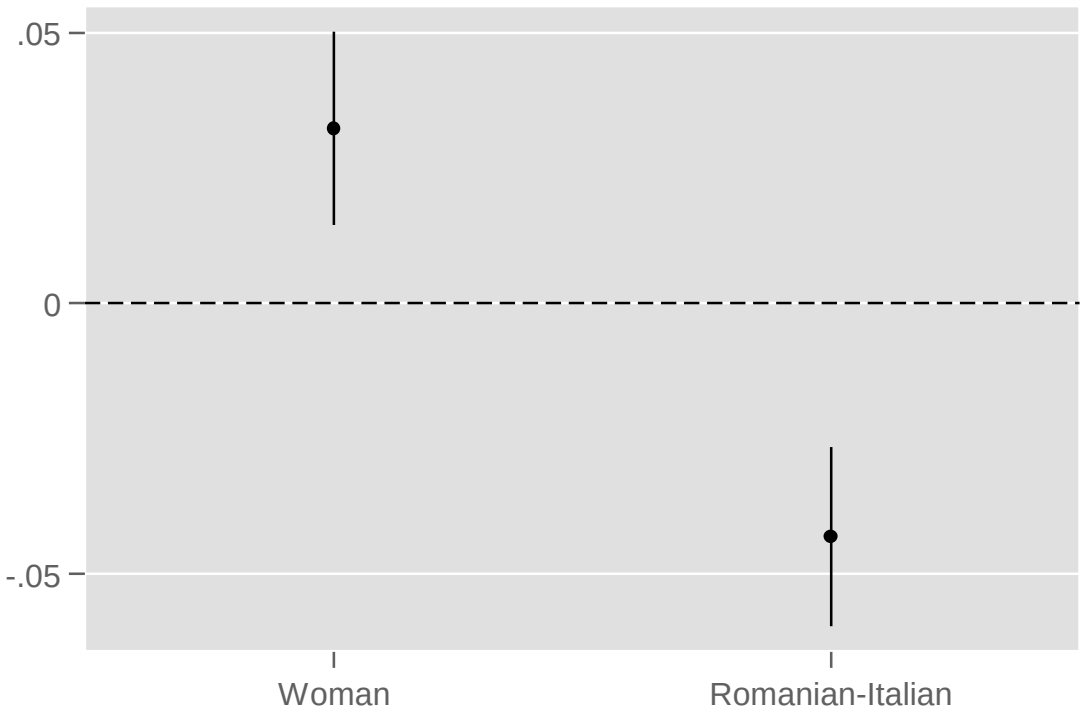
6.3 Discrimination in the screening phase

6.3.1 Striking a balance between lack of information and bias

The first part of the analysis aims to test whether *employers' differential treatment stems from bias rather than lack of information* (*H.5*). To assess whether it is a matter of information or bias, the analysis relies on the random effect model. Model (8) includes both gender and immigrant background along with other controls, including details of the individual employment histories, visual features of the resume, as well as period (COVID-19), sector, and region fixed effects. Model (8) also includes information about individual motivation, knowledge of job-specific software, and ongoing professional development.

Table 6.3.1.1 shows that average marginal effects for women are significantly positive compared to men. The same observation applies to the immigrant background, but the sign of the relationship is negative. Employers are significantly less likely to contact Italian applicants with a Romanian background than Italians with no immigration background.

Figure 6.3.1-1 Average marginal effects: gender and immigrant background on callback



Estimates from Model (8) thus indicate that employers rely on gender and immigrant background to sort applicants even if applicants are of equivalent quality. In this regard, results lend support to *H.5* meaning that bias is more likely to be the origin of discrimination in this sample rather than lack of information.

Further evidence in support of *H.5* is also provided in Table 6.3.1.1, which compares estimates for gender and immigrant origin from a probit model with clustered standard errors and a heteroskedastic one with cluster standard errors. As discussed in Section 5.2.2, the heteroskedastic probit model can help understand whether employers perceive candidates like Romanian-Italians and (wo)men as more heterogenous in the distribution of unobserved characteristics. The heteroskedastic probit, differently from the probit model, relaxes the assumption that the variance of the error term is the same between groups, namely men and women and Romanian-Italians and Italians.

The first indication that the variance of unobserved characteristics is equal between groups comes from the size of the average marginal effects in Table 6.3.1.1. Estimates suggest that effects are the same across models. Thus, employers do not seem to perceive between-group differences in the heterogeneity of unobserved characteristics. The second indication comes from the decomposition of the effect for women and Romanian-Italians. Relying on estimates from the heteroskedastic probit model is possible to decompose the average marginal effect in two parts[21]: 1) the effect through the level (i.e. mean the difference between men and women) and 2) the effect through the variance (i.e. mean difference in the perceived heterogeneity of unobserved details between men and women).

Table 6.3.3.1 shows that the estimate of the variance for both gender and immigrant background is of negligible size. The magnitude is also a hint that the design of fictitious profiles did not influence employers' perception of group heterogeneity of unobserved characteristics. The effect though the level, instead is larger, which tells that the effect detected in previous analyses captures substantive employers' differential treatment. The conclusion that the variance is the same across groups is also confirmed by the size of the relative standard deviation of unobserved variables for both men vs women (0. 982) and Romanian-Italians compared to Italians (0.997). Likewise, the very high value of the Wald Test indicates that there is no between-group difference in the standard deviation of the error term. These results confirm findings from Model (8) and strongly point to bias rather than lack of information (statistical discrimination) as the cause of differential treatment in line with *H.5*.

[21] The method that Neumark (2012) suggests for decomposing the total effect through the level and the variance inflates estimated standard errors by 2.5 times, or more, vis-à-vis the standard errors from the total average marginal effect (Carlsson, Fumarco, and Rooth 2014). This feature makes it more likely that the decomposed effects through the level and the variance are not statistically significant. Nonetheless, in this application the effect through the level is substantially larger than the effect through the variance, with the variance being basically zero. As such, the total average marginal effect almost entirely stems from the effect through the level, which means that the correspondence study is capturing substantive differential treatment.

Table 6.3.1-1 Average Marginal Effects: gender and immigrant background, probit, and heteroskedastic probit

Gender				*Immigrant background*			
	AME	S.E.	P>z		AME	S.E.	P>z
Probit				*Probit*			
Woman	0.0362	0.0101	0.000	IT_RM	-0.047	0.0089	0.000
Heteroskedastic				*Heteroskedastic*			
Woman	0.0362	0.0104	0.001	IT_RM	-0.0497	0.0117	0.000
Decomposition				*Decomposition*			
Level	0.03427	0.0816	0.670	Level	-0.0494	0.0956	0.524
Variance	-0.0015	0.0835	0.985	Variance	0.0003	0.1806	0.998
Relative standard deviation of unobserved variables		0.9825		Relative standard deviation of unobserved variables		0.9971	
Wald test statistic, standard deviation == 1 (p-value)		0.9855		Wald test statistic, standard deviation == 1 (p-value)		0. 9983	
CV Style		YES		CV Style		YES	
Emp. Hist		YES		Emp. Hist		YES	
Skills		YES		Skills		YES	
Job Sector FE		YES		Job Sector FE		YES	
Area FE		YES		Area FE		YES	
Time FE		YES		Time FE		YES	
N	4,079			*N*		4,079	

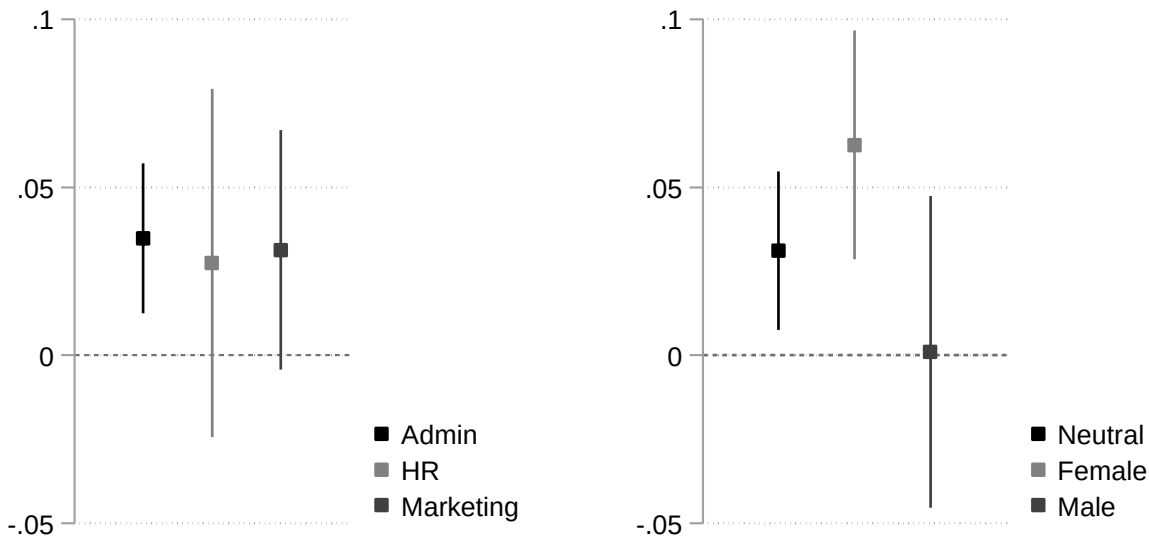
Note: regression tables and estimates for Model (8) are available in Annex G. Model (8) includes CV style variables: font, style, and the order the employers received the 4 resumes. It also includes details of the employment histories (Emp. Hist), particularly unemployment duration, the Italian macro-region of birth, whether it had one or two jobs, an internship, or a period of unemployment at the beginning of the career and whether the profile worked for a big company (more than 50 employees). Model (8) also includes the macro area of the employer (Area FE), the period (Time FE), and the sector of the job (Sector FE). Finally, Model (8) includes variables capturing a statement on motivation, volunteering, knowledge of job-specific software, and ongoing professional development (Skills).

6.3.2 Job types and requirements: how do they influence discrimination?

The analysis so far shows that employers consistently prefer women over men and Italians to Romanian-Italians. The analysis in this section tries to unpack this general pattern in employers' responses. Starting with gender, the analysis tests *H.6*, namely whether e*mployers are more likely to call back women than men for jobs that are expected to be women's jobs, but when jobs have no clear gender connotations, employers are more likely to consider men than women.*

To test *H.6* random effect models are estimated using Model (9) by sector (Admin, HR, Marketing) and using Model (10), which is estimated by the gendered nature of the language in the job ad (Neutral, male, or female-oriented). The average marginal effects of these two models for women and men are reported in Figure 6.3.2.1. The panel on the left provides estimates by Sector whereas the panel on the right is by type of language in the job ad. Starting with the left panel, an inspection of by-sector estimates shows that employers across sectors are on average more likely to call back women. While employers in Admin (p<.001) are significantly more likely to prefer women over men, in HR and Marketing[22] employers tend to prefer women over men as well but the difference is not significant with large standard errors. As such, estimates based on callbacks from employers in Admin lend support to *H.6*, whereas those from employers in Marketing are in contrast with expectations put forward under *H.6*.

Figure 6.3.2-1 Average Marginal Effect: gender, by job cluster and gendered language

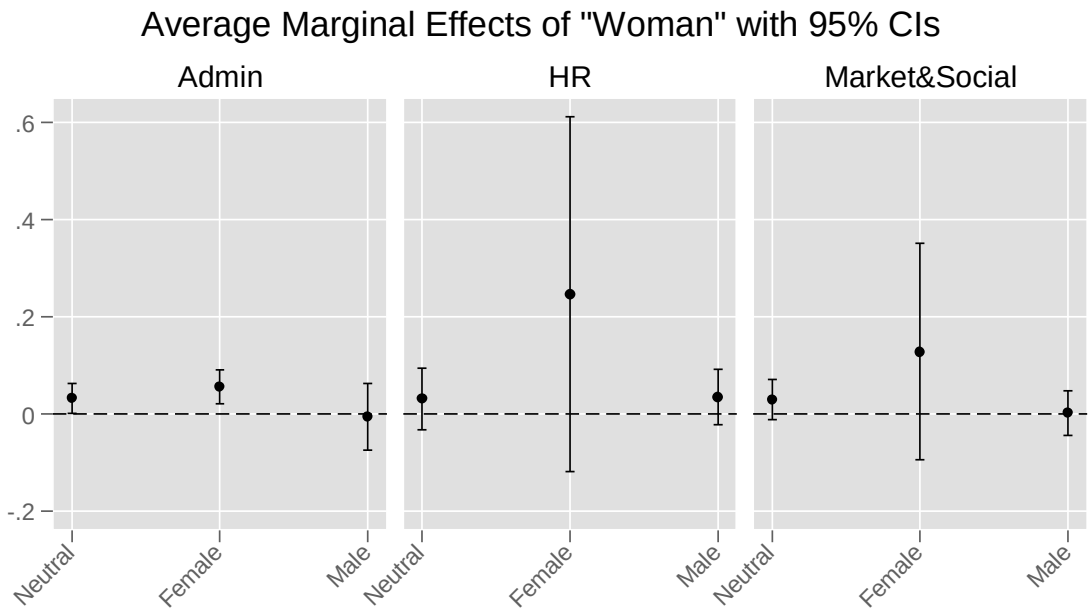


[22] When the analysis accounts for the probability of rejecting the null hypothesis given that it is true, the so-called familywise error rate (FWER) (Romano, Shaikh, and Wolf 2010), the mean difference in callbacks between women and men for marketing is not significant. See Anne H for a comparison of p-values.

Moving to the right panel, Figure 6.3.2.1 shows that employers are more likely to call back women than men when their language to describe the job is women oriented. When employers use gender-neutral language in job ads, they are still more likely to invite women over men for job interviews. The difference in call-back rate instead is zero when employers refer to the ideal candidate in the job ad as a man. Results thus suggest that employers prefer women when they describe the ideal candidate in their job ad using women-oriented language, which lends support to *H.6*. However, employers also prefer women when they use neutral language in the job description, which goes against expectations in *H.6*, and ultimately, provides mixed evidence in support for *H.6*.

This last result regarding language might stem from the fact that most jobs in this correspondence are in the Admin Sector. As such, even if employers use neutral language, most of them come from a sector where women are overrepresented and thought to be the best candidates. Consequently, women are preferred to men even when the language is neutral. This is what emerges from the further analysis carried out by interacting gender of the applicants, language in the job ad, and sector (see Figure 6.3.2.2). In Marketing and HR instead, employers tend to call at similar rates men and women regardless of how gendered is their job description.

Figure 6.3.2-2 Average Marginal Effect: gender, by Sector and gendered language



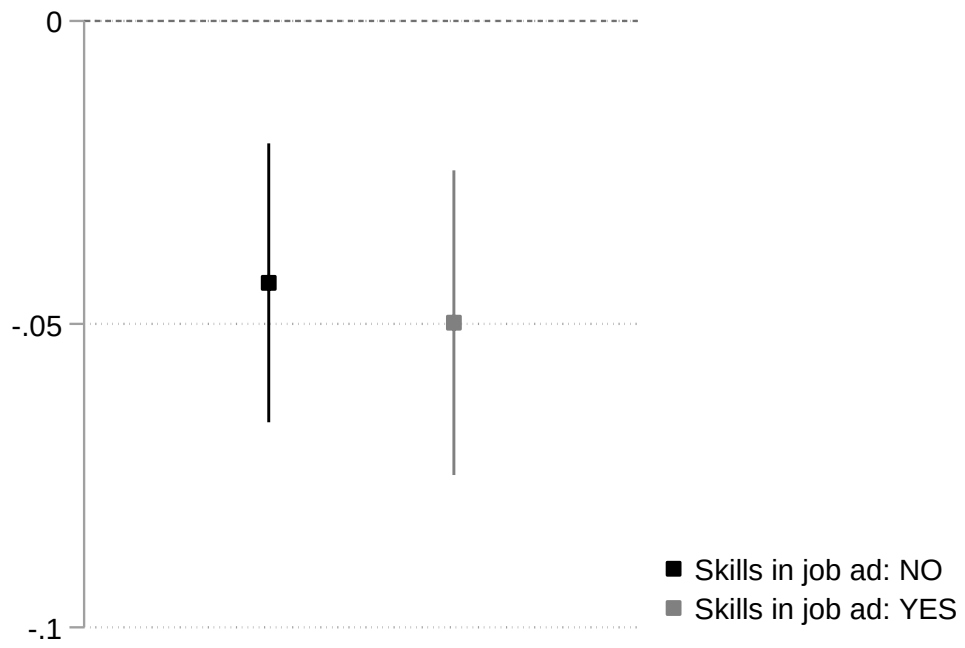
At this point, it is important to recall that Italian employers offering Admin jobs had the most gendered expectations about new hires. Most of these employers thought women were far better for their jobs than men. This view was not as strong in HR but still more favorable for women than men. In Marketing instead, views were far more balanced and in sum, results seem

to reflect the opinions expressed by employers across these three sectors. Thus, the analysis does not lend support to *H.6*, particularly that when jobs have no clear gender connotations, employers are more likely to consider men than women.

Also against theoretical expectations, estimates for marketing (gender-neutral sector) show that on average employers prefer women to men. While differences are not significant, this result might indicate that employers in this sample generally prefer women to men across sectors. The proposition seems to find support from the average marginal effects of men-oriented language (Figure 6.3.2.1): when the language would suggest that employers are looking for a man, women stand an equal chance of a callback. This result holds across sectors the gender of the applicant and the language in the job ad (Figure 6.3.2.2). Thus, while not definitive, these results seem to support the idea that women might be the high-status group in the service sector, which would make them more appealing than men to employers.

Turning to the immigrant background, the analysis tests whether e*mployers emphasizing communication and relational skills in job descriptions are less likely than employers who do not mention these requirements to consider applications from candidates with an immigrant background than applications from native job seekers* (*H.7*). Figure 6.3.2.3 reports average marginal effects from Model (11) of immigrant background on callbacks separating employers who mention communication and relational skills from those who do not. The Figure shows

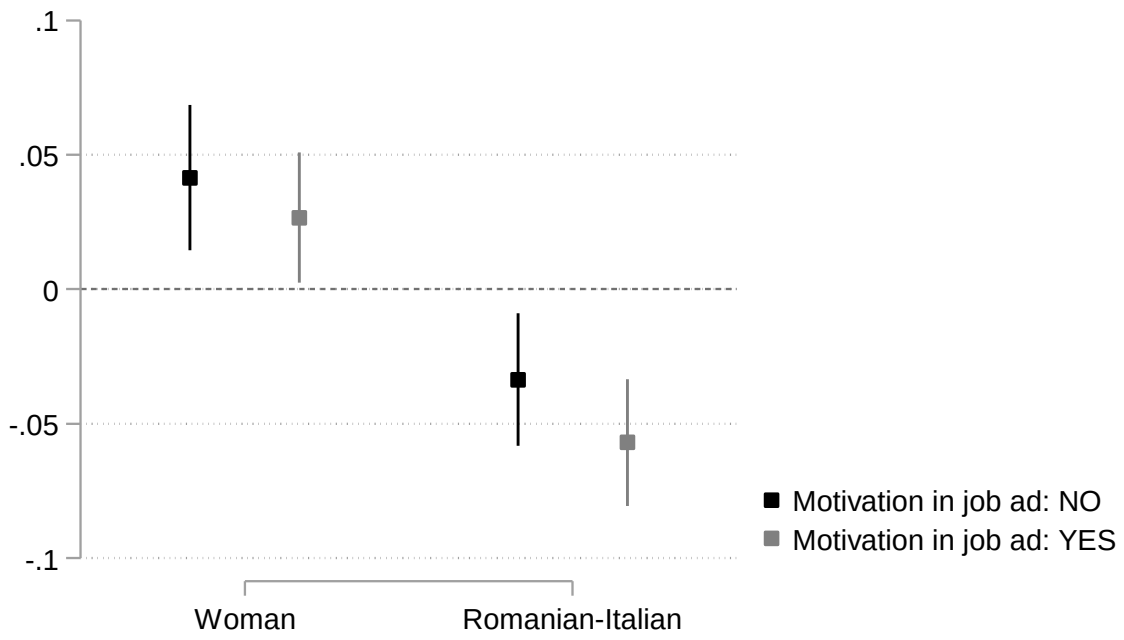
Figure 6.3.2-3 Average Marginal Effects: immigrant background, by employers (not) listing communication and relational skills



that there is no statistically significant difference between employers who set these job requirements compared to those who do not. Both groups of employers seem equally less likely to call back Romanian-Italians than Italian applicants. Thus, results do not lend support to *H.7*.

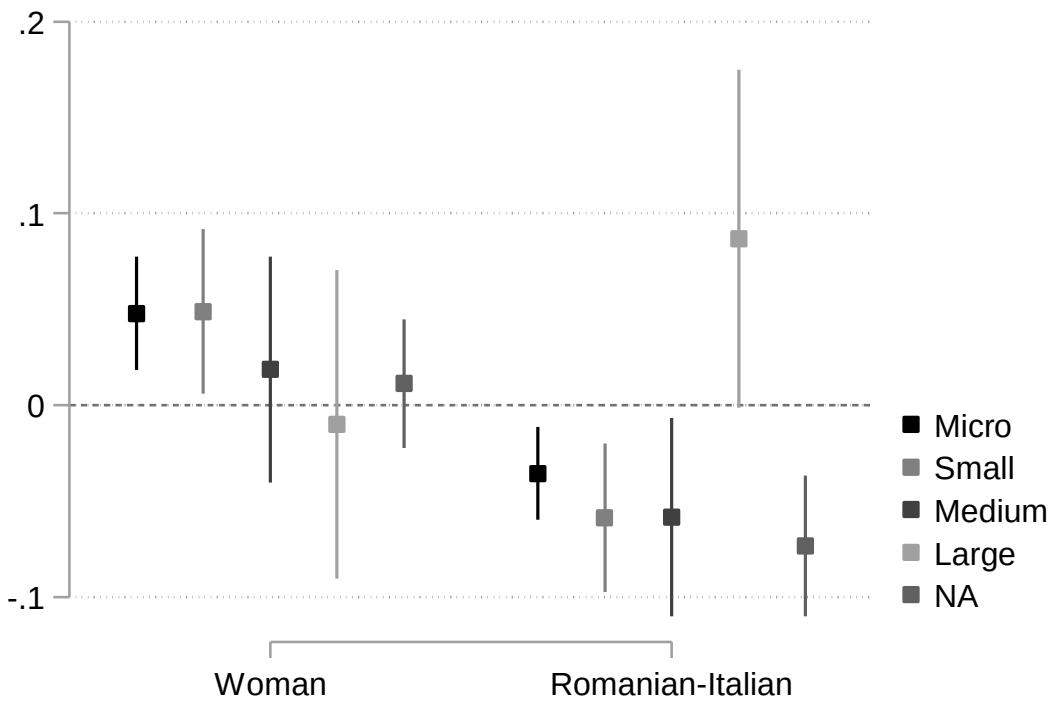
Next, the analysis tests the hypothesis that e*mployers emphasizing motivation in job descriptions are less likely than employers who do not mention these requirements to consider applications from women and those with an immigrant background than men and native workers* (*H.8*). Figure 6.3.2.4 provides average marginal effects of gender and immigrant background for employers listing motivation in the job ad and those who do not (Model 12). Estimates suggest that on average employers who mention motivation are less likely to call back Romanian-Italians than Italians compared to employers who do not list this requirement. Nonetheless, the difference between types of employers is not statistically significant. Both groups of employers are less likely to call back Romanian-Italians than Italians, which again may stem from a strong aversion to applicants with immigrant origins. Similar results emerge for gender and motivation as a job requirement. What differs compared to immigrant background is the sign of the relationship: employers prefer women to men, regardless of motivation in the job ad. While the estimate is larger when motivation is not mentioned, there is no statistically significant difference between groups of employers. Thus, the response pattern is in line with expectations, but the results do not lend support to *H.8*.

Figure 6.3.2-4 Average Marginal Effects: immigrant background and gender on callbacks, by employers (not) listing motivation



To further substantiate this discussion, the analysis then tests whether *employers using formal hiring procedures are as likely to consider men and women, as well as applicants regardless of their immigrant background (H.9)*. Results from Model (13) are presented in Figure 6.3.2.5. Results on gender lend support to the proposition that formalization reduces differential treatment *(H.9)*. The probability of a call back in favor of women goes down as the size of the firm increases till the point that medium and large firms call back women and men at similar rates. Similar conclusions can also be drawn when looking at estimates for immigrant background. Employers with micro (1-9 employees) to medium enterprises (20-49 employees) tend to discriminate against Romanian-Italian applicants. Large firms[23] instead, call back at similar rates Italians and Romanina-Italians[24]. Thus, these results lend support to the proposition that the formalization of hiring processes reduces discrimination *(H.9)*.

Figure 6.3.2-5 Average Marginal Effects: immigrant background and gender, by firm size



[23] When the analysis accounts for the probability of rejecting the null hypothesis given that it is true, the so-called familywise error rate (FWER) (Romano, Shaikh, and Wolf 2010), the mean difference in callbacks between Italians and Romanian Italians for large size firm is not significant, which mirros results on gender. This result supports the proposition that formalization curbs discrimination. See Annex H for a comparison of models p-values and those adjusted to account for the FWER. These are presented by chapter of the disseration.

[24] Interestingly, the further analysis presented in Annex C also shows that large firms prefer Romanian-Italians to Italians when they make a statement about equal opportunities in the job ad. Large firms that do not make this statement call back Romanian-Italians and Italian at the same rate. Also, firms with small to medium size call back at similar rates Italians and Romanian Italians when they make a statement on equal opportunities whereas they discriminate when they do not include it in the job ad.

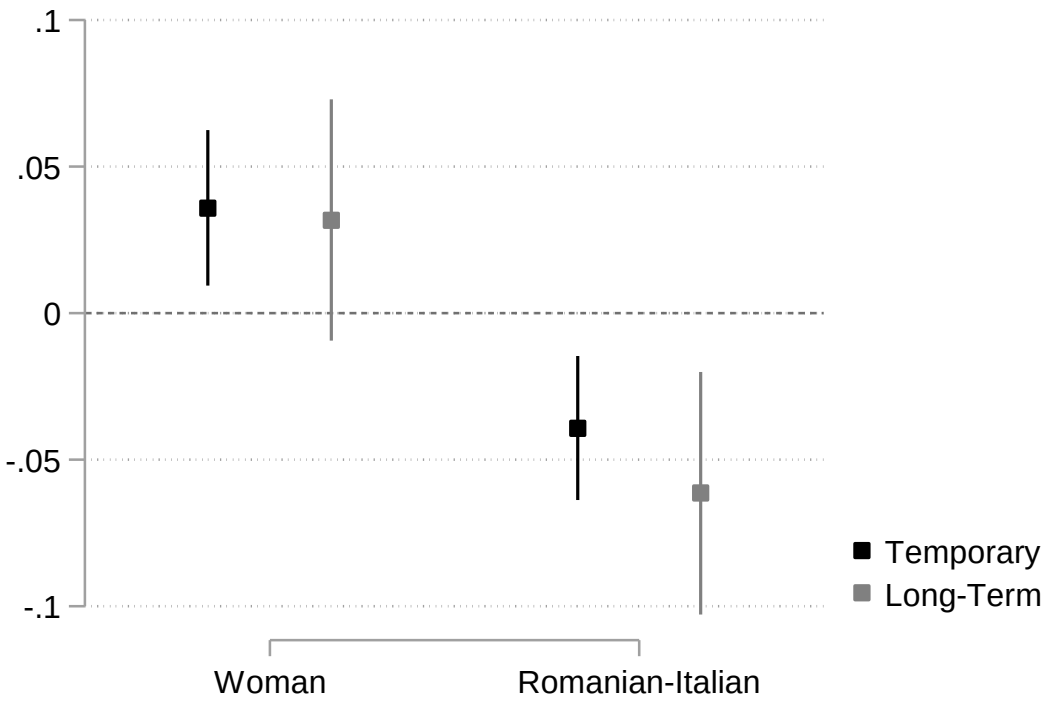
In sum, results from this section suggest that employers are moved by bias rather than lack of information. Particularly, findings suggest a strong preference, among the employers in this sample, for women especially when women and men apply for jobs where women are overrepresented. Contrarily, employers prefer Italians to Romanian-Italians, regardless of the job requirements they set on soft skills such as relational skills or motivation. Highlighting motivation also does not make employers less likely to contact women. Nonetheless, results on the formalization of hiring show that larger firms, tend to call back women and men at similar rates. This is also the case for immigrant background once employers' commitment to equal opportunities is factored in.

6.3.3 Does discrimination depend on what employers offer?

While the previous section focuses on whether discrimination is a matter of information or bias and whether it varies with job requirements, this section assesses whether discrimination also depends on job quality defined using job contracts and (mis)match of qualification. Starting with the former, the first test in this section concerns *H.10*, namely whether *employers offering short-term jobs call back at higher rates women and workers with an immigrant background than men and native workers, and vice versa if they offer long-term jobs.*

Using Model (15), two regressions are estimated: one for short-term contracts and another one for long-term contracts. Figure 6.3.3.1 provides average marginal effects for gender and immigrant background for these two models, which can help isolate any differences in how these two groups of employers respond. Looking at the immigrant background, both groups of employers, offering either a short- or long-term contract, are significantly less likely to call back Romanian-Italians than Italians. Employers who offer short-term contracts are instead significantly more likely to call back women than men, whereas the difference in callbacks between men and women is not statistically significant among employers offering long-term contracts. As such, estimates on immigrant background do not lend support to *H.10*, while those on gender provide just partial support.

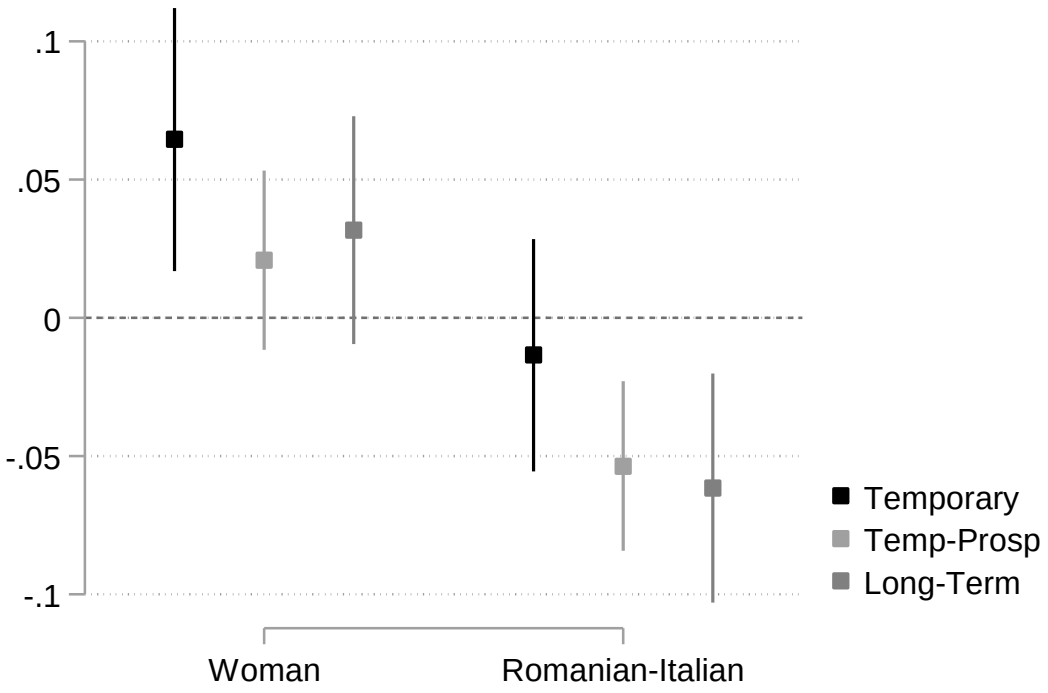
Figure 6.3.3-1 Average Marginal Effects: immigrant background and gender, by type of contract (a)



Further analysis of temporary contracts can be carried out to better understand these results. Particularly, a subset of employers offering temporary collaborations flagged in the job ad that the temporary job was a trial period, and a long-term offer was possible depending on performance. These jobs should offer better prospects than those from employers not mentioning future opportunities at all, or jobs offered for maternity leaves for example. Lumping together these genuinely temporary working opportunities with those that are meant to become long-term could help explain previous results.

Two additional models are estimated, along with the regression for employers offering long-term jobs: one for short-term jobs with no future employment prospects, and one for temporary jobs with prospects. Figure 6.3.3.2 provides average marginal effects for women and Romanian-Italians, compared to men and Italians, for employers offering short-term jobs, short-term jobs with prospects, and long-term jobs. The Figure shows that estimates for employers who offer short-term jobs with prospects are comparable to those for employers who offer long-term ones. In this regard, looking at gender, employers who offer truly temporary jobs are significantly more likely to call back women than men. Instead, those offering temporary jobs with prospects and long-term jobs are as likely to call back women and men.

Figure 6.3.3-2 Average Marginal Effects: immigrant background and gender, by type of contract (b)

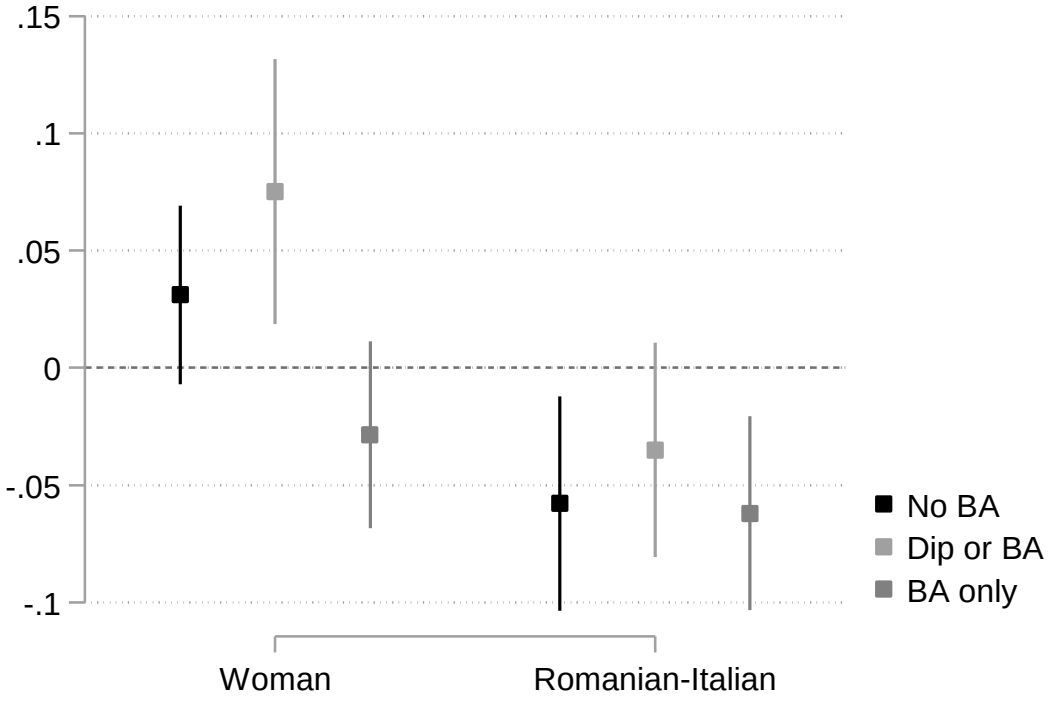


Turning to the immigrant background, employers who offer short-term jobs are as likely to call back Romanian-Italians and Italians. When employers offer a temporary contract with prospects or a long-term one, they are less likely to call back Romanian-Italians than Italians. This is quite interesting given that in the previous model, which did not divide temporary contracts based on employment prospects, employers offering temporary opportunities were significantly less likely to call back Romanian-Italians. Overall results provide mixed support for *H.10*. Employers prefer women to men for short-term collaborations, but women are as likely as men, rather than being less likely, to get a callback for more stable job opportunities. On the contrary, employers who offer more stable job opportunities prefer Italians to Romanian-Italians, in line with expectations under *H.10*. However, rather than being more likely, employers offering short-term jobs are as likely to call back Romanian-Italians and Italians.

The second hypothesis on job quality that this section aims to test concerns whether *employers are more likely to call back women and workers with an immigrant background compared to men and native workers when applicants' skills are slightly above those needed for the job. (H.11)*. Figure 6.3.3.3 provides average marginal effects from Model (16) on gender and immigrant background. Estimates come from three models estimated by qualifications required for the job, namely 1) High School Diploma or lower, 2) High School Diploma (minimum) or Bachelor, and 3) Bachelor's (minimum). Given that all applicants were assigned a BA, slight overqualification is proxied by 2) while substantial overqualification is proxied by 1). Starting with slight overqualification (Dip or BA in Figure 6.3.3.3), employers are more likely to call back women than men whereas there is no difference in the likelihood of a callback between Romanian-Italians and Italians. As such, results on gender lend support to *H.11* while those on immigrant background do not.

While results do not conform fully with empirical expectations, from a substantive standpoint, results resonate with those on job contracts. Employers prefer women over men for jobs of lower quality (truly temporary jobs and jobs for which applicants are slightly overqualified). Likewise, results on immigrant background further support the idea that employers consider them as much as Italian applicants for lower quality jobs (based on contract or qualifications alike). It is also interesting to note that results on jobs that require a BA as the minimum qualification, again, mirror those on long-term job contracts: employers call at the same rate men and women for these jobs while they are less likely to contact Romanian-Italians than Italian applicants. Thus, changing the definition of job quality does not change the conclusion

Figure 6.3.3-3 Average Marginal Effects: immigrant background and gender, by qualification requested in the job ad



from the analysis relying on contractual conditions. Figure 6.3.3.3 also provides the average marginal effects of gender and immigrant background for employers who require a High School Diploma or lower. Using these estimates, it is possible to understand how employers look at substantial overqualification and whether what they learn hinges on gender and immigrant background. Particularly, whether *employers are less, more, or as likely* to call back women and workers with an immigrant background compared to men and native workers when applicants' overqualification is substantially above those needed for the job.

Estimates on gender show that employers who require substantially lower qualifications than those held by fictitious applicants prefer on average women to men, but the difference is not statistically significant. Instead, these employers are significantly less likely to contact Romanian-Italians than Italians. Overall, results tell that substantial overqualification can be a liability. This seems to be more detrimental for Romanian-Italians than Italians. Nonetheless, overqualification negatively affects women if it is considered that employers are on average more likely to prefer them over men. In other words, employers generally call back women at higher rates. However, when there is a substantial mismatch between the credentials required and those held by the applicant, employers call back women and men at similar rates.

6.4 Labour market conditions and economic downturns

The job opportunities that have been targeted in this study span across the three Italian macro-regions, namely the North, the Center, and the South. The differences in labour market conditions across them can be exploited to test whether

H.12a Duration dependence and discrimination are higher in tight labour markets, and vice versa in those in a slack, as per screening models

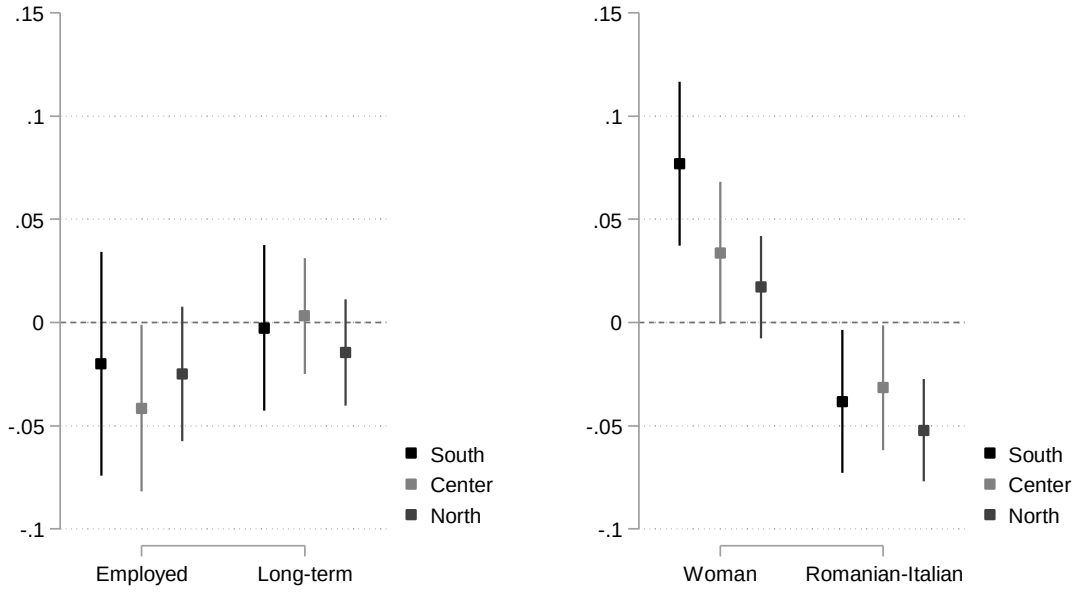
or

H.12b Duration dependence and discrimination are lower in tight labour markets, and vice versa in those in a slack, as per ranking models and status framework

In this regard, Figure 6.4.1.1 presents the average marginal effects of unemployment duration (left panel) and those of gender and immigrant background (right panel). Estimates are presented for each macro-region based on Model (17): a model was estimated for each of the areas. Focusing on unemployment duration first, Figure 6.4.1 does not point to significant regional differences in how employers judge candidates with different unemployment duration. Particularly, no statistically significant difference emerges between applicants in short- and long-term unemployment across regions. This finding resembles previous results on unemployment duration, which show that employers do not use unemployment duration in the screening phase (Section 6.2.1). Therefore, rather than providing support to *H.12a (screening*) or *H.12b (ranking*), results seem to suggest that unemployment duration is not relevant, regardless of the labour market conditions.

Nonetheless, one could argue that youth unemployment rates and long-term unemployment rates are lower in the North and the Center than in the South, but rates are generally quite high across Italy. A macro-region might be considered tighter than another, but overall, the Italian labour market can be considered "slack." As such, given that duration dependence does not emerge in the context of a slack, results would better align with screening models (*H.13a*). Let us recall that unemployment duration, within this model, should be seen as a signal of some unobservable individual properties. This signal is "meaningful" when there are few people in long-term unemployment (tight labour market). However, the signaling value diminishes as the number of people in this condition grows larger: the greater the pool of those in unemployment is, the more heterogeneous it becomes. As such, unemployment duration would no longer allow employers to sort applicants using time out of work in the context of slack.

Figure 6.4-1 Average Marginal Effects: unemployment duration, immigrant background, and gender, by macro-region



This interpretation also finds support in results on unemployment duration and urgency. While employers do not rely on unemployment duration to decide who to call back, employers are less likely to call back applicants in long-term unemployment when they have limited time to carry out the screening. As such, employers find unemployment duration meaningful and use it to sort resumes, under certain conditions. This finding rules out that unemployment duration is irrelevant in the Italian context, which in turn could have explained the lack of any differences in callbacks between candidates in short- vis-à-vis long-term unemployment.

Now turning, to discrimination, and first to gender, the right panel of Figure 6.4.1 shows that employers are on average more likely to call back women than men across regions. However, the callback gap shrinks from South to North, as well as differences are not statically significant in the North and the Center[25]. This means that gender discrimination is lower in tighter labour markets and vice versa in slack labour markets. Results would thus align with the ranking model and the status framework type of explanations (*H.13b*). In a strong labour market employers would grow more likely to call back women as there are fewer available men, and vice versa under weak labour market conditions.

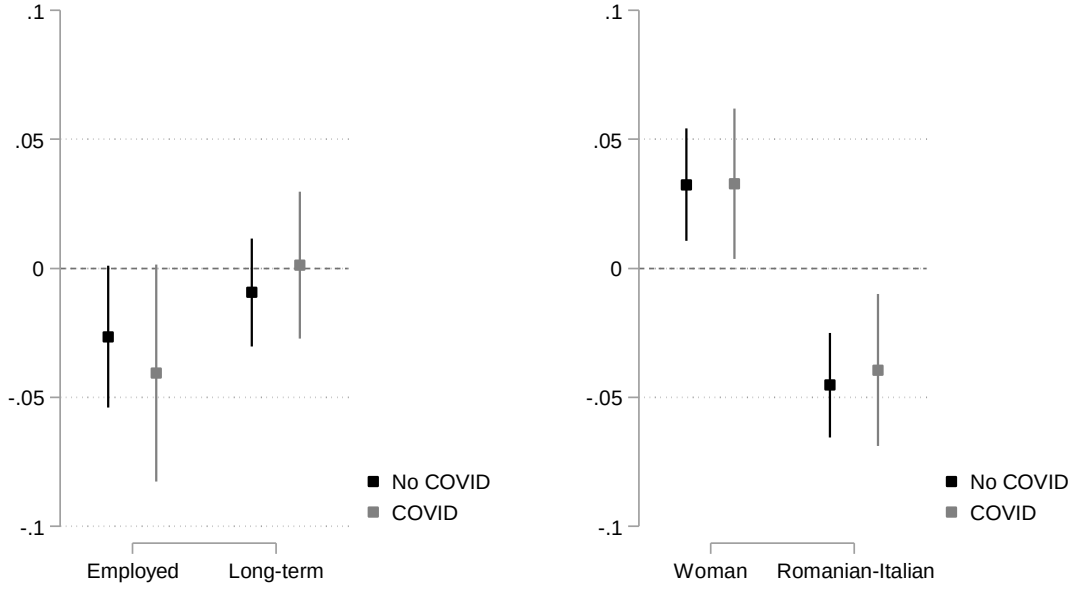
Interestingly, the further analysis presented in Annex D shows that job quality (overqualification) drives these regional differences: in regions with higher (lower) gender

[25] See Appendix H for a comparison of the p-values of the gender coeffiecient from the Model (17) with those adjusted for the familywise error rate (FWER) (Romano, Shaikh, and Wolf 2010).

inequalities in the labour market women receive more (fewer) callbacks than men. As such, results in Figure 6.4.1 mimic dynamics predicted under ranking models, but job quality might be the driver behind regional variation. Such a clear regional response pattern however does not emerge for immigrant background: employers across regions are less likely to call back Romanian-Italians than Italians. This suggests generalized discrimination rather than giving support to signaling (*H.12a*) or ranking models (*H.12b*). As such, discrimination based on the immigrant background does not depend on the conditions of labour markets.

Turning to economic downturns, during data collection, Italy and its labour market were overwhelmed by the COVID-19 outbreak. COVID-19 functioned as a negative shock, which makes it possible to test whether employers' assessment and differential callbacks are amenable to change as labour market conditions deteriorate. Particularly, *whether duration dependence/discrimination decreases, increases, or remains stable during economic downturns.* Results based on Model (18) for unemployment duration are shown in the left panel of Figure 6.4.2. Those on gender and immigrant background are on the right. Looking at the former, results show that discrimination remains stable across periods. Likewise, the likelihood of calling back applicants in short-term unemployment vis-à-vis those with long spells is not statistically different. These results support the conclusion of no between-period difference[26].

Figure 6.4-2 Average Marginal Effects: Unemployment duration, gender, and immigrant background, by pre- and post-COVID-19



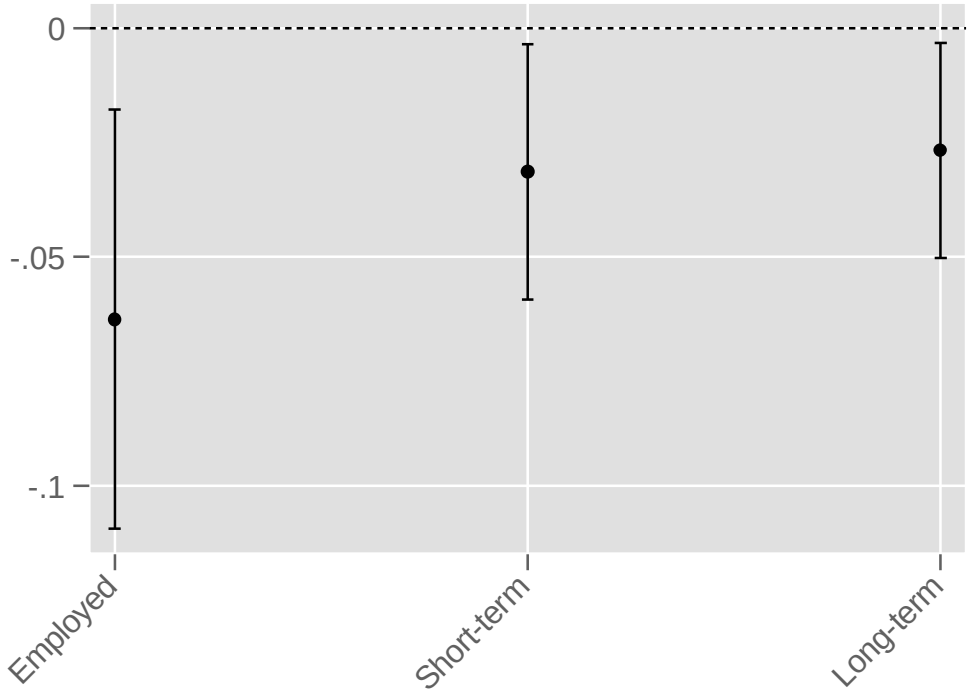
[26] Further analysis was carried out to inspect whether results on discrimination and duration dependence before and after COVID-19 differed across the three Italian macro-regions (Annex E). The test checks whether results could differ depending on the initial labour market ocnditions before the COVID-19 outbreak. Results lend further support to the conclusions drawn from Figure 6.4.2. There are no differences in callbacks based on gender, immigrant background and unemployment duration across the three macro-regions before and after COVID-19.

6.5 Assessing intersectionality

Having assessed how employers use and understand unemployment duration, gender, and immigrant origins, the last section crosses the three key variables of interest in this study. This part of the analysis focuses on intersectionality and how employers deal with it when deciding to call back applicants. Particularly, by crossing unemployment duration with gender and immigrant background it is possible to grasp whether unemployment spells bear the same effect on callback rates for all candidates (additive), or whether unemployment duration is more detrimental for some groups.

Figure 6.5.1 shows the marginal effects of gender over unemployment based on Model (19). The Figure reports differences in the probability of a callback between women and men (base category) when they are currently working, on short-term unemployment, or long-term unemployment. Marginal effects suggest that employers are less likely to call back men than women, at any given level of unemployment duration. The average difference between men and women shrinks when women are in unemployment. The response pattern thus indicates that employers prefer women to men even if unemployment, is either short or long. Nonetheless, this preference slightly fades as unemployment duration lengthens. It follows that employers look at both gender and unemployment duration and they infer from them something

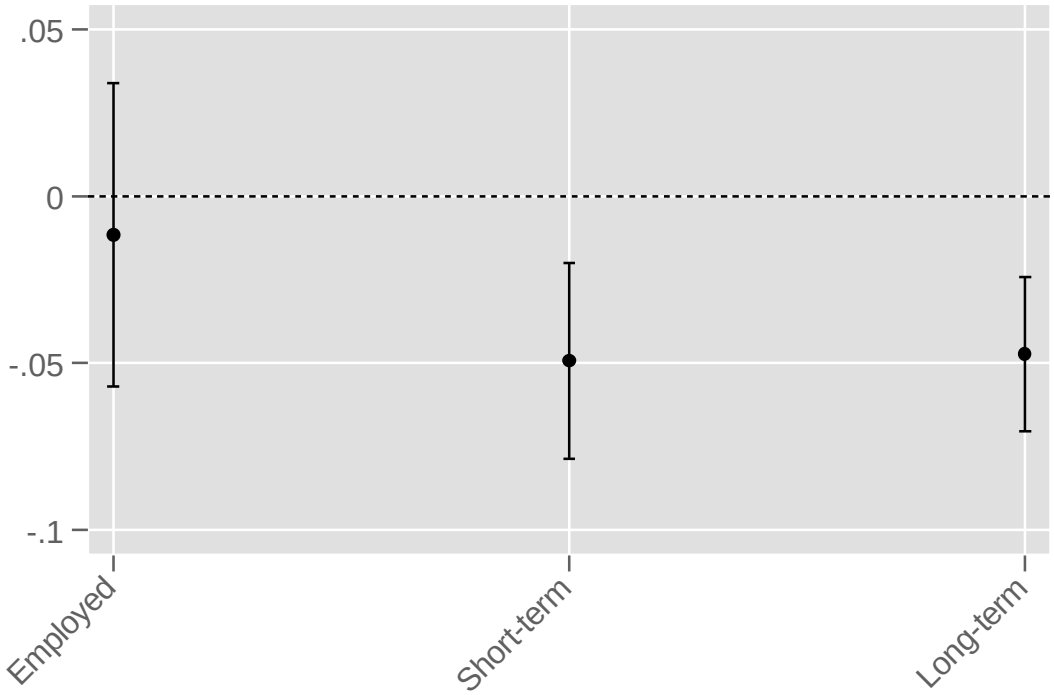
Figure 6.5-1 Average Marginal Effects: gender over unemployment duration



about applicants. Importantly, employers bring together what they learn from gender and unemployment duration in an additive manner. In this regard, estimates from Model (19), particularly the interaction term of gender and unemployment duration, which is not statistically significant (see regression tables, Annex G). In other words, unemployment duration is not more detrimental for either men or women and employers would assess those gender and time out of work independently when deciding who to call back.

Like gender, Figure, 6.5.2 shows the average marginal effects of immigrant background over unemployment duration based on Model (20). The panel reports the difference in the likelihood that employers call back for Romanian-Italians vis-à-vis Italian job seekers. Results suggest that employers are equally likely to call back a candidate who holds a job regardless of immigrant background. However, among applicants in unemployment, either with short or long spells, employers tend to call back Italians more frequently than Romanian-Italians. Thus, it seems that being in unemployment, rather than duration per se, matters to employers when comparing Romanian-Italians and Italians.

Figure 6.5-2 Average Marginal Effects: immigrant background over unemployment duration

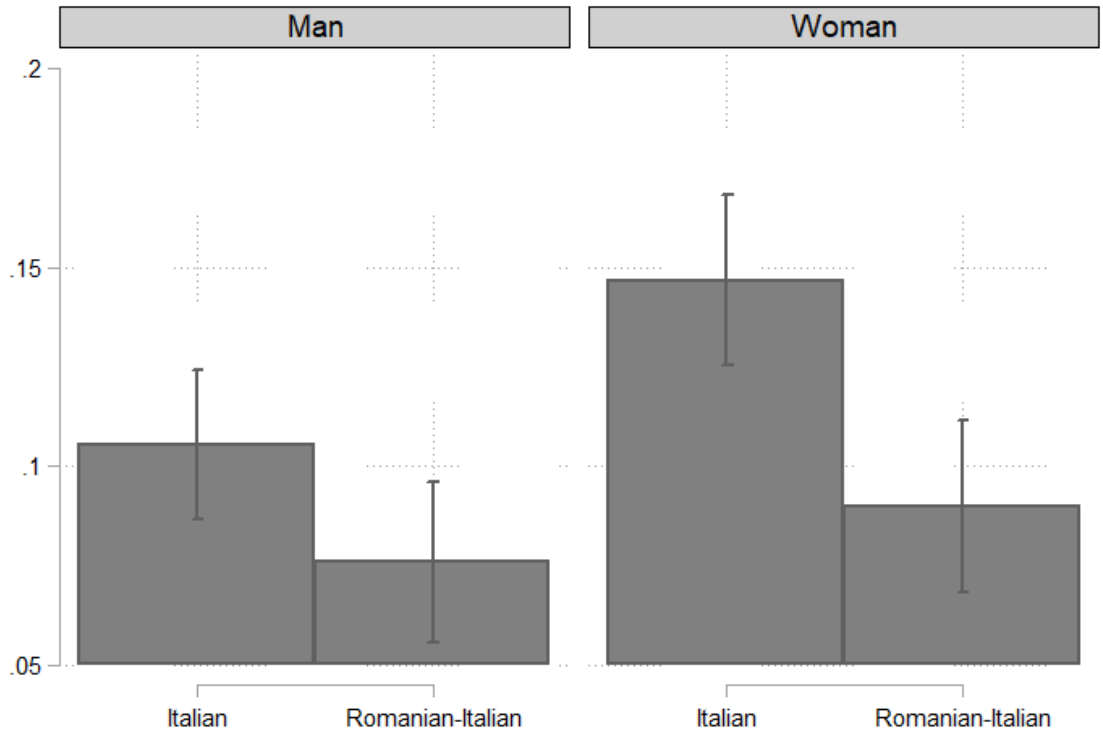


Also, looking at the regression coefficients from Model (20) (Annex G), particularly the interaction term of immigrant background and unemployment duration, tells that time out of work is not more detrimental, neither for Italians nor for Romanian-Italians. Like gender, employers would simply bring together in an additive manner any inferences about immigrant

background and time out of work. As such, it seems that how employers use unemployment duration does not hinge on considerations regarding applicants' immigrant background.

The next step of the analysis intersects gender and immigrant background using Model (21). The left panel of Figure 6.5.3 shows the predicted callback rates for Italians and Romanian-Italians among men whereas the right panel reports the predicted probabilities for Italian and Romanian-Italian women. Estimates for men indicate that employers call back Italians at slightly higher rates than Romanian-Italians ($p<0.05$), whereas the gap is larger among women when comparing applicants with a different immigrant background ($p<0.001$). Estimates from Model (21) show that the interaction term of gender and immigrant background is not significant, which indicates that the differences in callbacks between Italians and Romanian-Italians do not depend on gender. This means that what employers infer from gender and immigrant background is brought together additively.

Figure 6.5-3 Adjusted linear predictions: immigrant background by gender



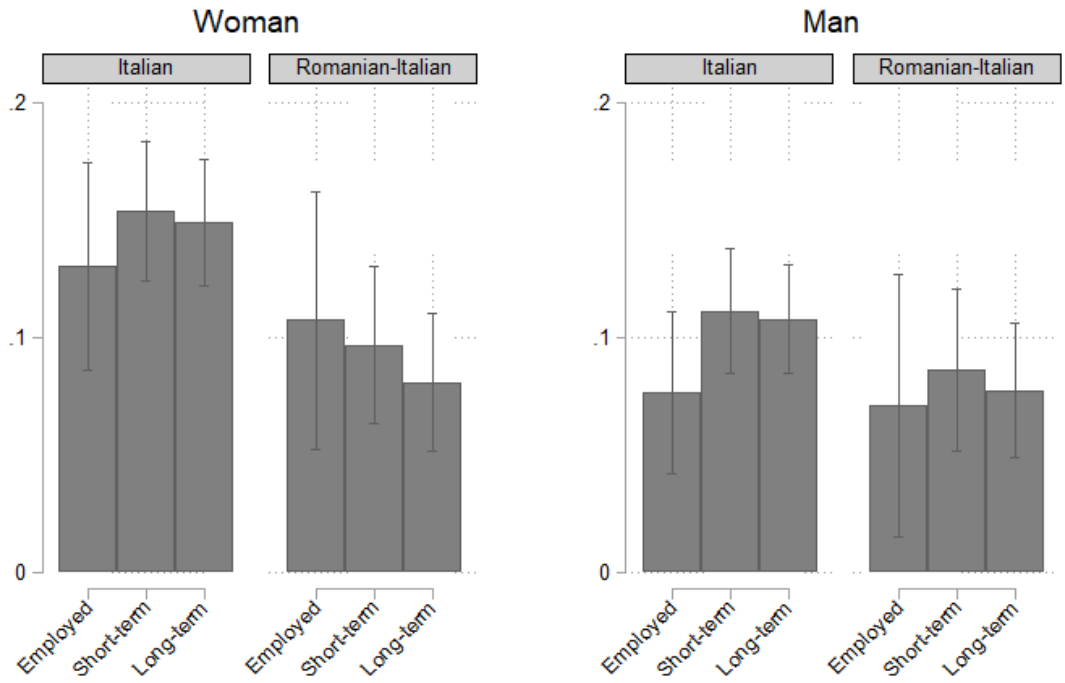
While there is no interaction between gender and immigrant background, the further analysis presented in Annex F, which intersects these two variables with the (gendered) language in the job ad, leads to the opposite conclusion. Employers prefer Italian men and women compared to, respectively Romanian-Italian men and women when employers use gender-neutral language. When employers describe the ideal candidate as a woman, employers call back at

similar rates for Italian men and Romanian-Italian men, but at lower rates, Romanian-Italian women compared to Italian women. Likewise, if the job ad uses a language that makes men the ideal candidates, employers make no difference between women with a different immigrant background, but they call back at higher rates Italian men than Romanian-Italian men. These results together suggest that what employers learn about gender depends on the immigrant background and the interaction is moderated by employers' gendered expectations about how the ideal candidate looks like.

Turning to the comparison of men and women with the same immigrant background in Figure 6.5.3, callback rates are higher for Italian women than those of Italian men ($p<0.001$), whereas there are no differences between men and women with Romanian origins. This result suggests that employers' preference for women identified in previous analyses is mainly driven by employers preferring Italian women to Italian men. Gender differences in callback rates are present only when employers assess Italian applicants whereas employers consider the same manner women and men with a Romanian background.

Building on these findings, Figure 6.5.4 presents predicted callback rates of immigrant background over unemployment duration and by gender based on Model (22). Two models were estimated: one for women and one for men both including an interaction term between immigrant background and unemployment duration. The left panel of Figure 6.5.4 shows the

Figure 6.5-4 Adjusted linear predictions: immigrant background, over unemployment duration by gender



callback rates among Romanian-Italian and Italian women at each level of unemployment duration. The right panel instead provides these estimates but for men. Overall, Figure 6.5.4 shows that duration dependence does not emerge for any group of applicants.

Nonetheless, there are some gender differences when comparing Romanian-Italians and Italians over unemployment duration. Among men, there are no differences in rates across immigrant background if the applicant is working or in short-term unemployment. Instead, callback rates are higher for Italian men than Romanian-Italian men in long-term unemployment ($p<0.10$). When comparing women, significant differences in callbacks emerge between Romanian-Italian women and Italian women when both are in short-term unemployment ($p<0.001$) or in long-term unemployment ($p<0.001$). Further, the overall pattern of callback rates differs among men and women. Figure 6.5.4 shows that callback rates on average get higher over unemployment duration for Italian women whereas they go down among Romanian-Italian women. Among men, the pattern of callback rates resembles the pattern of Italian women.

Thus, the average response pattern for Romanian-Italian women seems to indicate that unemployment duration is more detrimental for them compared to Italian women. However, the interaction term between immigrant background and unemployment duration estimated for women is not statistically significant. In other words, unemployment duration is not more detrimental for Romanian-Italian women. The same conclusion holds for men. From a substantive standpoint, results suggest that what employers infer from unemployment duration is independent of what they learn from immigrant background among both men and women. Therefore, employers aggregate in an additive manner what they infer from unemployment duration along with immigrant background for men and women.

Finally, the comparison of callback rates between Romanian-Italian men and women shows that there are no gender differences in the probability of a callback among applicants with an immigrant background. Instead, when looking at Italian women and men, employers are significantly more likely to call back Italian women than Italian men at any level of unemployment duration. Interestingly, the average difference in the likelihood of being contacted shrinks over the unemployment duration, from 6.3 percentage points to 2.3. Bearing in mind that interaction terms are not statistically significant, this result again indicates that what employers infer from unemployment duration does not depend on gender for both Romanian-Italian and Italians.

In sum, duration dependence does not emerge for any applicants, nor there is a differential impact of unemployment duration on callbacks depending on gender or immigrant background, nor on their intersection. Nonetheless, results on the "three-way interaction" still suggest that employers consider unemployment duration and learn something from it, particularly long-term unemployment when comparing Italian and Romanian-Italian men, Italian and Romanian-Italian women, as well as Italian men and women. In these cases, employers seem to 1) assess each piece of information, namely gender, immigrant background, and unemployment duration independently and 2) bring them together additively when deciding who to call back.

Unemployment duration is not more, nor less detrimental for any group. How employers use unemployment to screen applicants does not hinge on gender or immigrant background. Points 1 and 2, however, do not hold among Romanian-Italians. When interacting with gender, immigrant background, and unemployment duration, employers do not consider unemployment duration when sorting applications from Romanian-Italians. This is also consistent with previous findings on gender given that employers call back Romanian-Italian men and women at similar rates. As such, when comparing Romanian-Italian applicants, employers consider them all alike and discard additional information.

7 Bringing evidence together: what have we learned?

Chapter 7 aims to consolidate findings from the detailed analysis carried out as part of Chapter 6. In this regard, it first summarizes what this study can tell on duration dependence while contextualizing findings concerning existing literature and empirical evidence. Likewise, the second section looks at discrimination discussing results on the origin of discrimination in this study, as well as findings that emerged from the analysis of job requirements and quality. Finally, the third section concludes this project by discussing the relationship between discrimination and duration dependence in the context of this study. This section focuses on how employers in this study aggregate inferences based on gender, immigrant background, and unemployment duration and what can explain the pattern that these Italian employers follow.

7.1 Duration dependence and employers' decision-making

One of the overarching questions that this study tries to answer is about how employers use unemployment duration in the screening phase of the hiring process. In this regard, the thesis tested whether employers are more likely to consider applications from those in short-term unemployment than from candidates with a job or in long-term unemployment. Also, the thesis looked at whether the available time for screening resumes influence the callback gap between applicants in short- and long-term unemployment.

In this regard, the thesis does not find that employers call back at different rates applicants in short compared to those in long-term unemployment. Nonetheless, employers are more likely to call back applicants in short unemployment vis-a-vis those in long-term unemployment when employers face time constraints. This suggests that employers find unemployment duration meaningful and that they use it as a sorting criterion in line with the literature on the detrimental effect of unemployment on job prospects (Van Belle et al. 2017). Among Italian employers, this is the case when employers face time constraints only.

This finding on urgency is rather interesting. It is worth thinking that, like those in short-term unemployment, applicants in long-term unemployment should be readily available to start a job immediately as they do not have other commitments. Results suggest that employers are less likely to call back applicants who hold a job than those who are in short-term unemployment. This is also what Oberholzer-Gee (2008) finds in his correspondence study and Bills (1990) posits that employers see applicants currently working as less reliable or simply not able to start immediately because of their ongoing engagement with another firm.

While availability can be a concern for employers when assessing an applicant who is currently working, it should not be an issue for applicants with long-term unemployment. As they are not working, these applicants should be available to start immediately, which is what employers who face urgency need. However, results show that employers who need someone immediately make a difference between applicants in short- vis-à-vis long-term unemployment. Thus, differences in callbacks under urgency tell that employers learn something from unemployment duration, but what they learn differs for applicants in long-term unemployment and it cannot be about availability contrarily to applicants holding a job. In this regard, one could speculate that employers who look for someone immediately may need someone who can quickly pick up tasks and outstanding work. Employers may thus be afraid that applicants out of work for long might not be as quick to pick these up as those who recently

ended their last job. Also, employers may think that these applicants may lack the drive that is needed to quickly understand and perform the tasks that are required for the job.

In this regard, the thesis also investigates whether employers who set motivation as a job requirement are less likely to contact applicants in long-term unemployment than employers who do not emphasize motivation. Studies on unemployment and why it matters to employers underline that employers tend to see unemployment duration as a proxy of motivation (Bonoli 2014; Van Belle et al. 2017). However, when comparing callbacks for applicants in long-term unemployment between employers who set motivation as a job requirement, and those who do not, no difference emerges.

Nonetheless, when employers emphasize motivation, callbacks are lower for applicants in long-term unemployment who give information on this job requirement compared to those in long-term unemployment who do not include information on motivation in their resumes. As such, rather than improving individual chances of a callback, as suggested in Bonoli and Hinrichs (2010), providing more information on the motivation for those in long-term unemployment is more detrimental if motivation is in the job ad. Results indicate that additional information on motivation has the effect of priming long-term unemployment among employers who emphasize motivation in the job ad. When that happens, employers seem to stigmatize an applicant in long-term unemployment, which is in line with propositions from Goffman (1963) and Sherman and Karren (2012). No other candidate, either with a job or in short-term unemployment experiences negative returns from providing information on their motivation or volunteering when motivation is a job requirement. Also, when motivation is not in the job ad, employers are more likely to see information on individual motivation positively for candidates in long-term unemployment, or at worst they remain indifferent.

This finding, along with results on urgency, shows that duration dependence in this study does not emerge as clearly as in other correspondence studies carried out in the US (Kroft, Lange, and Notowidigdo 2013; Ghayad 2013) or in Sweden (Eriksson and Rooth 2014), where employers call back at lower rates applicants with long unemployment spells compared to similar workers with shorter ones. Likewise, results on unemployment duration do not align fully with findings from correspondence studies that do not find any differences based on unemployment duration (Farber et al. 2019; Nunley et al. 2017). In the Italian context, unemployment duration is not a key criterion to sort job applications, but it is still informative under certain conditions, namely available time for screening and the interplay of motivation as a job requirement and applicants providing evidence of it in resumes.

From a theoretical perspective, results thus suggest that Italian employers use unemployment duration as a categorical variable in line with screening models (Lockwood 1991; Manning 2000) rather than looking at unemployment duration as a continuous measure of individual productivity in line with ranking models (Blanchard and Diamond 1994). First, the probability of a callback does not diminish linearly over the unemployment duration. Employers instead compare groups of applicants with similar unemployment duration, which is also consistent with findings from other correspondence studies on duration dependence mentioned in the previous paragraph.

Also, screening models rather than ranking offer an employers' decision-making framework to explain how employers assess job applicants across macro-regions in Italy. While regional differences in (long-term) unemployment rates exist, the Italian labour market can be generally seen as slack. Italy is characterized by high youth unemployment rates (Adda and Triggari 2016), and it is common for young Italians to experience long unemployment spells (Pastore, Quintano, and Rocca 2021). In this context, the signaling value of unemployment duration weakens given that the pool of unemployed applicants is larger and more heterogeneous. As such, differences in callbacks between applicants in short- vis-à-vis those in long-term unemployment tend to fade, which is what the current study finds. COVID-19 has also no impact on how employers use unemployment duration, regardless of the pre-pandemic level of slack in macro-regional labour markets.

Overall, this thesis finds that Italian employers contribute little to duration dependence through their decision-making in the screening process. Nonetheless, the fact that employers still look at unemployment duration in the context of very high youth unemployment is striking. This research also highlights that in this context, individual constraints such as time available for the screening (Bandiera, Barankay, and Rasul 2011), rather than (changes in) local labour market conditions (Carlsson, Fumarco, and Rooth 2018), play a key role to disentangle how employers use unemployment duration when deciding who to call back. Further, what employers look for, particularly "soft skills" like motivation, does not directly affect the probability of a callback. However, emphasizing motivation still influences how employers look at the information that applicants in long-term unemployment provide to show they meet this job requirement. This is subtle. However, soft skills are increasingly important in the labour market (Kautz et al. 2014) and they are extremely hard to measure (Moss and Tilly 2001). As such, it may become harder, as well as more important, to understand how employers assess applicants based on their soft skills. This study suggests that some groups, like those in

long-term unemployment, might be impacted negatively because of perceived differences in reliability/quality of information shared to demonstrate they meet these soft job requirements.

7.2 Discrimination in the screening phase

Another goal of the current study was to assess whether employers discriminate based on gender and immigrant background in the screening phase of the hiring process. Importantly, to investigate whether they were moved by bias against some groups or whether it was a matter of lack of information. The analysis shows that the former is the origin of employers' differential treatment. In this regard, this study disentangles differences in callbacks based on gender and immigrant background for candidates of equivalent quality. Importantly, this study shows that these differences are substantive, and they do not stem from the way that fictitious profiles were designed.

Results on immigrant background align with those of second generations in other European labour markets (Zschirnt and Ruedin 2016; Baert 2018). Also, callbacks in this thesis, which focuses on Italians with a Romanian background (second generation), are comparable to callbacks for Romanians (first generation) in another correspondence study that Busetta, Campolo, and Panarello (2018) carried out in Italy. In other words, comparing callbacks between the current thesis and those in Busetta, Campolo, and Panarello (2018) shows that being born in Italy, having acquired education in the Italian education system, as well as three years of experience in Italian firms does not translate into better chances to get an interview. The cross-study comparison of outcomes for first and second generations provides suggestive evidence that access to labour market opportunities does not improve over time for those with an immigrant background.

As per gender, the study finds that Italian employers tend to favor women over men. Results in the current study are in line with findings from a multi-country correspondence study in Europe, which finds that employers are more likely to call back women than men (Birkelund et al. 2021). Like the current correspondence study in Italy, the authors leveraged a factorial approach whereby fictitious profiles in their design have several characteristics varying randomly in the resumes. The authors targeted, among others, admin-related jobs, and sales, which can be compared to those in this study, mainly in marketing and administration. Like in this thesis, the authors find that employers in Germany, the Netherlands, Spain, and the UK consistently prefer women to men, while they do not find any gender differential treatment in Norway.

Cross-country results in Birkelund et al. (2021) also highlight that women are always preferred to men in female-dominated occupations and that men are not preferred to women anywhere.

As such, these findings broadly align with those from the cross-country correspondence study. Employers are more likely to call women than men in occupations usually held by women or when the language used in the job to describe skills and tasks is women-oriented, as well as when employers use gender-neutral language. Callbacks are similar for women and men for jobs with less clear gender connotations, as well as when employers describe their ideal candidate as a man.

From a theoretical perspective, the results in this study provide partial support to propositions based on the expectations states theory (Correll and Ridgeway 2006). Nonetheless, it is worth highlighting that even if differences are not significant for gender-neutral jobs, these employers prefer on average women over men. This result may just imply that women are preferred to men in the service sector. In this regard, ILOSTAT data show that the percentage of female and male employment services[27], respectively, stood at 85% and 60% in 2019 in Italy. The gender employment gap in services suggests that women rather than men might be the "ideal candidate" making employers more likely to call back women than men even if occupations and language in the job ad are supposedly gender-neutral.

Interestingly, findings also highlight that employers' differential treatment does not stem from the stereotypical representation of applicants' motivation. Results on gender and motivation can be contextualized within the previous discussion on gender, sectors, and language, which posits that employers generally prefer women in the service sector. As such, emphasizing motivation would just be slightly detrimental for women compared to men, which is what the analysis disentangles: on average callbacks are lower for women vis-à-vis men but significantly different when employers mention motivation in the job ad.

Likewise, emphasizing communication and relational skills would just marginally decrease, if anything, the likelihood of a callback for Romanian-Italians compared to a situation where these aspects are not seen as a requirement. This study shows that employers are generally moved by bias against Romanian-Italians. As such, emphasizing aspects where these candidates are expected to be lacking would not affect substantially the chances of a callback. In this regard, results resonate with Oreopoulos (2011) who shows that during interviews

[27] "*Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The services sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social, and personal services, in accordance with divisions 6-9 (ISIC 2) or categories G-Q (ISIC 3) or categories G-U (ISIC 4)*", International Labour Organization, ILOSTAT database. Data retrieved on January 29, 2021. License: CC BY-4.0.

employers motivate differential treatment based on concerns about language. However, the quantitative analysis of callbacks received from these employers does not find any differences in callbacks between sectors that had communication as a core skill and those that did not. This finding suggests that, like in this thesis, differential treatment is pervasive, and it is not linked to real or perceived differences in skills. As such, no difference emerges when comparing employers who emphasize communication and relation skills and those who do not.

The lack of regional variation in discrimination across Italian macro-areas, as well as before and after COVID-19, also lends further support to this idea of pervasive bias and discrimination. From a theoretical standpoint, screening and ranking models of discrimination do not provide an adequate explanatory framework. Instead, results from this research resonate with the results of Vuolo, Uggen, and Lageson (2017) who did not identify any change in discrimination after the Great Recession. From a theoretical perspective, results align with the idea of *durable inequality* whereby categories like race and gender are ingrained in the functioning of organizations like firms generating a persistently skewed distribution of opportunities (Tilly 1998). This thesis shows that bias against Romanian-Italians strongly influences the outcome of employers' decision-making in the Italian context, which can explain why discrimination does not change in aftermath of the COVID-19 outbreak.

Gender discrimination dynamics do not change either after the COVID-19 pandemic. However, results show that discrimination is stronger in weaker labour markets (South), and vice versa (North). The findings lend support to the ranking logic rather than screening. Nonetheless, this result also suggests that gender discrimination (favoring women over men) is stronger in Italian macro-regions with higher levels of gender inequalities in the labour market. Amici and Stefani (2013) show that these inequalities are larger in the South compared to the Center and North of the Country. Similarly, Cirillo, Fana, and Guarascio (2017) describe that precariousness of women's employment is a feature characterizing women's participation in the Italian labour market, as well as its greater incidence in the South compared to the North.

In this regard, further analysis carried out to better understand regional variation in gender discrimination, presented in Annex F, indicates that aggregate regional differences in callbacks depend on overqualification. In the South, women are preferred to men for jobs with strong overqualification only; in the Center just for those with slight overqualification; in the North, employers are as likely to call back women and men regardless of the matching of qualifications between the job ad and what the applicants hold. From a theoretical perspective, while aggregate results on gender discrimination across regions may support the ranking logic

(Blanchard and Diamond 1994), it seems that considerations employers make about job quality drive these results. Also, if job quality is the leading factor driving regional gender dynamics, the status framework may provide a better framework to explain these differences in employers' responses. In this regard, women have a lower status than men labour markets with greater gender inequalities. Women, therefore, stand better chances than men for low-quality jobs whereas they are as likely as men for those opportunities that match their qualifications. Where the status of women is somewhat comparable to the status attributed to men, that is, in labour markets that are less gender unequal, callbacks are not stratified based on job quality and overall no differences between men and women emerge.

This proposition is also consistent with and improves the understanding of results on gender discrimination and type of contracts, which is another feature of job quality. Results show that employers prefer women over men when applying for truly temporary jobs only. These findings resonate with the macro-trend of women increasing labour market participation and concentration in more precarious jobs (Kalleberg 2000; 2009). The picture is grimmer for Romanian-Italians given that employers would call them back as much as Italians for low-quality jobs (truly temporary and those with slight overqualification). These findings are comparable to those of Zwysen, Di Stasio, and Heath (2021) who show that ethnic minorities who are born and get their education in the UK stand lower chances to find good employment opportunities than their white British counterparts.

Overall, results broadly resonate with theories of labour market segmentation (Doeringer and Piore 1985), which provide the theoretical foundations for the development of the empirical expectations on discrimination and job quality in this thesis. The findings in this thesis also suggest that employers' decision-making and their ingrained bias can push young Italian women and those with Romanian origins into a vicious circle of low-quality jobs. In this regard, Brunetti, Cirillo, and Ferri (2020) show that working in a job that does not match individual qualifications leads to lower wages among Italian graduates. However, the analysis in this thesis also tells that formalization of the hiring process wipes away bias based on gender and immigrant background, which is also in line with findings in Moss and Tilly (2001). As such, formalization might be one tool to keep bias at bay in hiring and help improve the quality of jobs that women and Romanian-Italians can get access to.

In this regard, further analysis tells that mentioning equal opportunities has an equalizing effect across firms of different sizes, but among larger ones, discrimination flips as employers prefer Romanian-Italians to Italians. In this regard, another correspondence study in the US finds that

employers making statements about diversity in the job ad were less likely, than any other employer, to call back minority candidates (Kang et al. 2016). Contrarily, Italian employers seem to walk the talk when they make public commitments to equal opportunities, especially when pairing formalization and making public commitments to equal opportunities among larger firms.

7.3 The relationship between duration dependence and discrimination

Having assessed duration dependence and discrimination independently, the thesis has assessed in the last part the relationship between discrimination and duration dependence. Particularly, by looking at how employers deal with intersectionality when deciding who to call back for a job interview.

In this regard, results highlight that employers consider unemployment duration, along with gender and immigrant background, when deciding who to call back. However, what employers infer from unemployment duration is not influenced by considerations employers make on gender and immigrant background. The fact that, for example, an applicant is a man, with Romanian-Italian origins and in long-term unemployment, all contributes to employers' decision-making. Importantly, employers aggregate these pieces of information additively. In a nutshell, results suggest that there is no duration dependence and when employers consider time out of work this is not more detrimental for any applicants.

Employers do not tend to make sense of applicants' intermittent employment histories using characteristics like gender and immigrant background, which is what Pedulla (2020) finds through a correspondence study and interviews with employers in the US. The author observes that employers' stereotypes about gender and race help them extract meaning from the complex "jungle" of applicants' employment histories that employers perceive as low-quality or non-standard. Results in this thesis instead resonate with Birkelund, Heggebø, and Rogstad (2017) who show that Swedish employers assess unemployment duration negatively in the screening phase of the hiring process, for both majority and minority applicants alike. These employers brought together, like in the current study, information on ethnicity and unemployment duration in an additive manner. As such, the current study highlights that discrimination does not shape whether and how employers use unemployment duration.

However, there are some caveats to the conclusion about employers using the additive logic when assessing information. The current thesis finds that employers do not consider gender and unemployment duration at all when comparing women and men with a Romanian background. This behavior, rather than conforming with an additive logic, is more consistent with the expectations states theory (Correll and Ridgeway 2006). Within this framework, when information and what is inferred from it is congruent with the status granted to a person, the additional information is discarded and not looked at. This is what employers do with gender when assessing Romanian-Italians. As such, no clear status hierarchy between men and women

emerges among those with an immigrant background. Also, employers do not tend to stigmatize more Romanian-Italian men or women, which is consistent with conclusions on gender from a meta-analysis on ethnic discrimination (Zschirnt and Ruedin 2016). The results on Romanian-Italians also resonate with the findings of Bartoš et al. (2016) who show that employers pay less attention and spend less time on applications filed by candidates reporting traits that employers associate implicitly with negative connotations.

Instead, when employers assess the majority of applicants against whom they do not hold any bias or stereotype, like Italians, employers look at gender and infer information from it (Hall, Galinsky, and Phillips 2015). This suggests that what information employers look at depends on the comparison they have to make. For example, when employers have to make "more complex" comparisons, they consider gender and unemployment duration. However, there is a caveat to this proposition too. When making comparisons between applicants with different immigrant backgrounds, results indicate that the generalized employers' preference for women over men (Section 6.3) is driven by employers' bias against Romanian-Italians, and employers' gender beliefs moderate this relationship.

In this regard, results broadly resonate with Midtbøen (2016) and Di Stasio and Larsen (2020) who show that gender and ethnic discrimination hinge on types of occupation, particularly whether women or men are overrepresented. The former shows that Norwegian employers prefer ethnic minority men to women in gender-neutral occupations, and vice versa for those usually held by women. The latter instead reports that British employers prefer ethnic majority women to ethnic minority women for occupations usually held by women, but no employers make a difference between men. In the current study, employers first sort applicants based on immigrant background. Then, depending on their gendered expectations of the ideal candidate, being either a man or a woman, employers prefer, Italian men and women, to respectively Romanian men and women. This aggregation pattern indicates that employers subordinate gender beliefs and expectations to those of immigrant background.

The findings align with Tajfel (1978) who posits that the meaning of a social category depends on beliefs associated with other intersecting categories. Italian employers use immigrant background as a sorting device, which they employ to decide who to call back and what kind of information to look at. Therefore, from a substantive standpoint, employers' bias against Romanian-Italians in the screening phase of the hiring process is and will be a factor hampering the integration of second generations in the Italian labour market.

8 Conclusions

The COVID-19 pandemic and its consequences have thrown a large share of the labour force into unemployment. Research points to the deterioration of employment prospects as unemployment duration lengthens (duration dependence), as well as to differential outcomes by gender and immigrant background/ethnicity (discrimination). So far, the literature on duration dependence and discrimination has rarely assessed their relationship. Studies have focused on gender or ethnicity, rather than intersecting them, along with employment histories. However, studying how men and women with and without an immigrant background fare in the aftermath of COVID-19 can help better understand who gets ahead and who remains behind during recovery. Like in the Great Recession, it is also key to disentangle whether the experience of unemployment will bring about scars on individual employment histories and if these will affect just some social groups.

By studying employers' decision-making in hiring processes, this thesis seeks to answer two overarching questions. The first one is why duration dependence and discrimination emerge. The second one is what is the relationship between duration dependence and discrimination. To address these questions, the current project relies on a correspondence study. In this research design, employers are contacted using fictitious resumes to elicit their answers. The researcher creates resumes of equivalent quality but varying in respect to key variables of interest: for the current research being gender, immigrant background, and unemployment duration. To this end, a computer programme was coded to ensure the randomization of these characteristics, which makes it possible to isolate the impact of each factor on employers' decision-making, as well as their interaction.

Using this computer routine, 4,079 fictitious resumes were sent to Italian employers in the service sector through online job portals. Data collection covered 11 major urban cities in three Italian macro-regions. Italy was selected as a case study because it is characterized by high unemployment rates, especially among youth. Italy also offers sharp within-country variations in the functioning of the economy, gender inequalities, as well as distribution of residents with foreign origins, particularly those with a Romanian background.

Results show that duration dependence emerges when employers are time constrained only, whereas employers' discrimination stems from bias before and after the COVID-19 outbreak. Employers also care about long unemployment spells and see them negatively when they require motivation and assess information that applicants provide to prove it. Discrimination

instead hinges on the length and stability of employment contracts and the quality of matching between qualifications that employers require and those held by applicants. Callbacks for Romanian-Italians show that discrimination against them is pervasive with no regional variation. Gender discrimination (against men) is pervasive across the service sector, but it gets stronger (weaker) in places where women experience higher (lower) levels of gender inequalities in the labour market.

Importantly, when employers intersect gender, immigrant background, and unemployment duration time out of work is not more detrimental for any applicants. However, the response pattern suggests that employers' gender beliefs are intertwined with those about immigrant background. Particularly, the latter is the primary frame that employers use to assess a candidate. In this regard, results tell that employers attribute a lower status to Romanian-Italians than Italians, which then influences whether they use or discard other pieces of information, such as gender and unemployment duration.

Overall, the findings match the picture of the Italian labour market being an institution and social space that is not very inclusive of women and those with an immigrant background (OECD 2018). Results on discrimination suggest that employers bear some responsibility for the making and reproduction of labour market inequalities. Employers treat differently applicants with an equivalent productivity potential. In this study, working experience and qualifications are equivalent for all applicants, as well as results on discrimination do not stem from the way that resumes were designed. Nonetheless, the stereotypes employers hold, and the resulting bias based on gender and immigrant background do not influence the use of unemployment duration in the screening phase. Employers seem to consider that piece of information in isolation and seldomly such that no differential negative effects on callbacks emerge. However, the fact that employers disregard applications from those in long-term unemployment even if in a rush tells that employers have still reservations about them.

Like any other correspondence study, the current one can detect differential treatment in the screening phase rather than in hiring decisions. This could be an issue given that Cahuc et al. (2019) suggest that levels of discrimination at the screening phase could be a poor predictor of hiring discrimination. In this regard, Allasino, Venturini, and Zincone (2004) also show that discrimination among private-sector employers decreases as candidates progress through the various stages of the hiring process. As employers get to know applicants, their stereotypes and bias might go down. However, one could argue that even if discrimination at screening may not predict well discrimination at hiring, the former remains relevant.

Even in the absence of duration of dependence stemming from employers' decision-making, as shown in this study, applicants progressively reduce the time they spend on job search as unemployment duration lengthens (Krueger and Mueller 2008; Mandrone et al. 2016). As time passes by, job seekers' confidence in their employability may decline (Mühlböck, Steiber, and Kittel 2022). Importantly, these job seekers will likely stop searching and will drop out of the labour force (Krueger et al. 2011). Thus, even if a research design, like in this thesis, focuses on discrimination at the screening stage, that study still captures relevant labour market outcomes.

More rejections and non-response to job applications will influence time spent on job search and, eventually, individual participation in the labour force unless interventions such as information sharing and reflection on own approaches to job search are implemented (Mühlböck et al. 2022). Similarly, interventions that may hamper discouragement among job seekers can entail the broadening of relevant job opportunities that those in unemployment would consider applying for (Belot, Kircher, and Muller 2019). As such, studying the screening stage of the hiring process and job search can be extremely relevant in the Italian context where youth labour force participation has been falling steadily as shown in Section 3.2.

Another limitation of this study is that it focuses on the service sector only. This sector is the focus of a large share of correspondence studies (Neumark 2018). It allows researchers to easily standardize applications and reach a large N, which is critical to isolate differential treatment. A more diverse pool of occupations, beyond the service sector, could help strengthen the external validity of the findings, especially on gender discrimination. This study shows the importance of considering the type of tasks to be performed to isolate and understand discrimination, in line with the expectations states theory (Correll and Ridgeway 2006).

Similarly, it would be interesting to test whether discrimination against those with an immigrant background varies between jobs that require different types of qualifications (i.e. natural sciences vis-à-vis social sciences). This comparison would provide another strategy to test whether discrimination is lower for jobs that require less relational skills (Oreopoulos 2011). In the current study, this was tested using the variation between job ads, but the test concerned the service sector only. Also, this study focused on Romanian-Italians only to inform discussions on their integration into the labour market. As such, this study cannot directly assess whether employers make differences between the first and second generations. Importantly, it cannot tell whether the latter experience improved labour market outcomes over time, in line with Alba (2005). Similarly, it cannot say whether second generations keep

experiencing labour market outcomes that are comparable to those of first generations and overall worse than natives, in line with (Portes and Zhou 1993). The current study can provide suggestive evidence only by comparing the results on second generations (Romanian-Italians) with those of first-generation (Romanians) in Busetta, Campolo, and Panarello (2018).

Finally, data have been collected at the very early stages of the COVID-19 pandemic for about four months. As such, these data can certainly inform discussions on the short-term effects of the pandemic on labour market outcomes. However, higher (lower) discrimination, for example, may emerge at later stages of this crisis. While the study has no data to test this proposition, results indicate that discrimination based on gender and immigrant background is quite pervasive. This suggests that it would be difficult to expect sharp changes in how employers assess immigrant background and gender at later stages of the crisis. With regards to unemployment duration, the average response pattern hinted toward this direction, but further research would be needed to substantiate this claim.

Bearing these limitations in mind, the results of this study can still contribute evidence to several strands of the literature on duration dependence and discrimination. First, this study assesses duration dependence in the context of high generalized unemployment. Duration dependence in these contexts has been studied mainly with observational studies (Lupi and Ordine 2002; Contini and Grand 2014; Bentolila and Jansen 2016). Also, the experimental literature on duration dependence has focused on high-performing economies like the US and northern European countries (Ghayad and Dickens 2012; Eriksson and Rooth 2014; Nunley et al. 2017; Farber et al. 2019). This literature exploited within-country variations in demand to assess differences in callbacks over unemployment duration under tight or slack labour markets (Kroft, Lange, and Notowidigdo 2013). In this regard, the current study shows that considering both different geographical locations (Pedulla 2018a) and the individual constraints that employers face (Bandiera, Barankay, and Rasul 2011) can help explain variation in labour market outcomes and when unemployment duration is salient.

Second, this thesis contributes to the experimental literature on gender discrimination by considering the influence of gendered occupations, in line with Azmat and Petrongolo (2014) and (Birkelund et al. 2021), along with employers' gender beliefs on the ideal candidate (Tilcsik 2011; Rho 2016; Sarsons et al. 2021). Similarly, this study provides evidence of discrimination based on an immigrant background in a context where second generations are growing in numbers (Colucci 2019) and with available evidence mainly from observational studies (Ballarino and Panichella 2015). Importantly, the current study expands the

experimental literature on intersectionality and hiring processes (Pedulla 2020). While theoretical propositions on the intersection of gender and ethnicity have been tested in the European context (Valentina Di Stasio and Larsen 2020), the current study also provides evidence on how employers assess individual employment histories when dealing with intersectionality. By doing that, the study helps fill a research gap on how the aggregation of different social categories, and how these are perceived, fuels labour market inequalities (Pedulla 2018a).

Third, the results of the current study on employers' decision-making and discrimination among young graduates can also help understand the heterogeneity of outcomes of school-to-work transitions in Italy (Pastore, Quintano, and Rocca 2021). The thesis expands on existing findings on the relationship between overqualification and labour market outcomes (Verhaest et al. 2018). In this regard, the thesis provides evidence of the role that employers and their decision-making play in skills mismatch (Di Pietro and Urwin 2006; Modestino, Shoag, and Ballance 2015). Importantly, it expands this research strand by looking at the differential impact of skills mismatch on callbacks based on gender and immigrant background. More broadly, the thesis helps understand the role of job quality in the reproduction of discrimination highlighting contributing factors to the persistence of labour market segmentation (Doeringer and Piore 1985).

From a methodological standpoint, this project shows that correspondence studies can play an important role in detecting discrimination (Gaddis 2018), but also in understanding the motives behind the discrimination they detect (Pedulla 2018a). Through a factorial design, researchers can learn much more about employers' decision-making than just quantifying the extent of their discrimination (Valentina Di Stasio and Lancee 2020). While such a finding is of great value to prompt action, it does not help understand what can be done about discrimination that is detected. In this regard, the use of information in resumes, coupled with data employers provide in job ads, is another interesting strategy that correspondence can leverage. For example, based on the analysis of contractual conditions offered and qualifications required, the current study shows when discrimination is more likely to emerge. This approach enables the study to identify key areas of concern and actions for policymaking.

Similarly, a factorial design and the use of data from job descriptions have been useful to study how employers utilize information on soft skills, such as motivation. Correspondence studies can help expand this strand of literature given that soft skills are growing in importance (Kautz et al. 2014) and might be particularly detrimental for some applicants, as shown in this study

(Moss and Tilly 2001). Finally, the use of a factorial design, which randomizes several variables within the resume, also allows us to rule out that research findings may be the result of design choices rather than real discrimination (Heckman 1998). In this regard, the current study provides additional evidence to this strand of literature on both genders (Baert 2015) and ethnic minorities (Carlsson, Fumarco, and Rooth 2014; Neumark 2018). Furthermore, a factorial design, which includes individual skills, can test formally two theories of discrimination, namely statistical discrimination and expectation states (Correll and Benard 2006) using the procedure developed by Neumark (2012). As shown in this research, the expectations states theory can help explain findings from correspondence studies, such as those on labour market segregation based on gender, which Neumark (2018) suggests statistical discrimination can hardly explain.

To conclude, discrimination could be detected because employers advertised these employment opportunities. However, most jobs that are available in the Italian labour market remain a matter of personal networks and contacts (Mandrone et al. 2016). The use of networks tends to enlarge inequalities in the allocation of employment opportunities favoring those with more numerous and better connections (Calvó-Armengol 2004; Calvó-Armengol and Jackson 2004). Formalization of the hiring process instead reduces discrimination, as this study shows. Likewise, employers adhere to equal opportunity statements when they make them public. While the study cannot tell whether employers comply because of visibility (Gërxhani and Koster 2015), rather than out of a real commitment to the cause of equality, employers seem to stick to it. As such, incentivizing employers to make job openings public certainly represents an area of action for policymakers, which could be of great value for both job seekers and employers.

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Annexes

Annex A: Resume Template

This is the basic structure/scheme of the resume template, before formatting, that has been sent to employers. The fields in the empty template that are highlighted below in black bold letters are those that were assigned randomly following the routine of the computer programme.

NAME SURNAME

Address**: via xxxx, city**, Italy

Email: xxxx.xxx@xxx.com

Phone: +39 **xxxxxxxx**

Date of Birth: **xx**/**xx**/198**x**

Nationality: Italiana **Romena**

Elevator Pitch (Motivation)

.

EDUCATION

mm/yy-mm/yy Laurea Triennale in Economics (average mark), **Institute-city**, Italy

mm/yy-mm/yy Maturità (average mark), Ragioneria, **Institute-city**, Italy

.

TRAINING

Professional development course

.

WORKING EXPERIENCE (either one or two jobs. First/oldest entry: internship or 6 months unemployment)

mm-yy **JOB A, enterprise, city, Italy**

- **Tasks:**
- **Tasks:**

mm-yy **JOB B, enterprise, city, Italy**

- **Tasks:**
- **Tasks:**

mm-yy **JOB C, enterprise, city, Italy**

- **Tasks:**
- **Tasks:**

.

LANGUAGE

English certificate

IT SKILLS AND COMPETENCIES

Office

Job-specific software and knowledge

VOLUNTEERING

Volunteering experience

OTHER INFORMATION

Owning a car (Automunit**o**/**a)** – Driving license

PRIVACY STATEMENT

Autorizzo il trattamento dei miei dati personali, ai sensi D.lgs. 196 del 30 giugno 2003

****

As explained in Section 4.3, four formatting schemes could be randomly assigned to the fictitious profile, which aimed to mitigate the risks that employers could realize the commonalities of the four resumes they received. Formatting included font type, and positioning of the name, among others. The fictitious resume below, which has been translated from Italian to English, provides an example of a resume that was shared with employers.

Erica Bianchi

via Ippodromo 5, Milan
E-mail: erica_bianchi@yahoo.com
Tel: 351 511 7991
Place of birth: Bologna
Date of birth: 28 November 1991
Citizenship: Italian

Availability

Flexibility in working hours with a willingness to work shifts and work overtime. Available for transfers and travel.

Education

January 2014 Bachelor's Degree in Economics and Commerce, University of Bologna
June 2010 Diploma in Accounting, Crescenzi-Pacinotti Technical Economic Institute, Bologna

Training Courses

Currently, A2 German Course, Goethe Institut

Work experiences

Mar 16 - Apr 18 Accounting and administration clerk, BDO Italia, Milan

- Drafting of audit documents and management of the agenda of appointments with customers
- Accounting analyzes for control of long-term customers
- Organization of documents and contracts to be signed between the customer and company
- Invoicing and drafting of accounting documents
- Management of records of issued and received invoices
- Labor cost analysis for budget preparation

Jan 15 - Dec 15 Accounting and administration clerk, GUT Edizioni SpA, Milan

- Registration of accounting prime entries
- Control of compliance with regulatory requirements
- Payment registration, passive, and active billing
- VAT Settlement
- Payment and asset management with F24 form
- Loan management, relations with banks, and relations with auditors
- Preparation of the budget
- Management of orders and relations with suppliers of the accounting office

May 14 - Oct 14 Internship in administration and accounting - Youth Guarantee, FrieslandCampina, Milan

- Management of administrative deadlines and archives
- Management of relationships with customers, suppliers, consultants, and accountants

Communication and Organization

Excellent communication skills developed in contact with clients and external companies
I manage my work independently and I can work with colleagues and supervisors
Able to develop and propose solutions in stressful moments

Languages

Advanced English Level - C1 (EF SET Plus Certification)

Technical and IT skills

Office Package
Management software: SAP, Team System, and Zucchetti
Tax return forms knowledge (PF, SP, and SC)

Volunteering

I have been volunteering in the ranks of the Red Cross since September 2016. I have helped the local Red Cross in the preparation of events and promotional materials.

Other Information

Car owner - Driving license B
I authorize the processing of my data according to art. 13 of Legislative Decree 196/2003 and the art. 13 GDPR 679/16

Annex B: Structure of the employment history of fictitious profiles

1 Job & Internship (age-adjusted to ensure the same amount of working experience)															
	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)
Unemp	-	-	0	-	-	2	-	-	6	-	-	14	-	-	22
Most recent Job	Jan. 17	-	30	Nov. 16	Apr. 19	30	Jul. 16	Dec. 18	30	Nov. 15	Apr. 18	30	March. 15	Aug. 17	30
Unemp.	-	-	4	-	-	4	-	-	4	-	-	4	-	-	4
Internship	March. 16	Aug. 16	6	Jan. 16	June. 16	6	Sept. 15	Feb. 16	6	Jan. 15	June. 15	6	May. 14	Oct. 14	6
Unemp	-	-	6	-	-	6	-	-	6	-	-	6	-	-	6
Unemp	-	-	4	-	-	4	-	-	4	-	-	4	-	-	4
End date BA	-	Oct. 15	0	-	Aug. 15	0	-	Apr. 15	0	-	Aug. 14	0	-	Jan. 14	0
Total experience			36			36			36			36			36
Total unemp without internship			14			16			20			28			36
Total unemp with internship			8			10			14			22			30

2 Jobs & Internship (age-adjusted to ensure the same amount of working experience)															
	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)	Start date	End date	months (#)
Unemp	-	-	0	-	-	2	-	-	6	-	-	14	-	-	22
Most recent Job	Jan.18	-	18	Nov. 17	Apr. 19	18	Jul. 17	Dec. 18	18	Nov. 16	Apr. 18	18	March . 16	Aug. 17	18
Unemp	-	-	2	-	-	2	-	-	2	-	-	2	-	-	2
First Job	Nov. 16	Oct. 17	12	Sept. 16	Aug. 17	12	May. 16	Apr. 17	12	Sept. 15	Aug. 16	12	Jan. 15	Dec. 15	12
Unemp	-	-	2	-	-	2	-	-	2	-	-	2	-	-	2
Internship	March. 16	Aug. 16	6	Jan. 16	June. 16	6	Sept. 15	Feb. 16	6	Jan. 15	June. 15	6	May. 14	Oct. 14	6
Unemp	-	-	6	-	-	6	-	-	6	-	-	6	-	-	6
Unemp	-	-	4	-	-	4	-	-	4	-	-	4	-	-	4
End date BA	-	Oct. 15	0	-	Aug. 15	0	-	Apr. 15	0	-	Aug. 14	0	-	Jan. 14	0
Total experience			36			36			36			36			36
Total unemp without internship			14			16			20			28			36
Total unemp with internship			8			10			14			22			30

Annex C: Exploratory analysis on the influence of equal opportunities over discrimination and formalization

Results from Model (13) regarding formalization of the hiring process and discrimination, based on immigrant background, indicate that employers with micro (1-9 employees) to medium enterprises (20-49 employees) tend to discriminate against Romanian-Italian applicants but large firms discriminate against Italians.

While counterintuitive, findings related to immigrant background and firms from Model (13) might indicate that firm size could capture other details about employers beyond the formalization of hiring processes. Larger firms, for example, might be pursuing more diversity in their labour force as part of organizational commitment (Rivera 2012). Larger firms may be more visible to the wider public and as such, they would be more likely to ensure fair treatment in the hiring processes of prospective applicants (Gërxhani and Koster 2015).

A hint about this and whether it can help explain results on formalization and immigrant background can come from job ads. A small number of employers (136) flagged that they comply with equal opportunity laws. Further analysis has therefore been carried out by interacting size and immigrant background (and gender) with a statement on equal opportunities in the job ad. Average marginal effects are presented in Figure C.1 The Figure compares the likelihood of a callback between Romanian-Italians and Italians (base category) over firm size. The left panel provides estimates for employers who do not mention the equal opportunity statement in the job ad. The right panel of employers who make that statement.

The left panel shows that large firms, that do not have a statement, do not make any difference based on the immigrant background of their applicants, whereas smaller firms do. When instead larger firms make the statement about equal opportunities there is a positive statistically significant difference in callbacks in favor Romanian-Italians compared to Italians. It is also interesting that smaller firms who make the statement firms call back applicants with a different immigrant background at a smaller rate.

As such, once the analysis separates employers based on their explicit commitment to equal opportunities, it becomes evident that larger firms call back at similar rates applicants with different immigrant background. These results from employers who do not make the statement lend support to *H.9*, namely that Employers using formal hiring procedures are as likely to consider men and women, as well as applicants regardless of their immigrant background. It is also interesting that those mentioning equal opportunities then walk the talk among smaller

firms. The behavior among larger firms suggests that once these large firms make explicit public commitments, they follow through even if at the expense of fair treatment of all applicants.

Figure C.1 Average Marginal Effects: immigrant background, by equal opportunity employer over firm size

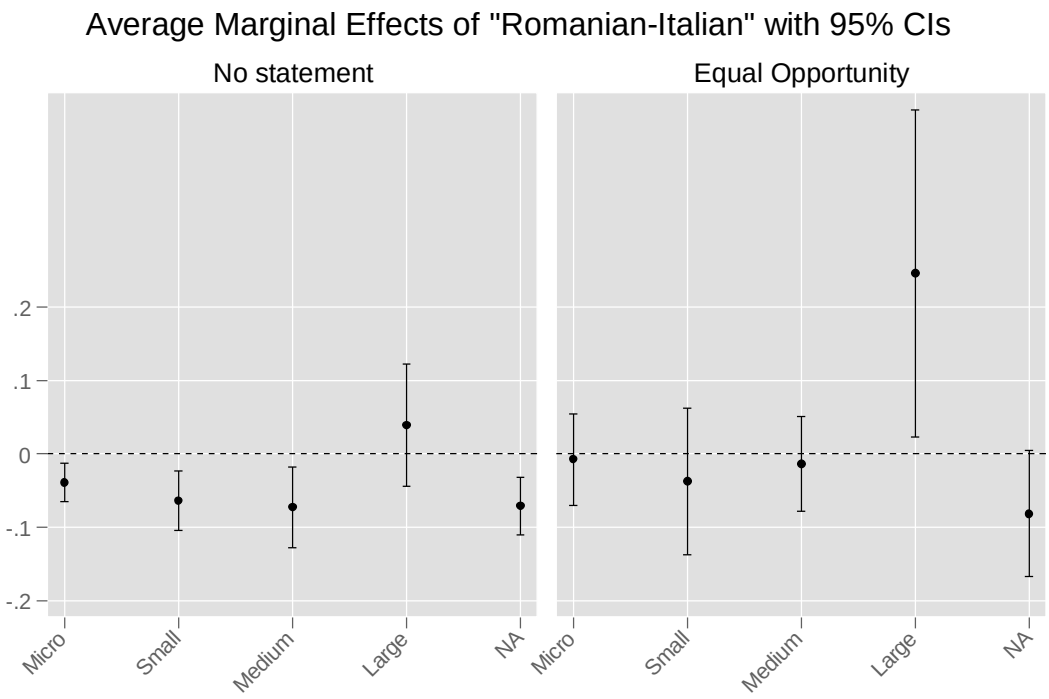


Table C.1: Interaction of gender, firm size, and equal opportunity employer, random effect linear coefficients displayed

	b	se
Romanian-Italian (IT_RM)	-0.046***	(0.009)
Employed	-0.026*	(0.012)
Duration: Short-term		
Long-term	-0.007	(0.009)
resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.003	(0.010)
CV style 3	-0.001	(0.011)
CV style 4	-0.007	(0.011)
Born - North		
Born - Centre	-0.016	(0.012)
Born - South	0.001	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.019	(0.011)
Intern	-0.010	(0.011)
2 job experiences	0.010	(0.008)
Big firm	-0.002	(0.007)
Region (North)		
South	0.011	(0.022)
Center	-0.013	(0.018)
Covid-19	-0.031	(0.017)
Sector (Admin)		
HR	-0.009	(0.038)
Market&Social	-0.021	(0.019)
Motivation	0.007	(0.008)
In training	-0.011	(0.008)
IT Skills	0.008	(0.008)
Volunteering	0.016*	(0.008)
Language ad (Neutral)		
Female	-0.058**	(0.018)
Male	-0.006	(0.025)
Relat. Skills (ad)	-0.007	(0.016)
Motivation (ad)	0.012	(0.017)
Equal opportunity	0.000	(0.038)
Firm size (Micro)		
Small	0.021	(0.025)

Medium	-0.001	(0.031)
Large	0.022	(0.042)
NA	0.025	(0.022)
Equal opportunity * Small	-0.093	(0.048)
Equal opportunity * Medium	0.065	(0.090)
Equal opportunity * Large	-0.078	(0.067)
Equal opportunity * NA	0.031	(0.084)
Woman	0.050**	(0.016)
Equal opportunity * Woman	-0.004	(0.041)
Small * Woman	0.000	(0.029)
Medium * Woman	-0.021	(0.037)
Large * Woman	-0.054	(0.042)
NA * Woman	-0.030	(0.024)
Equal opportunity * Small * Woman	0.025	(0.069)
Equal opportunity * Medium * Woman	-0.086	(0.071)
Equal opportunity * Large * Woman	0.042	(0.098)
Equal opportunity * NA * Woman	-0.112	(0.082)
Constant	0.138***	(0.029)
sigma_u	0.215	
sigma_e	0.238	
ICC	0.450	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Interaction of immigrant background, firm size, and equal opportunity employer, random effect linear coefficients displayed

	b	se
Woman	0.034***	(0.009)
Duration Short-term		
Employed	-0.028*	(0.012)
Long-term	-0.008	(0.009)
resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.004	(0.010)
CV style 3	-0.000	(0.011)
CV style 4	-0.009	(0.011)
Born - North		
Born - Centre	-0.015	(0.012)
Born - South	0.001	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.019	(0.011)
Intern	-0.010	(0.011)
2 job experiences	0.011	(0.008)
Big firm	-0.002	(0.007)
Region (North)		
South	0.012	(0.022)
Center	-0.014	(0.018)
Covid-19	-0.031	(0.017)
Sector (Admin)		
HR	-0.008	(0.037)
Market&Social	-0.021	(0.019)
Motivation	0.006	(0.008)
In training	-0.011	(0.008)
IT Skills	0.009	(0.008)
Volunteering	0.016*	(0.008)
Language ad (Neutral)		
Female	-0.059**	(0.018)
Male	-0.006	(0.026)
Relat. Skills (ad)	-0.006	(0.016)
Motivation (ad)	0.012	(0.017)
Equal opportunity	-0.012	(0.037)
Firm size (Micro)		
Small	0.029	(0.027)

Medium	-0.002	(0.035)
Large	-0.032	(0.039)
NA	0.020	(0.024)
Equal opportunity * Small	-0.079	(0.060)
Equal opportunity * Medium	0.026	(0.083)
Equal opportunity * Large	-0.102	(0.053)
Equal opportunity * NA	-0.015	(0.073)
Romanian-Italian (IT_RM)	-0.039**	(0.014)
Equal opportunity * IT_RM	0.032	(0.035)
Small * IT_RM	-0.025	(0.025)
Medium * IT_RM	-0.034	(0.031)
Large * IT_RM	0.078	(0.045)
NA * IT_RM	-0.032	(0.024)
Equal opportunity * Small * IT_RM	-0.004	(0.065)
Equal opportunity * Medium * IT_RM	0.029	(0.056)
Equal opportunity * Large * IT_RM	0.176	(0.126)
Equal opportunity * NA * IT_RM	-0.042	(0.060)
Constant	0.146***	(0.029)
sigma_u	0.216	
sigma_e	0.237	
ICC	0.453	
Adj R2		
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

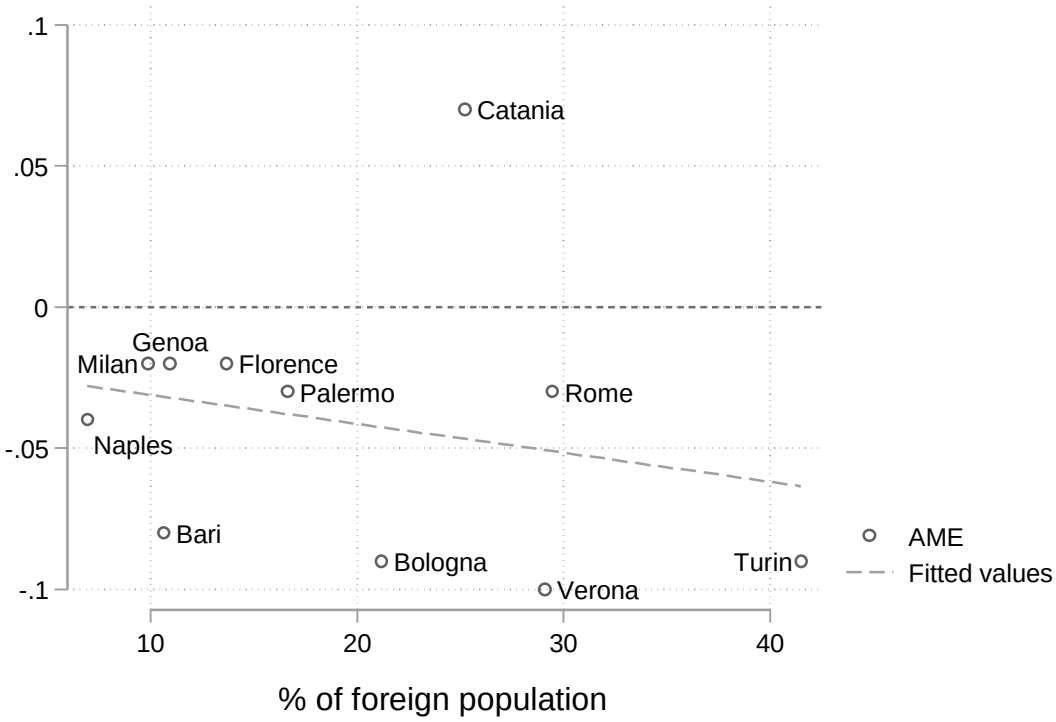
Annex D: Exploratory analysis of discrimination across Italian macro-regions

Results from Model (17) show that gender discrimination goes down to zero from the South (in a slack) to the North (tight labour market). In this regard, results on gender discrimination seem to align with the ranking model logic, whereby those groups of workers who are seen as less productive get ahead of the cue of job seekers in a tight labour market. With fewer available job seekers their chances of a callback go up and vice versa in labour markets in a slack. Nonetheless, this result in the context of the current study also means that employers call back women at higher rates than men in the macro-region with the highest level of gender inequalities in the labour market. Contrarily, results on discrimination against Romanian-Italians show no regional variation in discrimination. Nonetheless, as discussed in Sections 3.3/4, cities targeted in this study and their respective regions also vary in the number of Romanian (-Italian) residents they host.

Therefore, it can be useful to better understand results and to relate city-level average marginal effects for gender and immigrant background from Model (17), with the level of gender inequalities in local labour markets and the number of Romanians residents in the city where the correspondence study was carried out. That is, to assess the extent that differential treatment relates to structural features of places where the correspondence study has been implemented. Figure D.1 plots by city average marginal effects of immigrant background on callbacks against the percentage of Romanians, out of the total foreign population, who live in the cities included in this correspondence study. A larger percentage of Romanians in a city should imply a greater likelihood to enter into contact with native residents. In turn, the opportunity for contact may moderate the relationship between callback rates and immigrant background. What the figure shows, however, would suggest otherwise. Particularly, effects are negative everywhere, but Catania, which differs from Palermo, regardless of being in the same region (Sicily). The other takeaway is that higher shares of Romanians among the immigrant population are associated with lower employers' callbacks.

This descriptive finding confirms systematic discrimination against Romanian-Italians. While further research would be needed to substantiate the following, it seems that the greater potential possibility of contact does not translate into lower discrimination.

Figure D.1 Relationship between % of Romanians, out-of-the-city foreign population, and by city average marginal effect of immigrant background on callbacks

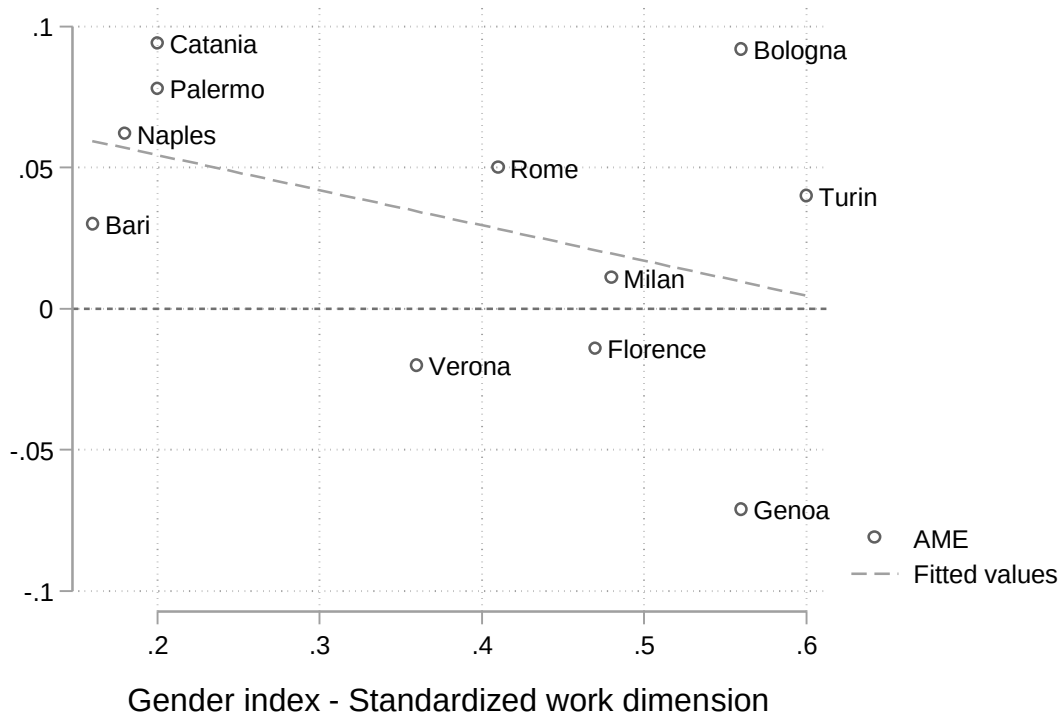


Source: Censimento permanente della popolazione - ISTAT (2020).

Turning to gender, D.2 plots by city average marginal effects for gender on callbacks in relationship with an index of gender inequalities in the labour market, where 1 represents equality (Amici and Stefani 2013). The values of the index in the chart are at the regional level such that each city is allocated the value of its respective region (i.e. Naples gets the value of gender inequality of its region, namely Campania). Figure 6.4.1.3 shows little within-macro area heterogeneity. Cities in the South are clustered in the top-left corner of the chart. These are cities with stronger gender inequalities but higher callback rates. Better labour market conditions for women are associated with lower callbacks for women compared to men (bottom-right corner).

While data at hand do not allow for further investigation of the relationship between callbacks and the presence of Romanians, the relationship between regional gender inequalities and callbacks can be inspected using data on job quality collected from job ads. To do this, D.3 plots the results of a three-way interaction term between gender, and qualification required for the job by macro-region. The difference between fictitious profiles' level of education (BA) and the qualifications employers require (<= high school diploma; high school or BA; only BA) can be used as a measure of overqualification and in turn lower job quality. The effect represents the probability of call back for women versus men over job quality by macro-region.

Figure D.2 Relationship between gender inequalities and by city average marginal effect of gender on callbacks



Source *Banca d'Italia (Amici and Stefani 2013)*

The left panel, which provides estimates for the South, shows a downward trend. As employers ask for higher educational attainment, they become less likely to call back women than men. Interestingly, rates for women compared to men when employers require a BA are very similar across regions and negative on average even if not statistically different from zero. Differential treatment also looks stronger, in favor of women, across regions when employers are fine with either a Diploma or BA, but significantly different from zero only in the Center where the point estimate is about 15%. In the North, instead, differential treatment does not seem to depend on job quality as the difference in callback rates across job qualifications is zero even if D.3 shows substantive variation among cities in the same macro-region.

The story that this graph tells for women in the South and the Center is quite in line with findings on job quality from Section 6.3.3. Employers prefer women to men for jobs for which they are (slightly) overqualified in the Center. Employers offering jobs that match qualifications instead consider equally fictitious profiles of women and men across all regions. Importantly, southern employers call back more frequently women than men for jobs with substantial overqualification. That is, those where employers ask for a Diploma or lower qualifications. This finding did not emerge from the aggregate analysis relating gender and

overqualification in Section 6.3.3. Nonetheless, it strengthens the point that even if women are more likely to be called back than men in this study, the result hinges on job quality.

Importantly, while results on gender discrimination by macro-regions conform with ranking models, the role of job quality across the three regions seems to provide a stronger explanation behind regional differences in gender discrimination.

Figure D.3 Average Marginal Effects: gender over qualifications required by the region

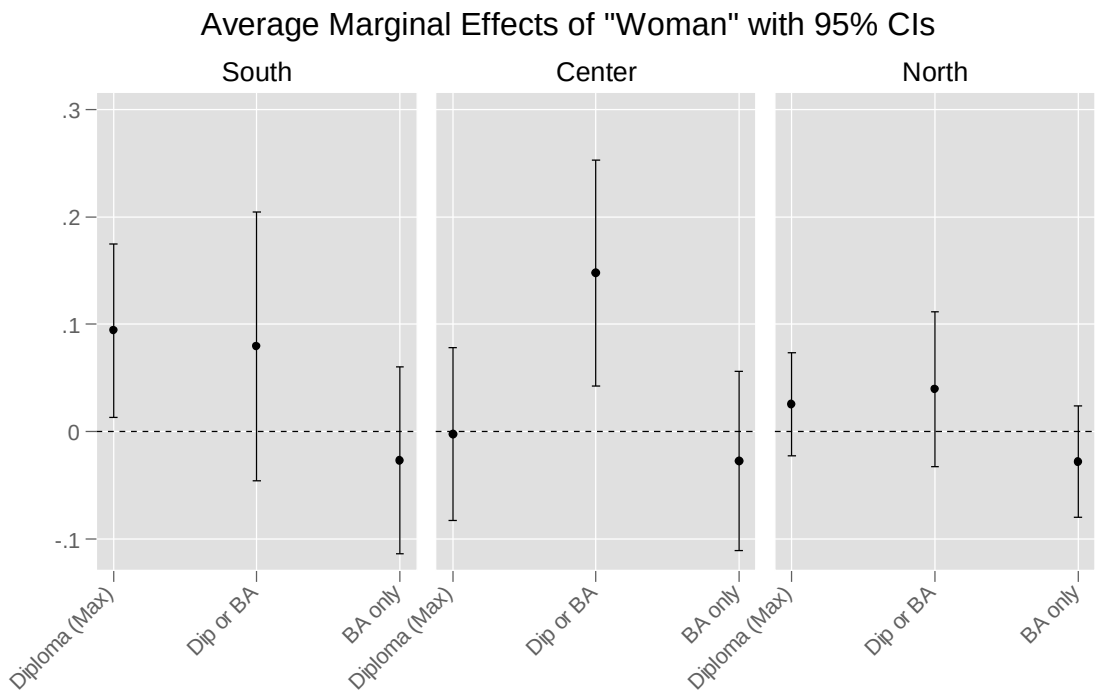


Table D.1: Interaction of gender, macro-region, and individual qualification, random effect linear coefficients displayed

	b	se
Romanian-Italian (IT_RM)	-0.052***	(0.013)
Duration: Short-term		
Employed	-0.023	(0.018)
Long-term	-0.007	(0.013)
Order resume	0.009	(0.005)
CV style (1)		
CV style 2	0.015	(0.015)
CV style 3	-0.001	(0.015)
CV style 4	-0.006	(0.016)
Born - North		
Born - Centre	-0.023	(0.016)
Born - South	0.001	(0.014)
Unemp (6 months)		
Youth Guarantee	-0.006	(0.014)
Intern	0.010	(0.016)
2 job experiences	-0.002	(0.011)
Big firm	-0.011	(0.011)
Sector (Admin)		
HR	-0.076	(0.051)
Market&Social	-0.059	(0.034)
Covid-19	-0.053*	(0.026)
Motivation	0.010	(0.011)
In training	-0.009	(0.012)
IT Skills	0.022	(0.012)
Volunteering	0.024*	(0.011)
Language ad (Neutral)		
Female	-0.078**	(0.026)
Male	0.011	(0.038)
Relat. Skills (ad)	-0.011	(0.024)
Motivation (ad)	0.033	(0.025)
Equal opportunity	-0.046	(0.028)
Firm size (Micro)		
Small	0.002	(0.031)
Medium	0.002	(0.044)
Large	-0.001	(0.045)
NA	-0.004	(0.030)

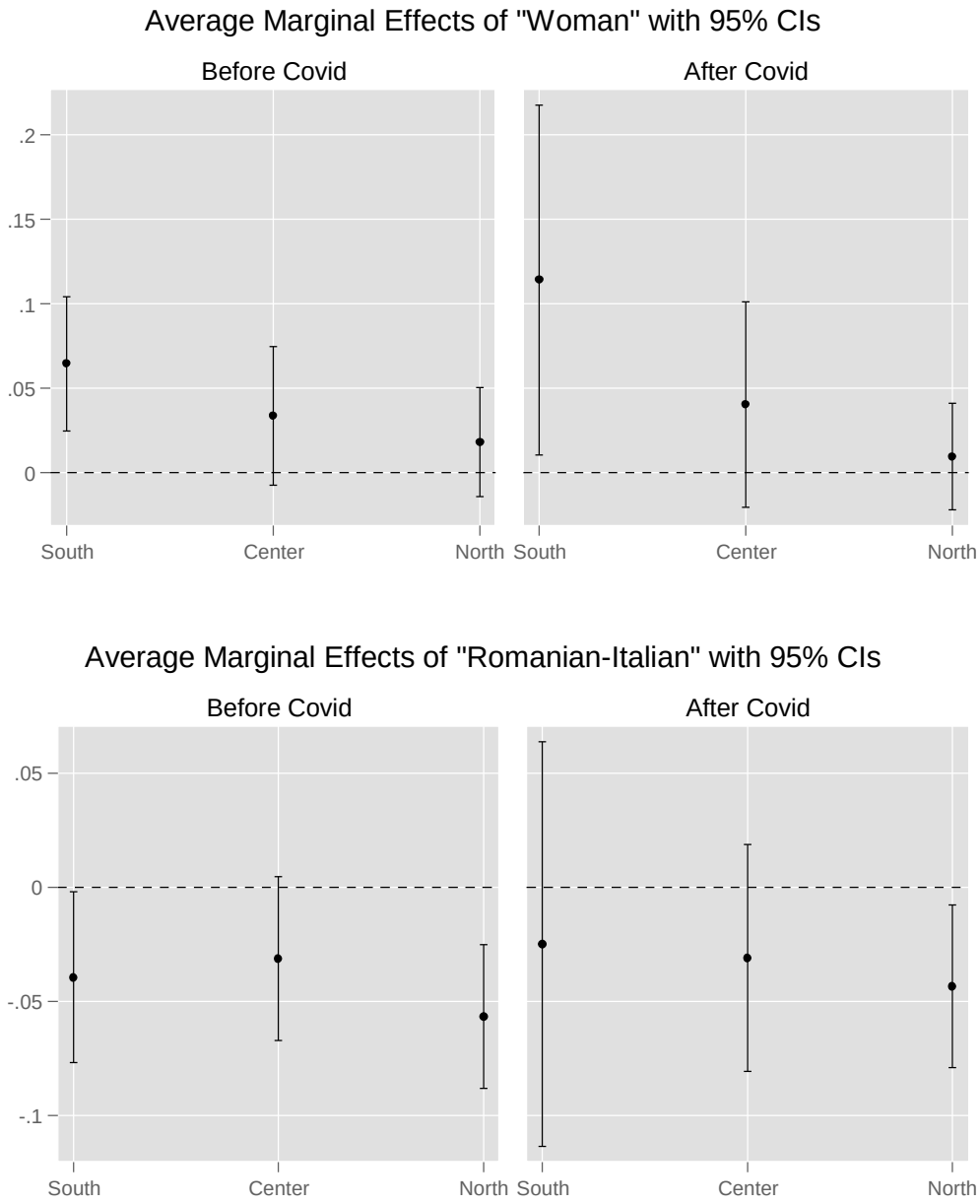
Contract (Temporary)		
Long-Term	-0.031	(0.031)
TBD	-0.036	(0.054)
Not in the job ad	-0.051*	(0.026)
Woman	0.026	(0.024)
Region (North)		
South	0.056	(0.056)
Center	0.063	(0.050)
Woman * South	0.068	(0.048)
Woman * Center	-0.028	(0.048)
Qualifications (Diploma Max)		
Dip or BA	0.040	(0.039)
BA only	0.098*	(0.044)
Woman * Dip or BA	0.014	(0.044)
Woman * BA only	-0.054	(0.036)
South * Dip or BA	-0.158*	(0.069)
South * BA only	0.007	(0.088)
Center * Dip or BA	-0.131	(0.070)
Center * BA only	-0.116	(0.073)
Woman * South * Dip or BA	-0.028	(0.087)
Woman * South * BA only	-0.066	(0.070)
Woman * Center * Dip or BA	0.137	(0.081)
Woman * Center * BA only	0.028	(0.069)
Constant	0.123**	(0.044)
sigma_u	0.234	
sigma_e	0.242	
ICC	0.483	
N	2115	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex E: Exploratory analysis on discrimination and duration dependence before and after COVID-19 across Italian macro-regions

Results from Model (18) suggest that discrimination and duration dependence dynamics remain stable after the COVID-19 outbreak. Nonetheless, the initial level of slack before COVID-19 varied across regions. As such, the impact of COVID-19 may depend on these differences between macro-regions. This proposition can be tested by interacting macro-region and the COVID-19 variable with gender or immigrant background or unemployment duration. Figure E.1 provides estimates of the three-way interaction terms between macro-region,

Figure E.1 Average Marginal Effects: Immigrant background and gender, by the period over the region



COVID-19 variable gender (right panel), or immigrant background (left panel). Both sets of panels suggest that employers across macro-regions do not change substantially the way they assess women and Romanian-Italians compared to men and Italians after the pandemic. As such, results provide further support to *H.14c*, namely that discrimination remains stable during economic downturns.

Figure E.2 replicates this analysis for unemployment duration. The Figure provides estimates before and after COVID-19 for applicants in long-term unemployment vis-à-vis those in short-term unemployment across the three macro-regions. The left panel gives an estimate for the South, the central panel for the Center, and the right panel for the North. Results point to the lack of statistically significant differences across regions and periods between those with short-term unemployment (base category) and long-term unemployment spells. As such, this further analysis on unemployment duration lends further support to *H.14c* like those on gender and immigrant background.

Nonetheless, it is still interesting to look at the response pattern, which suggests that on average employers adjusted to some extent the way they see and use unemployment duration after COVID-19. Particularly, it seems that the reactions of employers in the South and the North are opposed while the response pattern is the same between periods in the Center.

Figure E.2 Average Marginal Effects of unemployment duration on callbacks: before and after COVID-19, by region

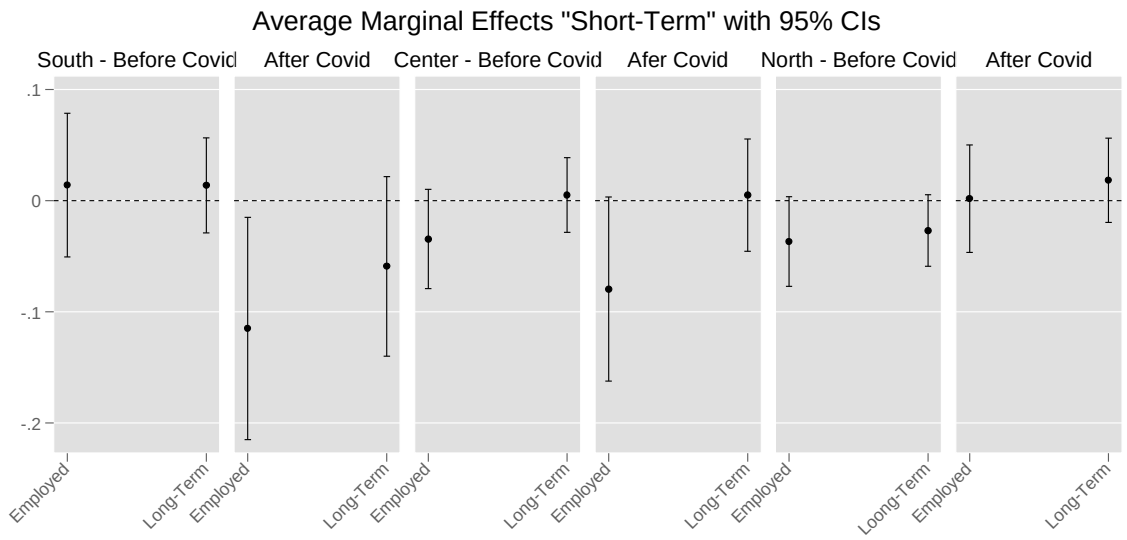


Table E.1: Interaction of unemployment duration, macro-region, and COVID-19, random effect linear coefficients displayed

	b	se
Woman	0.033***	(0.009)
Romanian-Italian (IT_RM)	-0.044***	(0.009)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.013	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.004	(0.011)
2 job experiences	0.013	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.030	(0.035)
Market&Social	-0.015	(0.020)
Motivation	0.006	(0.008)
In training	-0.010	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)		
Female	-0.045*	(0.018)
Male	-0.003	(0.024)
Relat. Skills (ad)	-0.010	(0.016)
Motivation (ad)	0.008	(0.016)
Equal opportunity	-0.037	(0.022)
Firm size (Micro)		
Small	0.003	(0.021)
Medium	-0.009	(0.029)
Large	-0.023	(0.032)
NA	0.003	(0.019)
Contract (Temporary)		
Long-Term	-0.024	(0.019)
TBD	-0.010	(0.039)

Not in job ad	-0.017	(0.017)
Qualifications (No BA)		
High-BA	0.025	(0.024)
Msc	-0.041	(0.061)
Not in job ad	-0.021	(0.022)
Region (North)		
South	-0.030	(0.029)
Center	-0.037	(0.025)
After Covid	-0.086***	(0.026)
South * After Covid	0.194**	(0.063)
Center * After Covid	0.065	(0.043)
Duration: Short-term		
Employed	-0.037	(0.021)
Long-term	-0.027	(0.016)
South * Employed	0.051	(0.039)
South * Long-term	0.041	(0.027)
Center * Employed	0.002	(0.031)
Center * Long-term	0.032	(0.024)
After Covid * Employed	0.039	(0.032)
After Covid * Long-term	0.045	(0.025)
South * After Covid * Employed	-0.168*	(0.068)
South * After Covid * Long-term	-0.118*	(0.053)
Center * After Covid * Employed	-0.084	(0.058)
Center * After Covid * Long-term	-0.045	(0.040)
Constant	0.170***	(0.035)
sigma_u	0.209	
sigma_e	0.235	
ICC	0.443	
Adj R2		
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.2: Interaction of gender, macro-region, and individual qualification, random effect linear coefficients displayed

	b	se
Duration: Short-term		
Employed	-0.029*	(0.012)
Long-term	-0.006	(0.009)
Woman	0.033***	(0.009)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.013	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.004	(0.011)
2 job experiences	0.012	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.030	(0.035)
Market&Social	-0.015	(0.020)
Motivation	0.006	(0.008)
In training	-0.009	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)		
Female	-0.046**	(0.018)
Male	-0.004	(0.024)
Relat. Skills (ad)	-0.010	(0.016)
Motivation (ad)	0.008	(0.016)
Equal opportunity	-0.038	(0.022)
Firm size (Micro)	0.000	
Small	0.003	(0.021)
Medium	-0.009	(0.029)
Large	-0.022	(0.032)
NA	0.003	(0.019)
Contract (Temporary)		

Long-Term	-0.024	(0.019)
TBD	-0.012	(0.039)
Not in job ad	-0.017	(0.017)
Qualifications (No BA)		
High-BA	0.025	(0.024)
Msc	-0.043	(0.060)
Not in job ad	-0.021	(0.022)
Region (North)		
South	-0.009	(0.028)
Center	-0.029	(0.024)
After Covid	-0.063*	(0.025)
South * After Covid	0.118*	(0.059)
Center * After Covid	0.038	(0.039)
Romanian-Italian (IT_RM)	-0.057***	(0.016)
South * IT_RM	0.017	(0.025)
Center * IT_RM	0.025	(0.024)
After Covid * IT_RM	0.013	(0.024)
South * After Covid * IT_RM	0.001	(0.055)
Center * After Covid * IT_RM	-0.013	(0.039)
Constant	0.163***	(0.034)
sigma_u	0.208	
sigma_e	0.235	
ICC	0.441	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.3: Interaction of gender, macro-region, and COVID-19, random effect linear coefficients displayed

	b	se
Employed	-0.028*	(0.012)
Long-term	-0.007	(0.009)
Romanian-Italian (IT_RM)	-0.043***	(0.009)
Order resume		(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.007	(0.011)
Born - North		
Born - Centre	-0.014	(0.012)
Born - South	0.003	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.014	(0.010)
Intern	-0.003	(0.011)
2 job experiences	0.012	(0.008)
Big firm	-0.003	(0.007)
Sector (Admin)		
HR	-0.031	(0.035)
Market&Social	-0.014	(0.020)
Motivation	0.007	(0.008)
In training	-0.009	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)	0.000	
Female	-0.046*	(0.018)
Male	-0.004	(0.024)
Relat. Skills (ad)	-0.010	(0.016)
Motivation (ad)	0.008	(0.016)
Equal opportunity	-0.037	(0.022)
Firm size (Micro)		
Small	0.004	(0.021)
Medium	-0.009	(0.029)
Large	-0.020	(0.032)
NA	0.003	(0.019)
Contract (Temporary)	0.000	
Long-Term	-0.023	(0.019)

TBD	-0.012	(0.039)
Not in job ad	-0.018	(0.017)
Qualifications (No BA)	0.000	
High-BA	0.025	(0.024)
Msc	-0.047	(0.060)
Not in job ad	-0.021	(0.022)
Region (North)		
South	-0.027	(0.025)
Center	-0.029	(0.023)
After Covid	-0.055*	(0.024)
South * After Covid	0.088	(0.052)
Center * After Covid	0.026	(0.036)
Woman	0.018	(0.016)
South * Woman	0.046	(0.026)
Center * Woman	0.015	(0.027)
After Covid * Woman	-0.009	(0.023)
South * After Covid * Woman	0.058	(0.061)
Center * After Covid * Woman	0.015	(0.044)
Constant	0.167***	(0.034)
sigma_u	0.209	
sigma_e	0.234	
ICC	0.444	
N	4079	

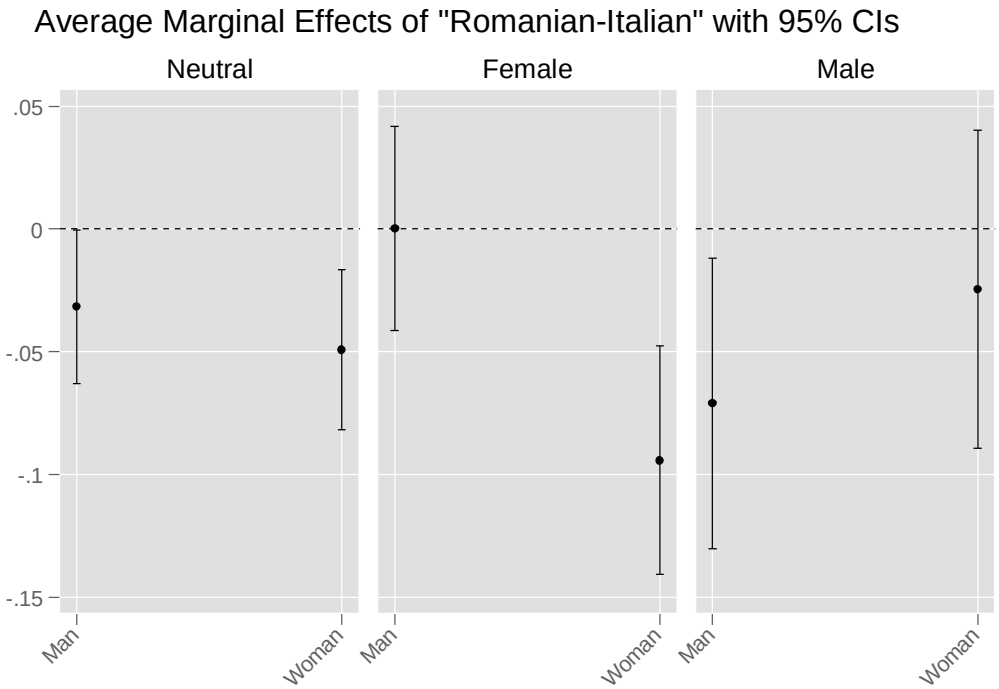
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex F: Exploratory analysis on intersectionality and gendered job ads

Results from Model (21), which intersects gender and immigrant background show that the interaction between these two variables is not statistically significant. The result thus indicates that employers look at gender and immigrant background independently. This means that when they assess a Romanian-Italian applicant what they infer from immigrant background does shape what they infer from the fact the applicant is a woman. However, results from Model (21) show that employers make differences between men and women if they are Italian. This suggests that immigrant background somehow shapes inferences about gender.

To better understand these two contrasting findings on the relationship between gender and immigrant background, Figure F.1 plots the average marginal effects of immigrant background on callbacks over the gender Model (21). Each panel shows the differences in the probability of a callback between Italian and Romanian-Italian men, as well as between Italian and Romanian-Italian men, by type of language used in the job ad, namely neutral female-oriented or men oriented. Interestingly, when employers use a neutral language both men and women with a Romanian background stand lower chances of being contacted than their respective Italian counterparts. When the ideal candidate is described as a woman, employers call at similar rates Italian and Romanian-Italian men, but they prefer Italian women to those with

Figure F.1 Average Marginal Effects of immigrant background on callbacks over gender, gendered language



Romanian background. Likewise, they prefer Italian men to Romanian-Italian men when the ideal candidate is described as a man, but these employers call back at similar rates for Italian and Romanian-Italian women. In other words, gendered language moderates the relationship between immigrant background and gender.

When employers' gendered representations of the ideal candidate are factored in, there is a clear interaction between gender and immigrant background. In other words, what employers infer from gender depends on what employers learn by looking at the origins of prospective job applicants. If employers look for a woman or man, they systematically choose Italian women and men over Romanian-Italians. Also, when the expectation about the gender of the ideal candidate is not set clearly defined, as in the neutral language condition, Italian men and women are both preferred to Romanian-Italians men and women.

Table F.1: Interaction of gender, immigrant background, and gendered language in job ads, random effect linear coefficients displayed

	b	se
Duration: Short-term		
Employed	-0.029*	(0.012)
Long-term	-0.006	(0.009)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.002	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.013	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.014	(0.010)
Intern	-0.002	(0.011)
2 job experiences	0.012	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.028	(0.036)
Market&Social	-0.016	(0.020)
info_comp	0.029	(0.017)
South	0.025	(0.022)
Center	-0.012	(0.017)
Region (North)		
Covid-19	-0.030	(0.017)
Motivation	0.007	(0.008)
In training	-0.009	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Yes	-0.012	(0.016)
Yes	0.005	(0.016)
Yes	-0.038	(0.022)
Micro		
Piccole	0.002	(0.021)
Medie	-0.013	(0.030)
Grandi	-0.020	(0.032)
NA	0.005	(0.019)

Temporary		
Long-Term	-0.021	(0.019)
TBD	-0.002	(0.039)
Not in job ad	-0.016	(0.018)
No BA		
High-BA	0.021	(0.024)
Msc	-0.031	(0.065)
Not in job ad	-0.021	(0.022)
Language ad (Female)		
Neutral	0.068**	(0.022)
Male	0.095**	(0.034)
Woman	0.090***	(0.024)
Neutral * Woman	-0.057*	(0.028)
Male * Woman	-0.105**	(0.036)
Romanian-Italian (IT_RM)	0.001	(0.021)
Neutral * IT_RM	-0.032	(0.027)
Male * IT_RM	-0.072	(0.037)
Woman * IT_RM	-0.095**	(0.033)
Neutral * Woman * IT_RM	0.078	(0.041)
Male * Woman * IT_RM	0.142**	(0.055)
Constant	0.070*	(0.034)
sigma_u	0.210	
sigma_e	0.234	
ICC	0.445	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex G: Regression tables

Table 1 Unemployment duration on callbacks, linear coefficients displayed –OLS with clustered employer standard errors Models (1)-(3) and Random Effect Model (4)

	(1)		(2)		(3)		(4)	
	b	se	b	se	b	se	b	se
Duration: Short-term								
Employed	-0.019	(0.015)	-0.019	(0.015)	-0.021	(0.015)	-0.029*	(0.012)
Long-term	-0.006	(0.010)	-0.006	(0.010)	-0.006	(0.010)	-0.006	(0.009)
Woman			0.037***	(0.010)	0.037***	(0.010)	0.032***	(0.009)
IT_RM			-0.047***	(0.009)	-0.047***	(0.009)	-0.043***	(0.008)
Order resume			0.000	(0.003)	0.000	(0.003)	0.000	(0.003)
CV style (1)								
CV style 2			-0.001	(0.010)	-0.001	(0.010)	-0.002	(0.010)
CV style 3			-0.001	(0.010)	-0.001	(0.010)	-0.003	(0.010)
CV style 4			-0.007	(0.011)	-0.007	(0.011)	-0.008	(0.011)
Born - North								
Born - Centre			-0.019	(0.014)	-0.019	(0.014)	-0.011	(0.012)
Born - South			0.004	(0.011)	0.004	(0.011)	0.003	(0.009)
Unemp (6 months)								
Youth Guarantee			-0.023	(0.012)	-0.024	(0.012)	-0.015	(0.010)
Intern			-0.007	(0.012)	-0.007	(0.012)	-0.003	(0.011)
2 job experiences			0.005	(0.010)	0.005	(0.010)	0.012	(0.008)
Big firm			-0.002	(0.007)	-0.002	(0.007)	-0.002	(0.007)
Sector (Admin)								
HR					-0.014	(0.035)	-0.016	(0.035)
Market&Social					-0.001	(0.017)	0.001	(0.017)
Region (North)								
South					0.015	(0.022)	0.015	(0.022)
Center					-0.022	(0.017)	-0.021	(0.017)
Covid-19					-0.038*	(0.016)	-0.036*	(0.016)
Constant	0.118***	(0.010)	0.127***	(0.019)	0.141***	(0.022)	0.134***	(0.021)
sigma_u							0.210	
sigma_e							0.235	
ICC							0.445	
Adj R2	0.000		0.010		0.015			
N	4079		4079		4079		4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2 Unemployment duration on callbacks, Random Effect linear coefficients displayed, by the urgency of the hiring - Model (5)

	(5a) Urgency: NO		(5a) Urgency: YES	
	b	se	b	se
Man	-0.030**	(0.010)	-0.060*	(0.026)
Romanian-Italian (IT_RM)	-0.047***	(0.009)	-0.032	(0.022)
Order resume	0.004	(0.004)	-0.024*	(0.009)
Duration: short-term				
Employed	-0.022	(0.013)	-0.037	(0.036)
Long-term	-0.001	(0.009)	-0.049*	(0.024)
CV style (1)				
CV Style 2	-0.002	(0.011)	-0.022	(0.030)
CV style 3	-0.004	(0.012)	0.021	(0.027)
CV style 4	-0.008	(0.012)	-0.012	(0.028)
Area of birth (North)				
Born - Centre	-0.022	(0.013)	0.031	(0.031)
Born - South	-0.002	(0.010)	0.014	(0.021)
Unemp (6 months)				
Youth Guarantee	-0.019	(0.011)	-0.016	(0.030)
Intern	-0.009	(0.012)	-0.005	(0.032)
Two job experiences	0.013	(0.009)	-0.010	(0.022)
Big firm in resume	0.001	(0.008)	-0.027	(0.021)
Sector (Admin)				
HR	-0.022	(0.039)	0.107	(0.094)
Marketing	-0.010	(0.018)	0.077	(0.053)
Region (North)				
South	0.008	(0.023)	0.006	(0.058)
Center	-0.013	(0.019)	-0.056	(0.038)
Covid-19	-0.052**	(0.018)	0.046	(0.049)
Constant	0.172***	(0.023)	0.247***	(0.057)
sigma_u	0.217		0.167	
sigma_e	0.236		0.246	
ICC	0.458		0.315	
N	3502		577	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 Interaction of motivation (job ad) and unemployment duration, Random Effect linear coefficients displayed – Model (6)

	b	se
Man	-0.033***	(0.009)
Romanian-Italian (IT_RM)	-0.046***	(0.009)
Order resume	0.000	(0.003)
CV style (1)		
CV style 2	-0.003	(0.010)
CV style 3	-0.000	(0.011)
CV style 4	-0.008	(0.011)
Area of birth (North)		
Born - Centre	-0.015	(0.012)
Born - South	0.000	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.019	(0.011)
Intern	-0.009	(0.011)
2 job experiences	0.010	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.005	(0.035)
Market&Social	-0.005	(0.017)
Region (North)		
South	0.012	(0.022)
Center	-0.018	(0.017)
Covid-19	-0.038*	(0.017)
Duration (short-term)		
Employed	-0.021	(0.015)
Long-term	-0.002	(0.010)
Motivation (job ad)	0.033	(0.023)
Employed # Yes motivation	-0.017	(0.027)
Long-term # Yes motivation	-0.018	(0.020)
Constant	0.170***	(0.022)
sigma_u	0.215	
sigma_e	0.238	
ICC	0.449	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 Interaction of motivation (job), motivation (in resume) and unemployment duration, Random Effect linear coefficients displayed – Model (7a)

	b	se
Woman	0.033***	(0.009)
Romanian-Italian (IT_RM)	-0.045***	(0.009)
Order resume	0.000	(0.003)
CV style (1)		
CV style 2	-0.003	(0.010)
CV style 3	-0.003	(0.011)
CV style 4	-0.009	(0.011)
Born - North		
Born - Centre	-0.017	(0.012)
Born - South	-0.000	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.019	(0.011)
Intern	-0.009	(0.011)
2 job experiences	0.011	(0.008)
Big firm	-0.003	(0.007)
Sector (Admin)		
HR	-0.007	(0.036)
Market&Social	-0.007	(0.017)
Region (North)		
South	0.012	(0.022)
Center	-0.019	(0.017)
Covid-19	-0.038*	(0.017)
Motivation (ad)	0.004	(0.016)
Motivation (resume)	-0.003	(0.027)
Motivation: ad * resume	0.077*	(0.034)
Duration: Short-term		
Employed	-0.020	(0.022)
Long-term	-0.006	(0.014)
Motivation (ad) * Employed	-0.003	(0.031)
Motivation (ad) * Long-term	0.009	(0.021)
Motivation (resume) * Employed	-0.013	(0.034)
Motivation (resume) * Long-term	0.055	(0.030)
Motivation (ad) * resume * Employed	-0.022	(0.052)
Motivation (ad) * resume * Long-term	-0.151***	(0.046)
Constant	0.137***	(0.023)
sigma_u	0.215	

sigma_e	0.237
ICC	0.452
N	4079

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 Interaction of motivation (job), volunteering (in resume) and unemployment duration, Random Effect linear coefficients displayed – Model (7b)

	b	se
Woman	0.034***	(0.009)
Romanian-Italian (IT_RM)	-0.045***	(0.009)
resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.003	(0.010)
CV style 3	-0.000	(0.011)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.017	(0.012)
Born - South	0.000	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.018	(0.011)
Intern	-0.009	(0.011)
2 job experiences	0.010	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.005	(0.036)
Market&Social	-0.005	(0.017)
Region (North)		
South	0.013	(0.022)
Center	-0.018	(0.017)
Covid-19	-0.038*	(0.017)
Volunteering	0.002	(0.015)
Motivation (ad)	0.023	(0.026)
Volunteering * Motivation (ad)	0.023	(0.031)
Duration: Short-term		
Employed	-0.036	(0.021)
Long-term	-0.015	(0.015)
Volunteering * Employed	0.030	(0.031)
Volunteering * Long-term	0.026	(0.020)
Motivation (ad) * Employed	-0.038	(0.033)
Motivation (ad) * Long-term	0.014	(0.029)
Volunteering * Motivation (ad) * Employed	0.034	(0.054)
Volunteering * Motivation (ad) * Long-term	-0.065	(0.041)
Constant	0.135***	(0.023)
sigma_u	0.215	

sigma_e	0.238
ICC	0.449
N	4079

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 Gender and immigrant background on callbacks, Random Effect linear coefficients displayed – Model (8)

	b	se
Woman	0.032***	(0.009)
Romanian-Italian (IT_RM)	-0.043***	(0.008)
Duration: Short-term		
Employed	-0.029*	(0.012)
Long-term	-0.006	(0.009)
Order resume	0.000	(0.003)
CV style (1)	0.000	
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.011	(0.012)
Born - South	0.003	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.003	(0.011)
2 job experiences	0.012	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.016	(0.035)
Market&Social	0.001	(0.017)
Region (North)		
South	0.015	(0.022)
Center	-0.021	(0.017)
Covid-19	-0.036*	(0.016)
Constant	0.134***	(0.021)
sigma_u	0.210	
sigma_e	0.235	
ICC	0.445	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 Gender on callbacks by sector, Random Effect linear coefficients displayed – Model (10a/c)

	(10a) Admin		(10b) HR		(10c) Marketing	
	b	se	b	se	b	se
Woman	0.035**	(0.011)	0.027	(0.026)	0.031	(0.018)
Romanian-Italian (IT_RM)	-0.053***	(0.011)	-0.013	(0.029)	-0.033	(0.017)
Duration: Short-term						
Employed	-0.025	(0.014)	-0.025	(0.032)	-0.027	(0.027)
Long-term	-0.009	(0.011)	-0.027	(0.026)	0.002	(0.018)
Order resume	0.003	(0.004)	0.004	(0.008)	-0.005	(0.008)
CV style (1)						
CV style 2	-0.013	(0.013)	0.044	(0.043)	0.009	(0.020)
CV style 3	-0.004	(0.013)	0.064	(0.037)	-0.008	(0.023)
CV style 4	-0.005	(0.013)	-0.003	(0.034)	-0.018	(0.022)
Born - North						
Born - Centre	-0.024	(0.014)	0.038	(0.040)	0.001	(0.027)
Born - South	-0.001	(0.011)	0.020	(0.029)	0.002	(0.018)
Unemp (6 months)						
Youth Guarantee	-0.018	(0.013)	-0.017	(0.042)	-0.015	(0.021)
Intern	-0.010	(0.013)	-0.016	(0.037)	0.001	(0.021)
2 job experiences	0.009	(0.010)	-0.028	(0.018)	0.018	(0.016)
Big firm	-0.005	(0.009)	-0.000	(0.018)	0.000	(0.016)
Region (North)						
South	-0.032	(0.025)	-0.028	(0.099)	0.120**	(0.045)
Center	-0.039	(0.021)	-0.083	(0.075)	0.046	(0.033)
Covid-19	-0.050*	(0.020)	0.126	(0.117)	-0.037	(0.027)
Motivation	0.010	(0.009)	-0.040	(0.028)	0.011	(0.018)
In training	-0.000	(0.010)	0.033	(0.025)	-0.040*	(0.017)
IT Skills	0.010	(0.010)	0.049	(0.026)	-0.001	(0.015)
Volunteering	0.022*	(0.009)	-0.018	(0.033)	0.016	(0.016)
Constant	0.146***	(0.027)	0.097	(0.076)	0.105*	(0.044)
sigma_u	0.213		0.271		0.197	
sigma_e	0.237		0.184		0.250	
ICC	0.447		0.684		0.383	
N	2740		258		1081	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 Gender on callbacks by gendered language in job ads, Random Effect linear coefficients displayed – Model (11a/c)

	(11a) Neutral		(11b) Female		(11c) Male	
	b	se	b	se	b	se
Woman	0.031**	(0.012)	0.063***	(0.017)	0.001	(0.024)
Romanian-Italian (IT_RM)	-0.044***	(0.011)	-0.051***	(0.015)	-0.041	(0.024)
Duration: Short-term						
Employed	-0.028	(0.017)	-0.043*	(0.019)	0.016	(0.040)
Long-term	-0.009	(0.012)	-0.017	(0.016)	0.008	(0.025)
Order resume	0.003	(0.004)	0.002	(0.007)	-0.006	(0.009)
CV style (1)						
CV style 2	-0.010	(0.013)	-0.023	(0.019)	0.044	(0.031)
CV style 3	0.002	(0.014)	-0.013	(0.019)	0.006	(0.028)
CV style 4	-0.007	(0.014)	0.002	(0.021)	-0.047	(0.032)
Born - North						
Born - Centre	-0.010	(0.016)	-0.022	(0.020)	-0.022	(0.028)
Born - South	-0.001	(0.012)	-0.017	(0.017)	0.031	(0.029)
Unemp (6 months)						
Youth Guarantee	-0.012	(0.014)	-0.034	(0.019)	-0.025	(0.032)
Intern	-0.002	(0.014)	-0.016	(0.021)	-0.024	(0.032)
2 job experiences	0.014	(0.010)	-0.003	(0.014)	0.002	(0.024)
Big firm	0.010	(0.010)	-0.026	(0.014)	-0.022	(0.021)
Region (North)						
South	0.007	(0.029)	0.003	(0.033)	0.019	(0.061)
Center	0.012	(0.026)	-0.016	(0.024)	-0.119**	(0.041)
Covid-19	-0.042	(0.022)	-0.034	(0.023)	0.070	(0.095)
Sector (Admin)						
HR	-0.000	(0.047)	0.097	(0.134)	-0.105	(0.060)
Market&Social	-0.018	(0.021)	0.037	(0.065)	-0.017	(0.051)
Motivation	0.003	(0.011)	0.011	(0.015)	0.016	(0.022)
In training	-0.015	(0.010)	-0.008	(0.016)	0.010	(0.020)
IT Skills	0.020	(0.011)	0.007	(0.015)	-0.041*	(0.017)
Volunteering	0.019	(0.010)	0.030*	(0.014)	-0.008	(0.020)
Constant	0.128***	(0.030)	0.115**	(0.036)	0.215**	(0.073)
sigma_u	0.233		0.143		0.232	
sigma_e	0.241		0.222		0.248	
ICC	0.483		0.294		0.467	
N	2482		1012		585	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9 Immigrant background on callbacks by relational skills in the job ad, Random Effect linear coefficients displayed – Model (12a/b)

	(12a) No Relational skills (ad)		(12b) Relational skills (ad)	
	b	se	b	se
Woman	0.042**	(0.013)	0.024	(0.013)
Romanian-Italian (IT_RM)	-0.043***	(0.012)	-0.050***	(0.013)
Employed	-0.022	(0.017)	-0.027	(0.018)
Duration: Short-term				
Long-term	-0.014	(0.012)	0.003	(0.013)
Order resume	-0.001	(0.005)	0.003	(0.005)
CV style (1)				
CV style 2	-0.022	(0.014)	0.023	(0.016)
CV style 3	-0.011	(0.015)	0.014	(0.015)
CV style 4	-0.020	(0.015)	0.009	(0.016)
Born - North				
Born - Centre	-0.021	(0.015)	-0.010	(0.019)
Born - South	0.012	(0.012)	-0.014	(0.014)
Unemp (6 months)				
Youth Guarantee	-0.017	(0.015)	-0.021	(0.016)
Intern	-0.015	(0.014)	-0.002	(0.016)
2 job experiences	0.002	(0.012)	0.022*	(0.010)
Big firm	-0.006	(0.010)	0.004	(0.011)
Region (North)				
South	0.005	(0.028)	0.025	(0.034)
Center	-0.014	(0.023)	-0.013	(0.027)
Covid-19	-0.036	(0.022)	-0.021	(0.026)
Sector (Admin)				
HR	-0.018	(0.051)	-0.022	(0.052)
Market&Social	-0.011	(0.027)	-0.030	(0.027)
Motivation	0.004	(0.012)	0.009	(0.012)
In training	-0.016	(0.011)	-0.003	(0.011)
IT Skills	0.015	(0.011)	0.003	(0.011)
Volunteering	0.023*	(0.010)	0.008	(0.012)
Language ad (Neutral)	=		=	
Female	-0.041	(0.023)	-0.086***	(0.026)
Male	-0.025	(0.031)	0.032	(0.041)
Constant	0.168***	(0.031)	0.125***	(0.037)
sigma_u	0.206		0.223	
sigma_e	0.242		0.232	

ICC	0.421	0.479
N	2250	1829

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10 Gender and immigrant background on callbacks by motivation in the job ad, Random Effect linear coefficients displayed – Model (12a/b)

	(13a) No motivation in job ad		(13b) Motivation in job ad	
	b	se	b	se
Woman	0.041**	(0.014)	0.027*	(0.012)
Romanian-Italian (IT_RM)	-0.034**	(0.013)	-0.057***	(0.012)
Employed	-0.023	(0.018)	-0.030	(0.017)
Duration: Short-term				
Long-term	-0.000	(0.012)	-0.014	(0.013)
Order resume	-0.006	(0.005)	0.006	(0.005)
CV style (1)				
CV style 2	-0.030*	(0.015)	0.021	(0.014)
CV style 3	-0.023	(0.016)	0.020	(0.014)
CV style 4	-0.021	(0.016)	0.003	(0.015)
Born - North				
Born - Centre	-0.037*	(0.018)	0.002	(0.016)
Born - South	0.009	(0.014)	-0.009	(0.013)
Unemp (6 months)				
Youth Guarantee	-0.019	(0.016)	-0.020	(0.014)
Intern	-0.002	(0.017)	-0.015	(0.014)
2 job experiences	0.014	(0.012)	0.010	(0.010)
Big firm	-0.010	(0.011)	0.002	(0.010)
Region (North)				
South	0.014	(0.029)	0.011	(0.033)
Center	-0.009	(0.023)	-0.014	(0.027)
Covid-19	-0.033	(0.023)	-0.030	(0.025)
Sector (Admin)				
HR	-0.043	(0.046)	-0.004	(0.054)
Market&Social	-0.001	(0.031)	-0.031	(0.025)
Motivation	0.001	(0.011)	0.013	(0.012)
In training	-0.013	(0.012)	-0.008	(0.011)
IT Skills	0.017	(0.012)	0.001	(0.011)
Volunteering	0.009	(0.011)	0.023*	(0.011)
Language ad (Neutral)				
Female	-0.070**	(0.024)	-0.033	(0.028)
Male	-0.016	(0.035)	0.004	(0.036)
Relat. Skills (ad)	-0.036	(0.023)	0.015	(0.023)
Constant	0.184***	(0.036)	0.123***	(0.035)
sigma_u	0.196		0.228	

sigma_e	0.241	0.234
ICC	0.398	0.486
N	1937	2142

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11 Gender and immigrant background on callbacks by firm size, Random Effect linear coefficients displayed – Model (14a/e)

	(14a) Micro		(14b) Small		(14c) Medium		(14d) Large		(14e) NA	
	b	se	b	se	b	se	b	se	b	se
Woman	0.048**	(0.015)	0.049*	(0.022)	0.018	(0.030)	-0.017	(0.042)	0.011	(0.017)
Employed	-0.015	(0.020)	-0.058*	(0.029)	0.040	(0.048)	-0.003	(0.046)	-0.042	(0.023)
Duration: Short-term										
Long-term	-0.005	(0.015)	-0.021	(0.018)	0.037	(0.028)	0.019	(0.039)	-0.019	(0.018)
Romanian-Italian (IT_RM)	-0.036**	(0.012)	-0.058**	(0.020)	-0.057*	(0.027)	0.087	(0.045)	-0.073***	(0.019)
Order resume	-0.005	(0.005)	0.006	(0.007)	-0.002	(0.011)	0.005	(0.014)	0.006	(0.007)
CV style (1)										
CV style 2	-0.002	(0.017)	-0.013	(0.023)	-0.001	(0.036)	0.001	(0.040)	-0.006	(0.021)
CV style 3	0.008	(0.016)	-0.005	(0.025)	-0.032	(0.035)	-0.034	(0.047)	0.007	(0.022)
CV style 4	-0.012	(0.016)	0.011	(0.026)	-0.030	(0.036)	-0.058	(0.054)	-0.006	(0.023)
Born - North										
Born - Centre	-0.021	(0.020)	-0.006	(0.028)	0.004	(0.043)	-0.008	(0.062)	-0.017	(0.021)
Born - South	-0.003	(0.014)	0.022	(0.022)	-0.013	(0.024)	-0.026	(0.056)	0.003	(0.019)
Unemp (6 months)										
Youth Guarantee	-0.034*	(0.017)	-0.021	(0.023)	-0.012	(0.038)	0.008	(0.045)	-0.007	(0.023)
Intern	-0.005	(0.017)	-0.015	(0.026)	0.011	(0.039)	-0.005	(0.050)	-0.028	(0.022)
2 job experiences	0.001	(0.013)	0.011	(0.017)	0.010	(0.026)	-0.050	(0.046)	0.034*	(0.016)
Big firm	-0.000	(0.012)	-0.017	(0.017)	0.007	(0.022)	-0.043	(0.037)	0.016	(0.014)
Region (North)										
South	0.032	(0.035)	0.079	(0.056)	-0.030	(0.075)	-0.234**	(0.077)	-0.035	(0.039)
Center	-0.051*	(0.025)	0.000	(0.040)	0.030	(0.083)	-0.093	(0.075)	0.002	(0.036)
Covid-19	-0.019	(0.029)	-0.056	(0.038)	-0.071	(0.047)	-0.080	(0.067)	-0.011	(0.032)
Sector (Admin)										
HR	0.046	(0.068)	-0.003	(0.108)	-0.018	(0.092)	-0.180	(0.095)	-0.146***	(0.027)
Market&Social	0.020	(0.031)	-0.083	(0.045)	0.057	(0.067)	-0.130*	(0.066)	-0.032	(0.038)
Motivation	-0.005	(0.013)	0.002	(0.018)	0.069*	(0.032)	-0.023	(0.041)	0.010	(0.017)
In training	-0.024	(0.014)	-0.007	(0.020)	0.024	(0.029)	0.027	(0.036)	-0.019	(0.014)
IT Skills	0.014	(0.013)	0.034	(0.020)	-0.034	(0.029)	-0.000	(0.039)	0.005	(0.015)
Volunteering	0.016	(0.012)	-0.005	(0.018)	-0.003	(0.025)	0.013	(0.040)	0.037*	(0.016)
Language ad (Neutral)										
Female	-0.015	(0.029)	-0.096*	(0.040)	-0.019	(0.076)	-0.096	(0.070)	-0.086**	(0.033)
Male	0.010	(0.043)	-0.086	(0.047)	0.026	(0.070)	0.124	(0.089)	0.039	(0.055)
Relat. Skills (ad)	-0.039	(0.028)	0.064	(0.035)	0.015	(0.052)	-0.006	(0.054)	-0.037	(0.032)
Motivation (ad)	0.041	(0.029)	-0.011	(0.037)	0.021	(0.047)	-0.099	(0.068)	-0.003	(0.033)

Constant	0.138***	(0.040)	0.155**	(0.060)	0.067	(0.074)	0.323**	(0.107)	0.170**	(0.057)
sigma_u	0.208		0.225		0.241		0.169		0.219	
sigma_e	0.232		0.248		0.240		0.253		0.233	
ICC	0.445		0.452		0.503		0.309		0.469	
N	1532		856		383		221		1087	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12 Gender and immigrant background on callbacks by contract type, Random Effect linear coefficients displayed – Model (15a/b)

	(15a) Temporary		(15b) Long-Term	
	b	se	b	se
Woman	0.036**	(0.014)	0.032	(0.021)
Romanian-Italian (IT_RM)	-0.039**	(0.013)	-0.062**	(0.021)
Employed	-0.047**	(0.018)	-0.009	(0.024)
Duration: Short-term				
Long-term	-0.005	(0.014)	0.015	(0.022)
Order resume	0.002	(0.005)	-0.008	(0.009)
CV style (1)				
CV style 2	-0.017	(0.015)	0.018	(0.023)
CV style 3	-0.020	(0.016)	0.040	(0.025)
CV style 4	-0.007	(0.016)	-0.012	(0.024)
Born - North				
Born - Centre	-0.008	(0.018)	-0.011	(0.029)
Born - South	-0.005	(0.013)	0.018	(0.022)
Unemp (6 months)				
Youth Guarantee	-0.015	(0.016)	-0.042	(0.028)
Intern	-0.010	(0.016)	-0.012	(0.027)
2 job experiences	0.021	(0.011)	-0.010	(0.020)
Big firm	-0.007	(0.011)	0.008	(0.018)
Region (North)				
South	-0.031	(0.033)	-0.005	(0.039)
Center	-0.033	(0.027)	0.013	(0.038)
Covid-19	-0.054*	(0.026)	-0.028	(0.037)
Sector (Admin)				
HR	0.002	(0.052)	-0.088	(0.056)
Market&Social	-0.018	(0.029)	-0.004	(0.046)
Motivation	-0.010	(0.012)	0.014	(0.020)
In training	0.007	(0.011)	0.004	(0.019)
IT Skills	0.002	(0.011)	-0.012	(0.017)
Volunteering	0.020	(0.012)	0.036*	(0.018)
Language ad (Neutral)				
Female	-0.071*	(0.030)	-0.025	(0.037)
Male	-0.073*	(0.032)	0.096	(0.063)
Relat. Skills (ad)	0.032	(0.024)	-0.047	(0.033)
Motivation (ad)	-0.025	(0.024)	0.028	(0.032)
Equal opportunity	-0.013	(0.038)	-0.017	(0.043)

Firm size (Micro)				
Small	-0.002	(0.032)	-0.033	(0.038)
Medium	-0.006	(0.044)	0.078	(0.109)
Large	-0.032	(0.046)	-0.043	(0.036)
NA	0.010	(0.030)	0.023	(0.039)
Constant	0.194***	(0.043)	0.112	(0.065)
sigma_u	0.236		0.174	
sigma_e	0.240		0.238	
ICC	0.490		0.347	
N	1959		733	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13 Gender and immigrant background on callbacks by contract type, Random Effect linear coefficients displayed – Model (15a/c)

	(15a) Temporary		(15b) Temp-Prospects		(15c) Long-Term	
	b	se	b	se	b	se
Woman	0.065**	(0.024)	0.021	(0.017)	0.032	(0.021)
Romanian-Italian (IT_RM)	-0.014	(0.021)	-0.054***	(0.016)	-0.062**	(0.021)
Duration: Short-term						
Employed	-0.018	(0.034)	-0.065**	(0.022)	-0.009	(0.024)
Long-term	-0.021	(0.023)	0.000	(0.017)	0.015	(0.022)
Order resume	0.008	(0.008)	-0.001	(0.006)	-0.008	(0.009)
CV style (1)						
CV style 2	-0.037	(0.026)	-0.007	(0.019)	0.018	(0.023)
CV style 3	-0.043	(0.027)	-0.006	(0.019)	0.040	(0.025)
CV style 4	-0.017	(0.029)	-0.003	(0.019)	-0.012	(0.024)
Born - North						
Born - Centre	-0.051	(0.032)	0.014	(0.023)	-0.011	(0.029)
Born - South	-0.019	(0.021)	0.006	(0.016)	0.018	(0.022)
Unemp (6 months)						
Youth Guarantee	0.000	(0.025)	-0.027	(0.020)	-0.042	(0.028)
Intern	0.028	(0.027)	-0.032	(0.020)	-0.012	(0.027)
2 job experiences	0.033	(0.019)	0.013	(0.014)	-0.010	(0.020)
Big firm	-0.021	(0.018)	-0.002	(0.014)	0.008	(0.018)
Sector (Admin)						
HR	-0.097	(0.067)	0.035	(0.074)	-0.088	(0.056)
Market&Social	-0.032	(0.051)	-0.010	(0.036)	-0.004	(0.046)
Region (North)						
South	-0.040	(0.056)	-0.037	(0.041)	-0.005	(0.039)
Center	-0.013	(0.051)	-0.051	(0.032)	0.013	(0.038)
Covid-19	-0.040	(0.059)	-0.060*	(0.030)	-0.028	(0.037)
Motivation	-0.023	(0.021)	-0.005	(0.015)	0.014	(0.020)
In training	0.008	(0.018)	0.000	(0.014)	0.004	(0.019)
IT Skills	-0.004	(0.018)	0.005	(0.014)	-0.012	(0.017)
Volunteering	0.016	(0.018)	0.025	(0.016)	0.036*	(0.018)
Language ad (Neutral)						
Female	-0.091	(0.055)	-0.056	(0.037)	-0.025	(0.037)
Male	-0.050	(0.052)	-0.087*	(0.041)	0.096	(0.063)
Relat. Skills (ad)	0.013	(0.047)	0.049	(0.028)	-0.047	(0.033)
Motivation (ad)	0.008	(0.047)	-0.039	(0.028)	0.028	(0.032)
Equal opportunity	0.028	(0.056)	-0.031	(0.050)	-0.017	(0.043)

Firm size (Micro)						
Small	-0.027	(0.055)	0.019	(0.040)	-0.033	(0.038)
Medium	-0.006	(0.078)	-0.009	(0.053)	0.078	(0.109)
Large	0.050	(0.082)	-0.068	(0.055)	-0.043	(0.036)
NA	-0.053	(0.056)	0.047	(0.035)	0.023	(0.039)
Constant	0.186*	(0.078)	0.200***	(0.055)	0.112	(0.065)
sigma_u	0.257		0.226		0.174	
sigma_e	0.238		0.241		0.238	
ICC	0.538		0.468		0.347	
N	691		1268		733	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13 Gender and immigrant background on callbacks by qualification required in the job ad, Random Effect linear coefficients displayed – Model (16a/c)

	(16a) =< Diploma		(16b) Diploma or BA		(16c) BA only	
	b	se	b	se	b	se
Woman	0.030	(0.019)	0.076**	(0.029)	-0.028	(0.020)
Romanian-Italian (IT_RM)	-0.058*	(0.023)	-0.034	(0.023)	-0.062**	(0.021)
Employed	0.022	(0.028)	-0.038	(0.036)	-0.066*	(0.031)
Duration: Short-term						
Long-term	0.001	(0.022)	-0.025	(0.025)	-0.005	(0.023)
Order resume	0.008	(0.008)	0.007	(0.009)	0.012	(0.009)
CV style (1)						
CV style 2	0.034	(0.023)	-0.005	(0.030)	0.011	(0.025)
CV style 3	0.017	(0.019)	-0.032	(0.031)	0.001	(0.029)
CV style 4	-0.003	(0.024)	-0.029	(0.030)	0.005	(0.029)
Born - North						
Born - Centre	-0.046	(0.029)	-0.006	(0.030)	-0.012	(0.026)
Born - South	-0.014	(0.023)	-0.015	(0.030)	0.032	(0.022)
Unemp (6 months)						
Youth Guarantee	-0.023	(0.022)	-0.006	(0.026)	0.008	(0.026)
Intern	0.002	(0.028)	0.004	(0.032)	0.029	(0.025)
2 job experiences	-0.003	(0.020)	-0.003	(0.022)	0.004	(0.018)
Big firm	-0.006	(0.020)	0.003	(0.019)	-0.024	(0.018)
Region (North)						
South	0.094	(0.063)	-0.092	(0.055)	0.055	(0.064)
Center	0.071	(0.048)	-0.017	(0.056)	-0.050	(0.046)
Covid-19	-0.046	(0.046)	-0.115**	(0.043)	0.019	(0.056)
Sector (Admin)						
HR	-0.209**	(0.075)	-0.097	(0.056)	-0.085	(0.067)
Market&Social	-0.009	(0.078)	-0.053	(0.067)	-0.097	(0.051)
Motivation	0.001	(0.018)	-0.004	(0.020)	0.026	(0.021)
In training	-0.031	(0.018)	0.037	(0.021)	-0.026	(0.022)
IT Skills	0.023	(0.020)	0.025	(0.024)	0.022	(0.021)
Volunteering	0.023	(0.019)	0.006	(0.021)	0.043*	(0.021)
Language ad (Neutral)						
Female	-0.050	(0.038)	-0.102	(0.053)	-0.128	(0.073)
Male	0.028	(0.079)	-0.046	(0.069)	0.015	(0.058)
Relat. Skills (ad)	-0.010	(0.041)	0.005	(0.048)	-0.025	(0.053)
Motivation (ad)	0.030	(0.040)	0.017	(0.043)	0.061	(0.049)
Equal opportunity	-0.150***	(0.042)	-0.041	(0.051)	0.005	(0.053)

Firm size (Micro)						
Small	0.001	(0.044)	0.049	(0.065)	-0.028	(0.060)
Medium	0.069	(0.101)	-0.017	(0.080)	-0.041	(0.070)
Large	0.119	(0.101)	0.003	(0.101)	-0.059	(0.062)
NA	0.041	(0.053)	-0.055	(0.047)	-0.036	(0.060)
Contract (Temporary)						
Long-Term	-0.026	(0.050)	0.035	(0.063)	-0.090	(0.057)
TBD	-0.062	(0.064)	-0.179*	(0.077)	0.021	(0.077)
Not in job ad	-0.053	(0.046)	-0.045	(0.046)	-0.066	(0.044)
Constant	0.110	(0.062)	0.187*	(0.075)	0.213*	(0.095)
sigma_u	0.237		0.230		0.239	
sigma_e	0.229		0.242		0.255	
ICC	0.516		0.475		0.467	
N	743		591		781	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14 Unemployment duration, gender, and immigrant background on callbacks by macro-region, Random Effect linear coefficients displayed – Model (17a/c)

	(17a) South		(17b) Center		(17c) North	
	b	se	b	se	b	se
Woman	0.077***	(0.020)	0.034	(0.018)	0.017	(0.013)
Romanian-Italian (IT_RM)	-0.038*	(0.018)	-0.032*	(0.015)	-0.052***	(0.013)
Duration: (Short-term)						
Employed	-0.020	(0.028)	-0.042*	(0.021)	-0.025	(0.017)
Long-term	-0.003	(0.020)	0.003	(0.014)	-0.014	(0.013)
resume	-0.003	(0.008)	-0.004	(0.006)	0.004	(0.005)
CV style (1)						
CV style 2	-0.018	(0.022)	-0.009	(0.019)	0.008	(0.015)
CV style 3	-0.001	(0.023)	0.001	(0.019)	-0.006	(0.015)
CV style 4	-0.009	(0.024)	0.015	(0.019)	-0.019	(0.015)
Born - North						
Born - Centre	-0.039	(0.026)	-0.022	(0.018)	-0.000	(0.018)
Born - South	0.011	(0.022)	0.010	(0.016)	-0.005	(0.013)
Unemp (6 months)						
Youth Guarantee	-0.019	(0.025)	-0.020	(0.019)	-0.009	(0.014)
Intern	-0.035	(0.020)	-0.022	(0.019)	0.018	(0.016)
2 job experiences	0.010	(0.017)	0.006	(0.015)	0.013	(0.011)
Big firm	-0.038*	(0.016)	0.011	(0.013)	0.002	(0.011)
Sector (Admin)						
HR	0.044	(0.091)	-0.077	(0.043)	-0.041	(0.055)
Market&Social	0.126*	(0.055)	0.028	(0.038)	-0.083***	(0.025)
Covid-19	0.098	(0.052)	-0.044	(0.027)	-0.061**	(0.023)
Motivation	0.016	(0.019)	0.028	(0.015)	-0.008	(0.011)
In training	-0.029	(0.018)	-0.014	(0.014)	0.001	(0.011)
IT Skills	-0.021	(0.019)	0.007	(0.015)	0.014	(0.011)
Volunteering	0.013	(0.016)	0.036**	(0.013)	0.013	(0.011)
Language ad (Neutral)						
Female	-0.004	(0.047)	-0.049	(0.029)	-0.056*	(0.026)
Male	0.078	(0.054)	-0.100***	(0.030)	0.011	(0.038)
Relat. Skills (ad)	0.020	(0.044)	-0.009	(0.025)	-0.011	(0.023)
Motivation (ad)	-0.028	(0.040)	0.012	(0.028)	0.018	(0.023)
Equal opportunity	-0.005	(0.057)	-0.085**	(0.031)	-0.035	(0.033)
Firm size (Micro)						
Small	0.043	(0.060)	0.039	(0.033)	-0.022	(0.028)
Medium	-0.050	(0.074)	0.119	(0.067)	-0.028	(0.035)

Large	-0.097*	(0.047)	0.065	(0.066)	-0.022	(0.045)
NA	-0.043	(0.043)	0.051	(0.030)	0.001	(0.028)
Contract (Temporary)						
Long-Term	-0.019	(0.044)	0.014	(0.035)	-0.037	(0.026)
TBD	0.039	(0.083)	-0.020	(0.084)	-0.025	(0.051)
Not in job ad	0.070	(0.049)	-0.011	(0.029)	-0.039	(0.024)
Qualification (No BA)						
High-BA	-0.035	(0.069)	-0.036	(0.047)	0.071*	(0.031)
Msc	-0.153	(0.099)	-0.057	(0.041)	0.084	(0.144)
Not in job ad	-0.100	(0.063)	-0.058	(0.042)	0.018	(0.027)
Constant	0.156	(0.096)	0.133*	(0.066)	0.153***	(0.039)
sigma_u	0.246		0.195		0.198	
sigma_e	0.231		0.218		0.244	
ICC	0.533		0.444		0.397	
N	828		1152		2099	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15 Unemployment duration, gender, and immigrant background on callbacks by COVID-19, Random Effect linear coefficients displayed – Model (18a/b)

	(18a) Before		(18b) After	
	b	se	b	se
Woman	0.032**	(0.011)	0.033*	(0.015)
Romanian-Italian (IT_RM)	-0.045***	(0.010)	-0.039**	(0.015)
Duration: Short-term				
Employed	-0.026	(0.014)	-0.041	(0.021)
Long-term	-0.009	(0.011)	0.001	(0.014)
resume	0.001	(0.004)	-0.001	(0.006)
CV style (1)				
CV style 2	0.003	(0.012)	-0.013	(0.017)
CV style 3	-0.005	(0.013)	0.004	(0.018)
CV style 4	-0.003	(0.013)	-0.016	(0.017)
Born - North				
Born - Centre	-0.020	(0.014)	0.002	(0.021)
Born - South	0.004	(0.011)	-0.000	(0.018)
Unemp (6 months)				
Youth Guarantee	-0.016	(0.012)	-0.007	(0.018)
Intern	0.005	(0.013)	-0.025	(0.016)
2 job experiences	0.018	(0.010)	-0.005	(0.011)
Big firm	-0.004	(0.009)	0.004	(0.012)
Sector (Admin)				
HR	-0.060	(0.034)	0.121	(0.109)
Market&Social	-0.011	(0.024)	-0.009	(0.032)
Region (South)				
Center	-0.021	(0.025)	-0.076	(0.049)
North	-0.001	(0.025)	-0.073	(0.047)
Motivation	0.001	(0.010)	0.022	(0.015)
In training	-0.006	(0.010)	-0.017	(0.013)
IT Skills	0.012	(0.010)	-0.007	(0.014)
Volunteering	0.023*	(0.009)	0.002	(0.015)
Language ad (Neutral)				
Female	-0.047*	(0.022)	-0.034	(0.031)
Male	-0.014	(0.025)	0.095	(0.102)
Relat. Skills (ad)	-0.008	(0.020)	0.001	(0.025)
Motivation (ad)	0.002	(0.020)	0.027	(0.028)
Equal opportunity	-0.050*	(0.023)	0.017	(0.059)
Firm size (Micro)				

Small	0.008	(0.024)	-0.021	(0.038)
Medium	0.005	(0.034)	-0.070	(0.051)
Large	-0.006	(0.039)	-0.066	(0.047)
NA	0.001	(0.023)	0.000	(0.033)
Contract (Temporary)				
Long-Term	-0.024	(0.025)	-0.013	(0.032)
TBD	-0.035	(0.040)	0.277*	(0.109)
Not in job ad	-0.028	(0.020)	0.003	(0.036)
Qualifications (No BA)				
High-BA	0.026	(0.029)	0.014	(0.046)
Msc	-0.120***	(0.033)	0.172	(0.171)
Not in job ad	-0.028	(0.026)	0.004	(0.040)
Constant	0.164***	(0.045)	0.162*	(0.066)
sigma_u	0.212		0.197	
sigma_e	0.246		0.198	
ICC	0.426		0.497	
N	3028		1051	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16 Interaction of Unemployment duration and gender on callbacks, Random Effect linear coefficients displayed – Model (19)

	b	se
Romanian-Italian (IT_RM)	-0.044***	(0.009)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.012	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.004	(0.011)
2 job experiences	0.013	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.028	(0.036)
Market&Social	-0.016	(0.020)
Region (North)		
South	0.025	(0.022)
Center	-0.011	(0.017)
Covid-19	-0.029	(0.017)
Motivation	0.006	(0.008)
In training	-0.010	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)		
Female	-0.042*	(0.018)
Male	0.000	(0.024)
Relat. Skills (ad)	-0.011	(0.016)
Motivation (ad)	0.004	(0.016)
Equal opportunity	-0.037	(0.022)
Firm size (Micro)		
Small	0.003	(0.021)
Medium	-0.013	(0.030)
Large	-0.019	(0.032)
NA	0.006	(0.019)

Contract (Temporary)		
Long-Term	-0.022	(0.019)
TBD	-0.004	(0.039)
Not in job ad	-0.016	(0.018)
Qualifications (No BA)		
High-BA	0.022	(0.024)
Msc	-0.034	(0.064)
Not in job ad	-0.020	(0.022)
Man	-0.027*	(0.012)
Duration: Long-term		
Employed	-0.004	(0.018)
Short-term	0.009	(0.013)
Man * Employed	-0.037	(0.026)
Man * Short-term	-0.005	(0.018)
Constant	0.164***	(0.035)
sigma_u	0.209	
sigma_e	0.234	
ICC	0.443	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17 Interaction of Unemployment duration and immigrant background on callbacks, Random Effect linear coefficients displayed – Model (20)

	b	se
Woman	0.033***	(0.009)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.008	(0.011)
Born - North		
Born - Centre	-0.013	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.004	(0.011)
2 job experiences	0.013	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.027	(0.036)
Market&Social	-0.016	(0.020)
info_comp	0.029	(0.017)
South	0.025	(0.022)
Center	-0.011	(0.017)
Region (North)		
Covid-19	-0.029	(0.017)
Motivation	0.006	(0.008)
In training	-0.009	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)		
Female	-0.042*	(0.018)
Male	0.000	(0.024)
Relat. Skills (ad)	-0.011	(0.016)
Motivation (ad)	0.004	(0.016)
Equal opportunity	-0.038	(0.022)
Firm size (Micro)		
Small	0.002	(0.021)
Medium	-0.013	(0.030)
Large	-0.020	(0.032)

NA	0.006	(0.019)
Contract (Temporary)		
Long-Term	-0.022	(0.019)
TBD	-0.004	(0.040)
Not in job ad	-0.016	(0.018)
Qualifications (No BA)		
High-BA	0.022	(0.024)
Msc	-0.034	(0.064)
Not in job ad	-0.020	(0.022)
Romanian-Italian (IT_RM)	-0.047***	(0.012)
Duration: Long-term		
Employed	-0.034**	(0.013)
Short-term	0.007	(0.011)
IT_RM * Employed	0.036	(0.026)
IT_RM * Short-term	-0.002	(0.019)
Constant	0.136***	(0.034)
sigma_u	0.209	
sigma_e	0.235	
ICC	0.444	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18 Interaction of gender and immigrant background on callbacks, Random Effect linear coefficients displayed – Model (21)

	b	se
Duration: Short-term		
Employed	-0.029*	(0.012)
Long-term	-0.007	(0.009)
Man	-0.041***	(0.011)
Romanian-Italian (IT_RM)	-0.057***	(0.013)
Man * IT_RM	0.027	(0.018)
Order resume	0.001	(0.003)
CV style (1)		
CV style 2	-0.002	(0.010)
CV style 3	-0.003	(0.010)
CV style 4	-0.007	(0.011)
Born - North		
Born - Centre	-0.012	(0.012)
Born - South	0.004	(0.009)
Unemp (6 months)		
Youth Guarantee	-0.015	(0.010)
Intern	-0.003	(0.011)
2 job experiences	0.012	(0.008)
Big firm	-0.002	(0.007)
Sector (Admin)		
HR	-0.028	(0.036)
Market&Social	-0.016	(0.020)
Region (North)		
South	0.025	(0.022)
Center	-0.011	(0.017)
Covid-19	-0.029	(0.017)
Motivation	0.006	(0.008)
In training	-0.009	(0.008)
IT Skills	0.006	(0.008)
Volunteering	0.018*	(0.008)
Language ad (Neutral)		
Female	-0.042*	(0.018)
Male	0.000	(0.024)
Relat. Skills (ad)	-0.011	(0.016)
Motivation (ad)	0.004	(0.016)
Equal opportunity	-0.038	(0.022)

Firm size (Micro)		
Small	0.002	(0.021)
Medium	-0.014	(0.030)
Large	-0.020	(0.032)
NA	0.005	(0.019)
Contract (Temporary)		
Long-Term	-0.021	(0.019)
TBD	-0.003	(0.039)
Not in job ad	-0.016	(0.018)
Qualifications (No BA)		
High-BA	0.021	(0.024)
Msc	-0.033	(0.063)
Not in job ad	-0.021	(0.022)
Constant	0.177^{***}	(0.034)
sigma_u	0.209	
sigma_e	0.234	
ICC	0.443	
N	4079	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19 Interaction of unemployment duration and immigrant background on callbacks by gender, Random Effect linear coefficients displayed – Model (22a/b)

	(22a) women		(22b) men	
	b	se	b	se
Order resume	0.000	(0.005)	0.001	(0.005)
CV style (1)				
CV style 2	-0.003	(0.015)	-0.019	(0.014)
CV style 3	-0.004	(0.016)	-0.014	(0.015)
CV style 4	-0.017	(0.016)	-0.013	(0.015)
Born - North				
Born - Centre	-0.003	(0.018)	-0.019	(0.016)
Born - South	0.005	(0.014)	0.010	(0.013)
Unemp (6 months)				
Youth Guarantee	-0.006	(0.015)	-0.007	(0.014)
Intern	0.006	(0.016)	-0.001	(0.014)
2 job experiences	0.016	(0.012)	0.005	(0.011)
Big firm	-0.010	(0.012)	-0.006	(0.010)
Sector (Admin)				
HR	-0.025	(0.041)	-0.040	(0.039)
Market&Social	-0.014	(0.025)	-0.028	(0.022)
Region (North)				
South	0.061*	(0.028)	-0.006	(0.023)
Center	-0.001	(0.022)	-0.020	(0.019)
Covid-19	-0.025	(0.022)	-0.032	(0.018)
Motivation	0.012	(0.013)	-0.003	(0.011)
In training	-0.008	(0.012)	-0.014	(0.011)
IT Skills	0.003	(0.012)	0.006	(0.012)
Volunteering	0.011	(0.013)	0.027*	(0.011)
Language ad (Neutral)				
Female	-0.026	(0.024)	-0.052**	(0.020)
Male	-0.021	(0.030)	0.020	(0.028)
Relat. Skills (ad)	-0.017	(0.021)	-0.002	(0.018)
Motivation (ad)	-0.001	(0.022)	0.011	(0.018)
Equal opportunity	-0.055*	(0.027)	-0.018	(0.026)
Firm size (Micro)				
Small	0.010	(0.028)	-0.006	(0.022)
Medium	-0.031	(0.039)	-0.010	(0.030)
Large	-0.031	(0.041)	-0.010	(0.037)
NA	-0.022	(0.023)	0.016	(0.022)

Contract (Temporary)				
Long-Term	-0.038	(0.025)	-0.022	(0.021)
TBD	0.017	(0.055)	-0.035	(0.042)
Not in job ad	-0.036	(0.022)	-0.009	(0.020)
Qualifications (No BA)				
High-BA	0.016	(0.030)	0.027	(0.027)
Msc	-0.026	(0.081)	-0.090**	(0.033)
Not in job ad	-0.017	(0.027)	-0.020	(0.024)
Duration: Long-term				
Employed	-0.018	(0.023)	-0.031	(0.019)
Short-term	0.005	(0.018)	0.003	(0.015)
Romanian-Italian (IT_RM)	-0.068***	(0.019)	-0.030	(0.017)
Employed * IT_RM	0.045	(0.038)	0.025	(0.035)
Short-term * IT_RM	0.010	(0.029)	0.005	(0.028)
Constant	0.162***	(0.046)	0.138**	(0.043)
sigma_u	0.242		0.211	
sigma_e	0.233		0.208	
ICC	0.519		0.507	
N	2063		2016	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex H: Multiple Hypothesis Testing: accounting for familywise error rate

Table 1. Multiple Hypothesis Testing: model and adjusted p-values of coefficients, H.1-H.4a/b (Duration Dependence)

Hypothesis	*Sub-Sample*	*Coefficient*	*Model p-value*	*Romano-Wolf p-value*
H.1 Employers are more likely to consider applications from candidates in short-term unemployment than from those with a job or in long-term unemployment.	-	Employed	0.0135	0.010
		Long-Term	0.479	0.755
H.2 Under urgency, the difference in employers' callbacks between applicants in short-term unemployment vis-à-vis those in long-term unemployment is larger than when employers are not as time constrained	-	Long-Term	0.958	0.962
		Employed	0.023	0.021
		Long-Term * Urgent	0.029	0.024
		Employed * Urgent	0.756	0.962
H.3 Employers who set motivation and commitment to work as a job requirement are less likely than those who do not call back applicants in long-term unemployment.	*Long-Term Unemployment*	Motivation in job ad (Yes)	0.422	0.713
H.4a/b Employers who (do not) set motivation and commitment to work as a job requirement are less (more) likely to consider applicants with long unemployment duration who (do not) provide evidence that they meet this requirement than applicants with the same duration (with) but no information on motivation	*Motivation in job ad (Yes) & long-term unemployment*	Motivation in Resume (Yes)	0.059	0.072
		Volunteering in Resume (Yes)	0.774	0.962

Table 2. Multiple Hypothesis Testing: model and adjusted p-values of coefficients, H.5-H.8 (Discrimination)

Hypothesis	*Coefficient*	*Sub-sample*	*Model p-value*	*Romano-Wolf p-value*
H.5: Employers' differential treatment stems from bias rather than a lack of information	Romanian-Italian	-	0.000	0.001
	Woman	-	0.000	0.004
H.6: Employers are more likely to call back women than men for jobs that are expected to be women's jobs. When jobs have no clear gender connotations, employers are more likely to consider men than women.	Woman	*Admin jobs*	0.002	0.005
		Human Resources	0.299	0.787
		Marketing	**0.085**	**0.295**
		Neutral language	0.009	0.015
		Female-oriented	0.000	0.004
		Male-oriented	0.967	0.997
H.7: Employers emphasizing communication and relational skills in job descriptions are less likely than employers who do not mention these requirements to consider applications from those with an immigrant background than those from native workers.	Romanian-Italian		0.000	0.004
	Soft Skills (Job ad)	-	0.982	0.997
	Interaction		0.669	0.974
H.8: Employers emphasizing motivation in job descriptions are less likely than employers who do not mention these requirements to consider applications from women and those with an immigrant background than men and native workers.	Woman		0.001	0.004
	Motivation (Job ad)	-	0.189	0.537
	Interaction		0.552	0.974
	Romanian-Italian		0.000	0.004
	Motivation (Job ad)	-	0.158	0.465
	Interaction		0.111	0.377

Table 3. Multiple Hypothesis Testing: model and adjusted p-values of coefficients, H.9-H.11 (Discrimination)

Hypothesis	*Sub-sample*	*Coefficient*	*Model p-value*	*Romano-Wolf p-value*
H.9: Employers using formal hiring procedures are as likely to consider men and women, as well as applicants regardless of their immigrant background	*Firm size: Micro*	Woman	0.002	0.005
		Romanian-Italian	0.004	0.007
	Small	Woman	0.029	0.097
		Romanian-Italian	0.003	0.005
	Medium	Woman	0.539	0.974
		Romanian-Italian	0.031	0.097
	Large	Woman	0.684	0.974
		Romanian-Italian	**0.057**	**0.193**
	Unknown	Woman	0.525	0.999
		Romanian-Italian	0.000	0.003
H.10: Employers offering short-term jobs call back at higher rates women and workers with an immigrant background than men and native workers, and vice versa if they offer long-term jobs.	*Type of Contract: Temporary*	Woman	0.008	0.013
		Romanian-Italian	0.002	0.005
	Long-Term	Woman	0.131	0.412
		Romanian-Italian	0.004	0.007
H.11 Employers are more likely to call back women and workers with an immigrant background compared to men and native workers when applicants' skills are slightly above those needed for the job.	*Qualification: Diploma (Max)*	Woman	0.120	0.403
		Romanian-Italian	0.013	0.032
	Diploma or BA	Woman	0.009	0.015
		Romanian-Italian	0.140	0.433
	At least BA	Woman	0.163	0.476
		Romanian-Italian	0.004	0.007

Table 4. Multiple Hypothesis Testing: model and adjusted p-values of coefficients, H.12a/b (Labour market status) and COVID-19

Hypothesis	*Sub-Sample*	*Coefficient*	*Model p-value*	*Romano-Wolf p-value*
H.12a Duration dependence and discrimination are higher in tight labour markets, and vice versa in slack labour markets, as per screening models. *H.12b Duration dependence and discrimination are lower in tight labour markets, and vice versa in slack labour markets, as per ranking models and status framework.*	*South*	Employed	0.468	0.791
		Long-Term	0.899	0.989
		Romanian-Italian	0.030	0.058
		Woman	0.000	0.001
	Center	Employed	0.044	0.099
		Long-Term	0.822	0.988
		Romanian-Italian	0.041	0.091
		Woman	**0.055**	**0.117**
	North	Employed	0.133	0.289
		Long-Term	0.271	0.563
		Romanian-Italian	0.000	0.001
		Woman	0.177	0.372
-	*Lockdown*	**Employed**	**0.059**	**0.117**
		Long-Term	0.384	0.727
		Romanian-Italian	0.000	0.001
		Woman	0.004	0.005
	No Lockdown	**Employed**	**0.058**	**0.117**
		Long-Term	0.930	0.989
		Romanian-Italian	0.009	0.016
		Woman	0.027	0.057

Table 5. Multiple Hypothesis Testing: model and adjusted p-values of coefficients, Section 6.5 (Intersectionality)

Sub-Sample	*Coefficient*	*Model p-value*	*Romano-Wolf p-value*
-	Employed	0.013	0.015
	Long-Term	0.433	0.905
	Romanian-Italian	0.000	0.001
	Woman	0.000	0.001
-	Employed	0.003	0.003
	Long-Term	0.501	0.949
	Romanian-Italian	0.001	0.001
	Romanian-Italian*Long-Term	0.894	0.994
	Romanian-Italian*Employed	0.171	0.477
-	Employed	0.006	0.006
	Long-Term	0.718	0.994
	Woman	0.026	0.044
	Woman*Long-Term	0.781	0.994
	Woman*Employed	0.227	0.628
-	Romanian-Italian	0.013	0.015
	Woman	0.000	0.001
	Romanian-Italian*Woman	0.122	0.344
Men	**Employed**	**0.081**	**0.204**
	Long-Term	0.814	0.994
	Romanian-Italian	0.234	0.628
	Romanian-Italian*Employed	0.607	0.986
	Romanian-Italian*Long-Term	0.857	0.994
Women	Employed	0.332	0.823
	Long-Term	0.774	0.994
	Romanian-Italian	0.007	0.008
	Romanian-Italian*Employed	0.383	0.881
	Romanian-Italian*Long-Term	0.722	0.994

Annex I: Ethics committee deliberation

European University Institute

Florence, 14 November 2018

To whom it may concern

It is a pleasure to state that the Ethics Committee at the European University Institute has reviewed the project description and documents presented by Mr. Mario Spiezio, doctoral researcher at the Department of Political and Social Sciences, for an Ethics Review for his research experiment under the supervision of Professor Klarita Gërxhani. The research experiment/project is titled: "The Role of Long-Term Unemployment in the Hiring Process: Evidence from a correspondence study in Italy."

After due consideration, the Ethics Committee is happy to state that the project description and design of the experiment comply with the rules, norms and values of the "EUI- Code of Ethics in Academic Research."

Sincerely;

Prof. Martin Scheinin
Chair of the Ethics Committee
Dean of Graduate Studies

Annex L: Gendered Language in job ads. Examples.

a. Gender Neutral

In the following job ad, the employer never refers to the prospective candidate using either male or female nouns and adjectives. Instead, the employer uses words such as “risorsa”, “persona”, or “figura”, which o not specify the gender of the ideal prospective employee. Some details regarding the tasks to be performed and the firm have been omitted to avoid identification of the employer. This approach is also followed for the job description with female-oriented and neutral language.

Supporto contabilità

che abbia voglia di mettersi in gioco in un contesto sfidante e in rapida crescita.

Stiamo cercando una nuova persona che possa unirsi al team ed abbia voglia di confrontarsi con le principali attività di tipiche del lavoro.

Cerchiamo una risorsa che sia diplomato in ragioneria o Amministrazione Finanza e Controllo e/o laureato in ambito economico e finanziario e ha un’ottima padronanza di tutto il Pacchetto Office (in particolare Excel).

Siamo diversi: il contesto è particolare, sfidante, giovane, energico, creativo.

Viene richiesto impegno, professionalità, rispetto dei tempi di consegna, precisione e ci aspettiamo che la figura sia in grado di prendersi in carico via via responsabilità crescenti.

Stiamo cercando una persona disponibile per un part-time da 30 ore settimanali.

***Si offre**: Tipologia contratto, livello e retribuzione in base all’esperienza nel ruolo*

***Partenza**: ASAP*

b. Female-Oriented

This job ad has been categorized as female-oriented given that the employer specifies in the job title that the prospective employee should be a woman. The gender of the name and nous are feminine, namely “Impiegata Amministrativa”. This is then repeated when the job ad describes the task that the administrative assistant should perform.

Impiegata amministrativa

DETTAGLI

Azienda: xxx

Contratto: ***Tempo indeterminato***

Disponibilità: ***Full time***

*Sede di lavoro:****xxx***

DESCRIZIONE

L'impiegata *si dovrà occupare di:*
- Inserimento note di lavorazione

- xxxx

Si richiede:
- Laurea in discipline economiche o ingegneria
- xxx

- xxx

Si offre:
- Inserimento in azienda con contratto CCNL Studi Professionali

- xxxxx

c. Male-Oriented

This job ad has been categorized as male-oriented given that the employer specifies in the job title that the prospective employee should be a man. The gender of the name and nous are feminine, namely "Impiegato Amministrativo". This is then repeated several times throughout the job ad.

Impiegato amministrativo

Tempo pieno, Tempo determinato

Azienda con sede in xxx, operante nel settore xx, ricerca impiegato amministrazione personale. Le principali responsabilità dell'impiegato saranno:

- *Raccolta documentazione xxxx*
- *xxxx*
- *xxxxx*

L'impiegato dovra' possedere:

- *Competenza generale in materia di amministrazione del personale*
- *xx*
- *xx*

Si offre contratto full time a tempo determinato con possibilità di rinnovo