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Essays in Discrimination and Inequality

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Abstract

This dissertation focuses on discrimination and inequality. The first chapter uses a large-scale randomized audit study to investigate whether socioemotional skills are valuable for employers in the hiring stage, and whether the signaling of socioemotional CVs can help women in getting hired. The unique dataset we collect allows us to differentiate the different processes in screening: long list, short list, and interview invitation. The findings suggest that a small percentage of employers filter out male candidates when they make a long list, and no gender discrimination occurs after this initial stage of filtering, including the stage when employers decide who to invite for an interview. Employers value socioemotional skill signals positively only when they specifically ask for them. On the other hand, they evaluate the socioemotional skills signals negatively when they do not specifically ask for them, but this holds only for female candidates. Using a discrete choice experiment, the second chapter focuses on how to signal socioemotional skills in CVs, and finds that socioemotional skills in CVs are valuable to employers in the hiring stage, but only when signaled through costly activities rather than adjectives. By means of a laboratory experiment, the focus of the final chapter is a different question, on inequality and its consequences on disruptive behavior. We investigate how the unequal distribution of monetary payoffs can trigger disruptive behavior against people with whom there is no previous or expected future contact. We compare an environment in which reducing inequality is safe for the rich with one in which reducing inequality puts the rich in a vulnerable position, and we find that inequality triggers the poor's disruptive behavior towards rich strangers. Moreover, the experience of the same level of inequality leads to a higher degree of frustration and disruptive behavior among the poor, when the rich can safely reduce inequality. This behavioral change is driven by a change in the poor's expectations on the behavior of the rich, which are more optimistic compared to the case in which the rich are in a vulnerable position.

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Chapter 1

Gender Discrimination and Socioemotional Skills: An Experiment

This chapter is based on joint work with Stefan Hut, Victoria Levin and Ana Maria Munoz Boudet.[1]

Are socioemotional skill signals in CVs important in employers' hiring decisions? A vast literature shows the importance of socioemotional skills in earnings or employment, but whether they matter in getting hired remains unanswered. This study seeks to answer this question, and further investigates whether socioemotional signals have the same value for male and female candidates. In a large-scale randomized audit study, we use an online job portal to send fictitious CVs to real job openings, and collect a unique dataset that enables us to investigate different stages of candidate screening. We find that a small percentage of employers filter out male candidates when they make a long list, and no gender discrimination occurs after this initial stage of filtering, including the stage when employers decide who to invite for an interview. We also find that employers value socioemotional skill signals positively only when they specifically ask for them. On the other hand, they evaluate the socioemotional skills signals negatively when they do not specifically ask for them, but this holds only for female candidates.

JEL classification: *J71, C93, J24*

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1.1 Introduction

Do socioemotional skill signals in CVs play a role in employers' hiring decisions? A vast literature shows the importance of socioemotional skills in labor market outcomes in the form of earnings or employment, but whether signals of these skills matter in getting hired remains unanswered. Suppose that a young graduate is looking for a job, and comes across a vacancy ad with a requirement of, say, teamwork skills, listed along with other requirements such as education and experience. Should she include a signal demonstrating she has strong teamwork skills, along with the schools she graduated from, and the jobs she worked at? Furthermore, does the answer to this question change according to the gender of the young graduate? This study seeks to provide answers to these questions.

Economics literature has firmly established that socioemotional skills are valuable in the labor market, but whether they are important in getting hired remains unanswered. Numerous studies show the possession of socioemotional skills has a positive impact on lifetime earnings (e.g., Cameron and Heckman, 1993; Heckman and Rubinstein, 2001; Bowles et al., 2001a,b; Heckman et al., 2006; Cunha et al., 2006; Cunha and Heckman, 2008). It is also quite common to see socioemotional skills requirements in vacancy ads, and online job search websites recommend job seekers to include some aspect of socioemotional skills in their CVs. On the other hand, the usefulness of this advice is not proven as it is not known whether including socioemotional skill signals in CVs actually help candidates in securing an interview - if these signals are not credible, it might even hurt the applicant by signaling an attempt to oversell oneself. Evidence from the literature is scarce and indirect (e.g., the effect of volunteering activities as studied in Baert and Vujić, 2018), with Piopiunik et al. (2018) among the first studies to provide evidence that socioemotional skills may matter for employers when they evaluate the candidates, although the evidence is collected using an unincentivized survey with hypothetical CVs. Even if employers do consider socioemotional skills important during hiring, where employers can get the relevant information on the candidate's level in terms of her socioemotional skillsremains unanswered: While they can rely on educational attainment or technical certifications of prospective workers as signals of cognitive and technical skills, socioemotional skills are more difficult for employers to assess and for job seekers to signal.

A more important dimension where the literature would stay silent in helping a candidate in signaling socioemotional skills is telling her what kind of skills to signal and how, largely as a result of the vagueness in the definition of, and the difficulty in measuring socioemotional skills. There is still no consensus on the definition or the name: "soft skills", "personality traits", "non-cognitive skills", "non-cognitive abilities", "character", and "socioemotional skills" are all used to identify the personality attributes (Heckman and Kautz, 2012), and in practice, the investigation of certain socioemotional skills in the literature depends heavily on data availability (Brunello and Schlotter, 2011). Perhaps the most used measure of socioemotional skills is the Big Five personality traits,[2] and many studies find them important in career success (e.g., Boudreau et al., 2001; Seibert, Scott E. and Kraimer, Maria L., 2001; Gelissen and de Graaf, 2006) and earnings (e.g., Nyhus and Pons, 2005; Mueller and Plug, 2006; Heineck and Anger, 2010). Depending on data availability, some studies use more specific measures such as misbehavior in childhood (Segal, 2013), leadership positions or behavioral reports in high school (Kuhn and Weinberger, 2005; Protsch and Solga, 2015), and skills such as locus of control, aggression, and withdrawal (Groves, 2005), but most of these studies use information on skills and labor market outcomes for real individuals, limiting the skills measurements to those acquired before adulthood in order to provide causal estimates for the effect sizes.[3] This is because job experience is not orthogonal to socioemotional skills once the individual has started their career: A person with high teamwork skills might be likely to get a job that requires teamwork, but working in a team would improve teamwork skills as well, making it difficult to disentangle the effect of socioemotional skill from that of job experience. An ideal case study would be the random assignment of socioemotional skills to two identical individuals, which is highly unrealistic to expect in real life.

Our methodology is an experimental one, aiming to replicate the thought exercise of randomly assigning socioemotional skills to two identical individuals. We have a 2x2 design where the first dimension is the existence of socioemotional skills signals in the CV, and the other is gender. For the socioemotional skills treatment, we first carefully define and match socioemotional skills for four different occupational clusters, accounting, marketing, sales and IT, using precise skill requirements from the task definitions in O*NET, the occupation dictionary widely used in labor market research. We experimentally vary the socioemotional skill signals and gender in the CV, apply for a total of 2,687 real job ads using 10,748 CVs. We collect a unique dataset that enables us to investigate different stages of candidate screening.[4] The first stage is on whether the candidate appeared in the list after the employer filtered the candidates using hard criteria (such as gender, education, experience level, etc.). The second stage includes whether the employer clicked on the candidate's profile to view his or her CV, and as in all other similar studies, the final stage includes whether the candidate received an invitation for an interview from the employer. We are thus able to pinpoint at which stage, if any, different CV characteristics including gender and socioemotional skills, come into play during

[2] The Big Five personality traits are: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism.

[3] Apart from Protsch and Solga (2015) which uses an experimental methodology with fictitious CVs.

[4] To our knowledge, the only other study using a similar dataset, albeit with a smaller sample, is Balkan and Cilasun (2018) that investigate whether gender discrimination plays a role in the low female labor force participation in Turkey.

screening.

One particular strength of our design is the matching of occupations and skills, capturing the heterogeneity of skills requirements for each occupation. If the value of socioemotional skills is heterogeneous in occupations, an analysis at the labor market based on one specific aspect of socioemotional skills level would provide biased estimates. In fact, O*NET classifications do point out a difference in daily tasks of each occupation, and hence the required socioemotional skills. For example, a financial analyst needs to have attention to detail skills, whereas persuasion is listed for a retail salesperson. In addition to these classifications, conventional job ads also specify the required socioemotional skills along with the tasks expected from the candidate. The limited availability of different dimensions of socioemotional skills makes it difficult for observational studies to capture this heterogeneity, but we solve this weakness with our experimental methodology.

The value of socioemotional skill signals may be particularly important for women, who experience higher rates of joblessness or long-term unemployment in most countries. While there is no consensus on the existence of gender discrimination in hiring (see Bertrand and Duflo, 2017 for a review), there is evidence that the gender wage gap may, to some degree, be explained by the differences in socioemotional skills between men and women (Palomino and Peyrache, 2010; Cobb-Clark and Tan, 2011). Furthermore, gender differences in preferences and actions are important in labor market outcomes. For example, individuals' own perception of "male" traits are linked to entry into male-dominated study-fields and occupations (Antecol and Cobb-Clark, 2010), and there is evidence that women negotiate wages less often compared to men (Babcock and Laschever, 2009). Studies also show women are more risk-averse, less likely to prefer competition, and are less likely to overestimate themselves, whereas men are more overconfident compared to women (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Dohmen and Falk, 2011; Ludwig et al., 2017). These qualities may lead to unfavorable labor market outcomes for women compared to men, not only because women shy away from asking for more favorable outcomes, but also because employers expect them to have less competitive preferences. Signaling their socioemotional skills may thus be a way for women to mitigate employers' potential biases arising from these socially ascribed qualities based on gender. On the other hand, it may be that the same socioemotional skills are valued differently in the labor market for women and men, which may lead to more unfavorable labor market outcomes for women who signal the socioemotional skills that are rewarded for men. To investigate whether including socioemotional skill signals in CVs might help women in job market prospects, we selected a labor market with a traditionally low representation of women. The experiment is run in the two largest cities of Turkey, a labor market characterized by the lowest female labor force participation and among the highest female unemployment rate among the

OECD countries.[5] We consider the high-skilled segment of the Turkish labor market, where women with a university degree form almost a quarter of the total unemployed population in Turkey, although women with a university degree or above makes up less than 7 percent in population.[6]

We find that employers value socioemotional skill signals positively only when they specifically ask for them. On the other hand, they evaluate the socioemotional skills signals negatively when they do not specifically ask for them, but this holds only for female candidates. Our results suggest that socioemotional skill signals in CVs by themselves can only improve labor market outcomes when they are carefully tailored to reflect the socioemotional skills asked in the vacancies; and that they are not useful in improving the labor market outcomes for women, at least in the CV screening stage. We also find a slight preference for women when making the long list, and that gender discrimination does not exist conditional on candidates making it to the long list.

The following section provides the design and the specifics of the collected data, Section 1.3 provides the results, and Section 1.4 concludes the paper.

1.2 Experimental design and data

The experimental design follows the classic design of Bertrand and Mullainathan (2004): we create fictitious CVs and apply for real job ads. All procedures used in the experiment are approved by the IRBs of the Middle East Technical University in Ankara, Turkey and the University of Bologna in Bologna, Italy.

Our treatments are summarized in Table 1.1. We have a 2x2 design where the first dimension is related to whether socioemotional skills are signaled in the CV: In the first dimension, we signal socioemotional skills in treatment CVs explicitly through extracurricular activities (e.g., participating in debate tournaments to signal persuasion skills), in the job description (e.g., by indicating that the candidate persuaded current customers to try new products, thus enabled surpassing targeted sales volume and profit) and in the tagline (as a summary of individual's work experience). The control CVs have neutral text of similar length in the same fields. The second dimension is the gender of the applicant.

Within this design, we first select the details of the labor market we consider, including

[5]According to the OECD statistics, in 2017, Turkey had the third lowest female unemployment rate with 14.4 percent after Greece and Spain; and had the lowest female labor force participation rate with 38 percent.

[6]Source: Calculated using Turkey Household Labor Force Micro Dataset 2016

Table 1.1: Treatments

	No Socioemotional Skills Signal	**Socioemotional Skills Signal**
Male	(C , M)	(T , M)
Female	(C , F)	(T , F)

occupational clusters, location and the job portal we use. We then create control and treatment CVs for fictitious male and female candidates. Using these CVs, we apply for a total of 2,687 vacancies that we collected between June 2017 and January 2018. The sections below outline these procedures.

1.2.1 Labor market

Labor markets

The experiment is conducted in Turkey, where about 32 million people are currently in the labor force. We focus on the two cities with the largest labor markets that make up about 27 percent of the total employed population in Turkey: Istanbul (20 percent) and Ankara (7 percent). Around 40.000 positions are available for Istanbul and Ankara each day on average. Furthermore, we separate Istanbul into two regions, Istanbul-Asia and Istanbul-Europe, since they largely represent two different labor markets in terms of hiring decisions. The European side has the largest labor market in Turkey.

Occupational clusters

The list of occupational clusters we have selected for this experiment is given in Table 1.2. The clusters include financial occupations, retail and sales occupations, as well as technical occupations. This varied set of jobs allows us to draw conclusions about the role of gender and socioemotional skills in the broader labor market and to compare effects across occupations that vary in terms of the type of work done and hence may require and value different skills.

Selection of the specific occupational clusters chosen is based on multiple criteria. The first is the gender composition of occupations: we have selected occupations that do not have extreme shares of females in employment based on data from the Turkish Household Labor Force Survey. We also collected vacancy information from newspapers and online job portals for a period of 3 months, and we filter out occupations that tend to indicate they look for exclusively male or female candidates in the vacancy ad texts in these sources.

Second, we use occupations that have a large pool of vacancies in the online job portal: the four occupational clusters that we select encompass around 65 percent of the total job ads in

Table 1.2: Occupational clusters used in the experiment

Occupational cluster	Socioemotional skill	Share of cluster in total number of vacancy ads	Job search department criteria
Accounting	detail orientation, organization, communication	%9	Accounting Audit Finance
Marketing	dynamic teamwork persuasion	%11	Marketing Business Development
Sales	persuasion networking teamwork	%19	Sales
IT	detail orientation perseverance teamwork	%20	IT Engineering R&D

Note: The shares of females in total number of employed people are prepared using data from the 2015 Household Labor Force Survey. The classification of the data only allows for an analysis based on 2-digit ISCO 08 codes, therefore the shares presented here are not very precise. Average share of cluster in total number of vacancy ads are calculated using the ad counts in the online job portal. Search criteria for the IT cluster included the sector Informatics only.

the online job portal for the geographical regions we consider. Finally, we aim to use clusters that have different socioemotional skills use in their daily tasks, based on the classifications in O*NET and the organizational psychology literature. More information on this final aspect is given in Section 1.2.2.

Job vacancies

We collect the vacancy ads and make our applications using the largest online job portal in Turkey, where around 75 thousand companies and 24 million CVs are registered.

Table 1.2 provides the criteria we used in searching for vacancies. We focus on job vacancies where the minimum required work experience did not exceed 3 years. Our focus on early-career candidates is because socioemotional skills especially in the form of extracurricular activities are arguably more salient in CVs for early-career candidates. On the other hand, for mature candidates, job experience itself may be a strong sign that makes other signals less salient.

In terms of minimum education requirements, we mostly focus on jobs that require a university degree. However, for the jobs in the sales cluster, we also apply for jobs that consider candidates with high school degrees.

1.2.2 Treatments and resume construction

Socioemotional skill signals

The selection of occupation-specific socioemotional skills involved two steps. In the first step, we reviewed the organizational psychology literature and the O*NET occupation descriptors carefully to identify which socioemotional skills are attributed higher importance for the occupations we have selected. O*NET categorizes occupations using one or more of the categories 'Realistic, Investigative, Artistics, Social, Enterprising, Conventional', based on the daily tasks involved in the occupation.[7]

[7] Definitions for these categories are as follows (from www.onetonline.org): *Realistic*: Realistic occupations frequently involve work activities that include practical, hands-on problems and solutions. They often deal with plants, animals, and real-world materials like wood, tools, and machinery. Many of the occupations require working outside, and do not involve a lot of paperwork or working closely with others. *Investigative:* Investigative occupations frequently involve working with ideas, and require an extensive amount of thinking. These occupations can involve searching for facts and figuring out problems mentally. *Artistic:* Artistic occupations frequently involve working with forms, designs and patterns. They often require self-expression and the work can be done without following a clear set of rules. *Social:* Social occupations frequently involve working with, communicating with, and teaching people. These occupations often involve helping or providing service to others. *Enterprising:* Enterprising occupations frequently involve starting up and carrying out projects. These occupations can involve leading people and making many decisions. Sometimes they require risk taking and often deal with business. *Con-*

In the second step, we collaborated with a private company that was about to post two vacancy ads and included our specific socioemotional skills in their ad text. In return, the company provided the research team with (anonymized) CV information, from which we were able to obtain the ways in which candidates signal their socioemotional skills (more information on both steps are provided in Appendix 1.B).

Using the two steps, we can identify and construct realistic socioemotional skills that match the socioemotional skill descriptors in the literature as well as the O*NET. Although a rather long list of socioemotional skills are provided in O*NET, in practice, we select three socioemotional skills for each occupational cluster based on their usage in real CVs. These skills are given in Table 1.2.

We signal all socioemotional skills through activities that are done in the context of tasks at job, or through the extracurricular activities during undergraduate studies. We selected to signal socioemotional skills through activities and not as mere adjectives as a result of a discrete choice experiment conducted with senior undergraduate students of psychology and MBA students, which showed socioemotional skills are salient in the CV, but matter only when signaled through activities and not as mere adjectives. More details on this discrete choice experiment is given in the second chapter of this dissertation.

We include these skills in three different places in the CV: job descriptions within the listed current job experience, through extracurricular activities during undergraduate studies, and in the CV tagline that is shown at the top of the CV on the online job portal. For the job descriptions, we create sentences of neutral job descriptions and alternative sentences for treatment CVs that include socioemotional skill signals, both providing information on the same type of task done at work. For example, for the IT cluster we include four types of tasks that we use to create four sentences of job descriptions: tasks related to server, internet, software or website, and hardware and maintenance. For each of these types of tasks, we create alternative bullets that define the same type of task. For example, the neutral sentence for hardware-related tasks would state "Providing support for technical failures with equipment such as PC, printer or scanner", whereas the sentence that signals teamwork would state "Working as a team in identifying deficiencies and supplying the necessary hardware". We then randomly allocate four neutral sentences to the Control job description, and one neutral sentence and three sentences that signal each of the three socioemotional skills separately to the Treatment job description.

ventional: Conventional occupations frequently involve following set procedures and routines. These occupations can include working with data and details more than with ideas. Usually there is a clear line of authority to follow.

For the extracurricular activities, we benefitted from the way candidates signaled their socioemotional skills in the reverse audit study as well as interviews with human resources personnel and a focus group discussion with university placement directors of two prominent universities in Ankara, Turkey. We generated extracurricular activities from both the real examples and the good practices suggested by the placement directors and the human resources personnel. All extracurricular activities were added to the section Scholarships and projects for the treatment CVs. To keep the CV length compatible and to signal high cognitive skills for our candidates, in the same section we also added a sentence in both control and treatment CVs that indicates the candidate was an honors student in their undergraduate university.

Finally, for the taglines, we create comparable statements regarding the current job of the candidate. For the control versions, we include information that is available in the CV characteristics listed below the tagline, for example, of the form "IT specialist who has an experience of 3 years in solving problems in software, hardware, internet or servers". For the treatment versions instead, we signal at least one socioemotional skill within the tagline as well, such as: "A determined IT specialist who can coordinate with team members to provide detailed solutions to server, internet, software or hardware problems". Examples of alternative job descriptions, taglines and extracurricular activities created in this way are given in Table 1.17 in Appendix 1.C.[8]

While we can randomly assign socioemotional skills to vacancies, the assignment of gender is somewhat more complicated. To ensure comparability across genders, we create duplicate CVs for men and women that have exactly the same information in terms of all background characteristics, except name, photo, contact information and the date of birth. The imposed difference in the latter characteristic is due to most vacancies requiring men to have completed their compulsory military service at time of application: Military service in Turkey lasts for about 6 months, and is compulsory only for men, which means that, since regularly both men and women graduate at the same time of the year, our male and female CVs would have either the same experience level in terms of months, or the same age on average. We selected to have the same experience level and opted to have men who are on average 6 months older than females. How we assign job duration is explained in the next part. When running the analysis, we control for this difference.

[8]Note that the signals used in the experiment are in Turkish. Translations provided are for information purposes.

Background characteristics

The goal in the design of the CVs is to generate CVs that are equivalent except for the treatment variable. We therefore assign the other background characteristics either randomly, or we make it the same for all candidates within the same cluster and/or location.

Job experience

Jobs are assigned randomly from a set of available jobs and positions collected from online sources. We assigned the number of positions held so that 75% of the profiles have two jobs, and 25% have one job.

We assigned the job duration independent from the number of jobs, and by making sure that males and females have the same average experience level. We allowed females and males to graduate at the same time of the year and yet allow all male profiles to have completed the military service. To do this, we used different assignment probabilities of work experience for each gender, and ensure that average work experience for both genders is 3.25 years.[9]

Neighborhood and education

Candidates' residence neighborhoods within cities are selected so that they have similarly large populations (over 100 thousand, close to 1 million in the case of Cankaya in Ankara), and similar ratios of votes for the conservative-religious or the secular political party. This was done so that there are no confounders based on perceptions of political inclination of candidates. High schools are assigned based on neighborhood: We selected high schools that have comparable entry scores in the centralized national high school entry exam. Similarly, for universities, we selected large, established public universities that have at least 25 thousand students. Our candidates are graduates of Computer Engineering for the IT Cluster, and graduates of Business Administration for the remaining clusters. We make sure that, within occupational clusters, departments have similar minimum entry scores at the centralized national university entrance exam; so that the departments are comparable in terms of quality signals.

Photos and beauty

We also needed to include photos for each candidate since there is no regulation against including photos in CVs in Turkey and as a result, over 80 percent of all candidates in the online job portal include photos. The photos used in the experiment are generated using publicly available photos or volunteer face shots of Italian and Turkish males and females aged 22 to 30. The photos collected in this manner were handed over to a graphic designer, who created sets

[9]Note that average years of experience increased during the time between CV creation and job applications. See Table 1.3 for details.

of new photos using combinations of facial features of different photos. None of the photos were exactly the same with the real versions, but pieces of several photos were used to create fictitious photos using Photoshop. The photos obtained were then grouped according to their gender, and then two different measures of beauty and attractiveness were collected for each of the photos: objective and subjective beauty scores. The first measure, objective beauty score, is the attractiveness score based on the face shape, distance between the eyes and lips, mouth size and face symmetry, using the golden ratio where appropriate. This type of measurement, which we call the objective beauty score, is on a scale of 0 to 100. The software at www.prettyscale.com was used for this part.

The objective beauty score depends solely on the placement of facial features without any reference to details such as hair color, color of the eyes and other features that may affect how beautiful the person in the photo is perceived. Moreover, whereas the objective beauty scores do not change according to country, individuals from different countries may have different conceptions of beauty. This is why we also collected data on a second measure that we call the subjective beauty score. These scores are the average beauty scores obtained from the ratings collected through an online survey.[10] We then generated average subjective beauty scores for all photos using the total of 32,676 ratings that we collected through the survey. In selecting the final set of photos, we eliminated those that have extreme scores on either the objective or the subjective measure; and obtained two sets of photos that have no significant difference in mean objective or subjective beauty scores by gender. More details on how we do this is given in Appendix 1.A.

Other signals

All candidates have a advanced level of English, but we vary the levels of listening, speaking, writing and reading randomly between level 4 and 5, the two highest levels in the online job portal.

Computer skills are included only for the IT cluster, where we provide a list of software that is the same for all candidates, but we randomize the order that they are listed.

1.2.3 Data for experimental variables

The online job portal used in this experiment allows us to collect three different layers of information for each applicant. Figure 1.1 provides the details on the screening stages for em-

[10]The link to the survey was distributed through the Twitter accounts of the World Bank Turkey and Economic Policy Research Foundation of Turkey. There was no limitation in access to survey, but both the tweet and the survey itself was in Turkish.

ployers in the online portal. The first stage consists of making the long list. In screening the applicants, member firms can use a filtering stage in which they enter criteria to create a long list of applicants. For each vacancy that a job seeker applied for, the job portal provides information on whether the applicant has made it to this first list. In other words, for each application of all our fictitious applicants, we obtain information on whether the fictitious applicant made it to this long list. We create a variable that captures this information.

After creating the long list, employer starts screening the long list. In this stage, the employer can observe the name, photo, current position and city for all applicants. If interested, employer can click on a CV from the long list to obtain more information on the candidate. The job portal provides this information for each vacancy that a job seeker applied for. In other words, for each application of all our fictitious applicants, we obtain information on whether the fictitious applicant's CV has been clicked on. We create a variable that captures this information as well.

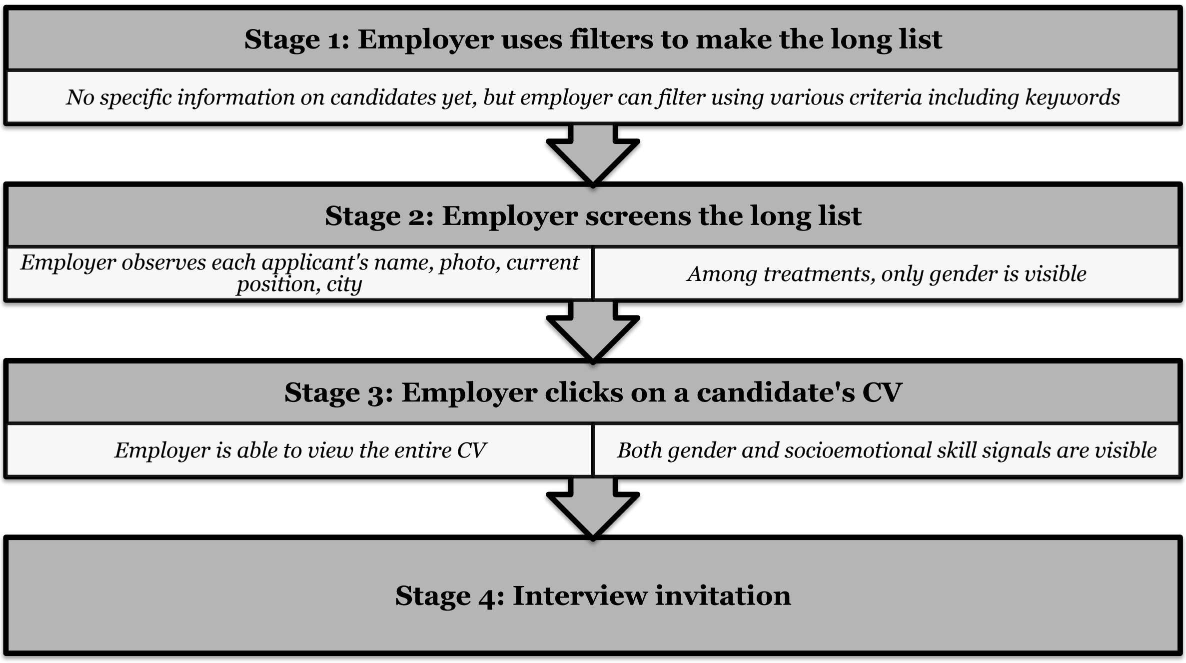
After clicking on the CV and obtaining more information on the candidate, the employer can decide whether to invite the applicant for an interview. Like all similar studies, we collect information on whether our fictitious applicant has received a callback from the firm for an interview. We immediately reject any interview offers and collect this information as a separate variable. Note that, among our treatments, gender is visible to the employer in all of the three stages. On the other hand, they can only view our treatments for socioemotional skills after they click on the profile.

1.3 Results

The results are organized around two main blocks. First, we consider the aggregate effect of gender treatment and differentiate the treatment effect for the three layers of information we obtained through our experiment. We then move to the socioemotional skills treatment and show the aggregate results, as well as differentiating between genders. Table 1.3 provides the descriptive statistics for our sample. About 71% of our applicants made it to the long list, 32% had their CVs clicked on and 6% on average received a callback for an interview. Figure 1.2 provides the distribution of CVs on the three outcome variables.

Our applicants are relatively young (around 26 years old) and all of them have a university degree. Average experience is around 49 months, and 26% of applicants spent all their job experience in one job only. In terms of beauty, 94% of our fictitious applicants are classified to be pretty according to the website's classification (see Appendix A for details). Finally, appli-

Figure 1.1: Employers' screening process after application



cants have around 4.5 on a scale of 0 to 5 for each of speaking, reading and writing in English. In terms of vacancy characteristics, Jobs at the IT cluster are more limited compared to other occupational clusters, with 13% in IT, 30% in sales, 29% in accounting and 28% in marketing. Total application size at time of data collection is 549 on average, but increases to over 30 thousand for some vacancies. 87% of vacancies mention the requirement for a socioemotional skill. Furthermore, most vacancies are from Istanbul Europe region, as expected since the European side of Istanbul is the largest and most complex labor market in Turkey. 31% of vacancies are from the Asian side of Istanbul, and the remaining 18% are from Ankara.

1.3.1 Gender

Table 1.4 provides the balance table for the gender treatment. Female applicants are significantly younger (about 8 months) by design, as explained in Section 1.2. They also have a higher level of experience, although the difference is less than two weeks. Also, 27% of male compared to 24% of female candidates spent all their job experience in one job only. Furthermore, female applicants have higher objective and subjective beauty scores, although these differences are quite small. Accordingly, all results for gender comparisons include these five variables as controls whenever it is possible for the employers to use these variables in their decision (see below for further explanation).

Table 1.3: Descriptive statistics

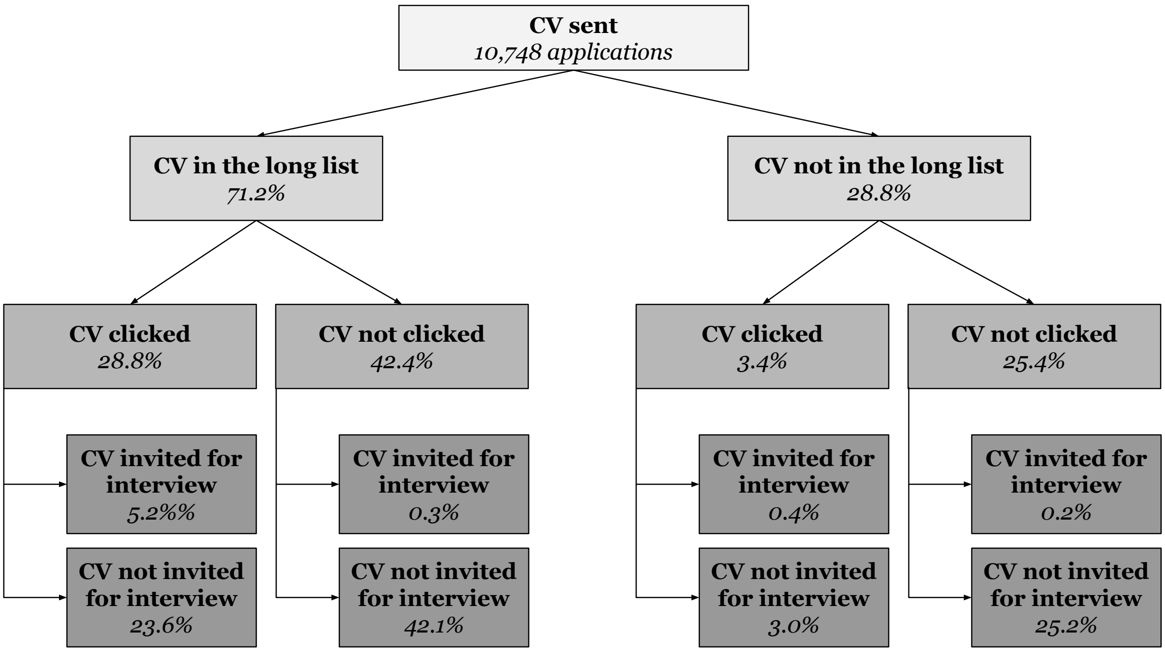
	N	Mean	Std. dev.	Min	Max
Dependent variables					
Applicant in the long list	10748	0.71	0.45	0	1
Applicant profile clicked on	10748	0.32	0.47	0	1
Applicant invited for an interview	10748	0.06	0.24	0	1
Experimental variables					
Female	10748	0.50	0.50	0	1
SES treatment	10748	0.50	0.50	0	1
Resume attributes					
Experience (months)	10748	49.17	5.62	37	61
Age	10748	26.41	0.65	25	28
Worked in one firm only	10748	0.26	0.44	0	1
Objective beauty	10748	0.94	0.23	0	1
Subjective beauty	10748	0.50	0.50	0	1
Speaking	10748	4.52	0.50	4	5
Reading	10748	4.58	0.49	4	5
Writing	10748	4.51	0.50	4	5
Vacancy attributes					
Accounting	10748	0.29	0.45	0	1
Marketing	10748	0.28	0.45	0	1
Sales	10748	0.30	0.46	0	1
IT	10748	0.13	0.33	0	1
Total application size (100)	10748	5.49	9.11	0	302
Signaled SES required in vacancy	10748	0.66	0.47	0	1
Locality attributes					
Ankara	10748	0.18	0.38	0	1
Istanbul Asia	10748	0.31	0.46	0	1
Istanbul EU	10748	0.51	0.50	0	1
Besiktas	10748	0.46	0.50	0	1
Kadikoy	10748	0.31	0.46	0	1
Kagithane	10748	0.05	0.22	0	1
Cankaya	10748	0.18	0.38	0	1

Table 1.4: Balance table for gender treatment

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Istanbul Asia	0.311	0.311	-0.000
	(0.463)	(0.463)	(0.009)
Istanbul EU	0.509	0.509	0.000
	(0.500)	(0.500)	(0.010)
Experience (months)	48.954	49.388	0.434
	(5.578)	(5.651)	(0.108)***
Age	26.767	26.043	-0.725
	(0.561)	(0.509)	(0.010)***
Accounting	0.292	0.292	0.000
	(0.455)	(0.455)	(0.009)
Marketing	0.276	0.276	0.000
	(0.447)	(0.447)	(0.009)
Sales	0.304	0.304	0.000
	(0.460)	(0.460)	(0.009)
IT	0.128	0.128	0.000
	(0.334)	(0.334)	(0.006)
Worked in one firm only	0.270	0.247	-0.023
	(0.444)	(0.431)	(0.008)***
Objective beauty	0.926	0.963	0.037
	(0.262)	(0.189)	(0.004)***
Subjective beauty	0.450	0.549	0.100
	(0.498)	(0.498)	(0.010)***
Reading	4.581	4.574	-0.007
	(0.493)	(0.495)	(0.010)
Speaking	4.520	4.522	0.002
	(0.500)	(0.500)	(0.010)
Writing	4.518	4.508	-0.009
	(0.500)	(0.500)	(0.010)
Besiktas	0.460	0.460	-0.000
	(0.498)	(0.498)	(0.010)
Kadikoy	0.311	0.311	-0.000
	(0.463)	(0.463)	(0.009)
Kagithane	0.050	0.050	0.000
	(0.218)	(0.218)	(0.004)
Cankaya	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Observations	5,374	5,374	10,748

Notes: Standard errors are given in parentheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Figure 1.2: Distribution of CVs on outcome variables



Our first finding indicates that a small share of employers use gender as a filter and are significantly more likely to select female CVs when making their long lists. Employers can create their long list of applicants by entering criteria manually. The criteria can include many variables, including age, gender, experience, city and neighborhood, sector, occupation as well as a keyword search. Note that, when making the long list, employers cannot filter using beauty, for two reasons. First, photos are not visible at this stage. Second, it is simply not possible to enter beauty as a criterion for filtering. This is why we do not use objective and subjective beauty measures as controls for this stage. Furthermore, whether the candidate has worked in one firm only is also not possible to use as a filter at this stage. Table 1.5 provides the results from OLS regressions, using cluster-robust errors at the vacancy level. Models 1 to 6 show that females are 2% to 3% more likely to be in the long list. Although small in magnitude, this systematic difference indicates that employers enter gender as a filter when making their long list and have a preference to include applications from female over male candidates. Model 3 shows that this result does not change according to clusters. Models 4 and 5 show that employers with vacancies that receive high and low number of applications behave similarly. On the other hand, the tendency to filter males out seem to be somewhat less pronounced in Ankara compared to the European side of Istanbul (Model 6). Finally, the models show occupational clusters (in particular accounting) and total application size also affect the probability of passing through the filter and making it to the long list.

Not all employers use the long list as the first stage: 11% of applicant CVs that are clicked

Table 1.5: Determinants of applicant making it to the long list

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.019*	0.019*	0.022**	0.018*	0.021**	0.028**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.012)
Accounting			-0.103***		-0.098***	-0.097***
			(0.022)		(0.022)	(0.022)
Marketing			0.008		0.005	0.005
			(0.021)		(0.021)	(0.021)
IT			0.045*		0.014	0.013
			(0.027)		(0.031)	(0.031)
Istanbul Asia						-0.001
						(0.019)
Ankara						0.015
						(0.023)
Total application size (100)				-0.003**	-0.002**	-0.002**
				(0.001)	(0.001)	(0.001)
Female * Istanbul Asia						-0.010
						(0.007)
Female * Ankara						-0.016*
						(0.009)
Female * Acct			0.005			
			(0.006)			
Female * Mrkt			-0.006			
			(0.005)			
Female * IT			-0.001			
			(0.004)			
Female * Total application size				0.000	0.000	
				(0.000)	(0.000)	
Vacancy and CV sectors match		0.065***		0.061***	0.032	0.033
		(0.019)		(0.019)	(0.021)	(0.021)
Constant	-0.240	-0.245	-0.298	-0.211	-0.267	-0.272
	(0.332)	(0.332)	(0.331)	(0.332)	(0.331)	(0.332)
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	10748	10748	10748	10748	10748	10748
R-squared	0.002	0.004	0.015	0.007	0.017	0.017

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant makes it through the first screening and into the long list. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupation clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Individual characteristics include experience in months and age in years, calculated at time of application. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

on are CVs that are not in the long list. This is why we consider both unconditional regressions and regressions conditional on applicant CV being in the long list when looking at the determinants of what makes an employer click on a CV. Note that in this stage, applicant's photo is visible to the employer, and therefore we control for subjective and objective beauty measures in all models. Unconditional regressions are shown in Table 1.6. A similar result to the case with long list emerges in this case, where female applicants are significantly more likely to be clicked on compared to their male counterparts. On the other hand, this tendency seems to be more a feature for sales and accounting occupations: Model 3 shows that the effect disappears for marketing and IT clusters. While there seems to be no difference in behavior according to local labor markets, models 2, 4, 5 and 6 show that applicants that are in the same sector with the firm opening the vacancy are more likely to be clicked on by the employers. Finally, as the total application size increases, employers presumably have more CVs to go through and the probability of a particular CV being clicked on gets smaller. In these cases, female CVs are slightly less likely to be clicked on (Models 4 and 5).

Table 1.7 shows the determinants of applicant CV being clicked on, this time conditional to the applicant making it to the long list first.[11] Results show that, once they make it to the long list, females and males are equally likely to be clicked on, and factors other than gender, such as the type of occupation, total application size for the vacancy and whether the sector of applicant and firm matches affect click behavior.

We now move to the final component of our analysis for the gender treatment, callbacks for an interview. Note that 8% of our applicants that are invited for an interview are those whose CVs are not clicked on by the employer before, which is why we present our results in this part both unconditionally and conditional on the applicant's CV being clicked. Our findings show no gender difference in being invited for an interview, both unconditionally and conditional on the applicant CV being clicked on. Table 1.8 provides the correspondence table. Overall, around 7.5% of females compared to 4.2% of males are invited for an interview, indicating a preference for female over male candidates. However, this result may be affected by the remaining imbalances, which is why we look at the regression results. Tables 1.9 and 1.10 provide the regression results, both unconditionally and conditional on applicant's CV being clicked on, respectively.[12] Both tables show that there is no significant gender effect in the probability of being invited for an interview. Model 3 in both tables show that the insignificance of gender holds through different occupational clusters, apart from a small positive effect of being female for the sales occupations, significant at 10%, when the regressions are unconditional

[11] Conditional balance tables are provided in Appendix 1.D.
[12] Conditional balance tables are provided in Appendix 1.D.

Table 1.6: Determinants of applicant's CV being clicked on

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.023*	0.023**	0.026**	0.028**	0.031**	0.031**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)
Accounting			-0.124***		-0.122***	-0.121***
			(0.019)		(0.018)	(0.018)
Marketing			-0.064***		-0.074***	-0.074***
			(0.020)		(0.019)	(0.019)
IT			0.208***		0.152***	0.150***
			(0.028)		(0.032)	(0.033)
Istanbul Asia						0.010
						(0.018)
Ankara						0.011
						(0.022)
Total application size (100)				-0.003***	-0.002***	-0.003***
				(0.001)	(0.001)	(0.001)
Female * Istanbul Asia						-0.015
						(0.016)
Female * Ankara						-0.008
						(0.019)
Female * Acct			-0.001			
			(0.009)			
Female * Mrkt			-0.019*			
			(0.010)			
Female * IT			-0.025*			
			(0.015)			
Female * Total application size				-0.001*	-0.001*	
				(0.001)	(0.001)	
Vacancy and CV sectors match		0.200***		0.195***	0.047**	0.047**
		(0.020)		(0.020)	(0.022)	(0.023)
Constant	0.421	0.400	0.398	0.449	0.442	0.430
	(0.317)	(0.313)	(0.309)	(0.311)	(0.308)	(0.310)
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	10748	10748	10748	10748	10748	10748
R-squared	0.001	0.025	0.047	0.030	0.051	0.051

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant's CV is clicked on. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupation clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Individual characteristics include experience in months, age in years, objective and subjective beauty score measures. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.7: Determinants of applicant's CV being clicked on, conditional on applicant making it to the long list

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.016	0.017	0.018	0.022	0.022	0.025
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)
Accounting			-0.096***		-0.092***	-0.091***
			(0.024)		(0.023)	(0.023)
Marketing			-0.063***		-0.071***	-0.071***
			(0.024)		(0.023)	(0.023)
IT			0.238***		0.171***	0.169***
			(0.030)		(0.036)	(0.036)
Istanbul Asia						0.012
						(0.023)
Ankara						0.012
						(0.026)
Total application size (100)				-0.003***	-0.003***	-0.003***
				(0.001)	(0.001)	(0.001)
Female * Istanbul Asia						-0.028
						(0.021)
Female * Ankara						0.001
						(0.025)
Female * Acct			-0.004			
			(0.013)			
Female * Mrkt			-0.017			
			(0.013)			
Female * IT			-0.018			
			(0.017)			
Female * Total application size				-0.001	-0.001	
				(0.001)	(0.001)	
Vacancy and CV sectors match		0.227***		0.221***	0.066**	0.066**
		(0.022)		(0.022)	(0.026)	(0.026)
Constant	0.990**	0.941**	0.972***	1.010***	1.029***	1.028***
	(0.385)	(0.378)	(0.374)	(0.376)	(0.372)	(0.376)
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	7654	7654	7654	7654	7654	7654
R-squared	0.002	0.031	0.048	0.036	0.052	0.052

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant's CV is clicked on. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupation clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Individual characteristics include experience in months, age in years, objective and subjective beauty score measures. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.8: Correspondence table for gender treatment on callbacks for an interview

Equal treatment			Females favored			Males favored		
	Freq.	Percent		Freq.	Percent		Freq.	Percent
0M 0F	2313	86.08	0M 1F	124	4.61	1M 0F	76	2.83
1M 1F	28	1.04	0M 2F	45	1.67	2M 0F	21	0.78
2M 2F	34	1.27	1M 2F	31	1.15	2M 1F	15	0.56
Total	2375	88.39	Total	200	7.44	Total	112	4.17

(Model 3 in Table 1.9). This effect disappears when conditioning on whether the CV is clicked on. On the other hand, although the interaction of female with the accounting cluster has a slightly significant coefficient in both tables, joint significance tests show that the effect for the accounting cluster is not significant, either.

Local labor markets respond differently to our gender treatment: In Istanbul Asia, females are significantly more likely to be invited for an interview, both unconditionally and conditional on their CV being clicked on. Overall, both of Tables 1.9 and 1.10 show that factors other than gender have an effect on the probability of being invited for an interview. Applicants for occupations in accounting and marketing are significantly less likely to be invited for an interview, while the same holds in Istanbul Asia compared to Istanbul Europe.

The findings for the three stages above lead us to the main result of this part:

Result 1. *Employers show their preferences for female applicants when they make their initial long list for screening. Once applicants pass through this first stage, employers do not differentiate between the two genders at least until the interview phase.*

1.3.2 Socioemotional skills

Table 1.11 provides the balance table for our socioemotional skills treatment. Results indicate that randomization has done a fairly good job in generating subsamples that are similar to each other apart from the treatment. In addition, a joint significance test provides an F-statistic of 0.47, implying that variables do not jointly affect the treatment variable.

Our socioemotional skills treatment is visible only when the applicant's CV is clicked. This is why we only consider the treatment effect on callbacks for an interview and not the earlier stages of screening. Table 1.12 shows the results from OLS regressions using cluster-robust standard errors at the vacancy level. Model 1 shows an overall insignificant treatment effect for socio-emotional skills treatment. On the other hand, we get a differential result by interacting the treatment variable with a dummy variable that takes on the value 1 if the vacancy asks for the skill we signal in treatment CVs. Models 2 to 5 show that employers evaluate a

Table 1.9: Determinants of applicant being invited for an interview

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.010	0.010	0.011*	0.010	0.011	0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Vacancy and CV sectors match		0.022**		0.021**	-0.006	-0.007
		(0.010)		(0.010)	(0.012)	(0.012)
Female * Acct			-0.010*			
			(0.005)			
Female * Mrkt			0.001			
			(0.006)			
Female * IT			0.009			
			(0.011)			
Accounting			-0.045***		-0.049***	-0.049***
			(0.009)		(0.009)	(0.009)
Marketing			-0.042***		-0.041***	-0.042***
			(0.010)		(0.009)	(0.009)
IT			0.002		0.011	0.011
			(0.015)		(0.017)	(0.017)
Total application size (100)				-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)
Female * Istanbul Asia						0.016*
						(0.009)
Female * Ankara						-0.007
						(0.012)
Istanbul Asia						-0.015*
						(0.008)
Ankara						-0.002
						(0.011)
Constant	0.391**	0.388**	0.409***	0.394**	0.414***	0.424***
	(0.156)	(0.156)	(0.155)	(0.156)	(0.155)	(0.155)
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	10748	10748	10748	10748	10748	10748
R-squared	0.003	0.004	0.012	0.004	0.012	0.013

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupation clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Individual characteristics include experience in months, age in years, whether the candidate worked in one job only, and objective and subjective beauty score measures. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.10: Determinants of applicant being invited for an interview, conditional on applicant's CV clicked

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.024	0.023	0.023	0.025	0.023	0.008
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)
Vacancy and CV sectors match		-0.029		-0.027	-0.041	-0.041
		(0.019)		(0.019)	(0.028)	(0.027)
Female * Acct			-0.038*			
			(0.020)			
Female * Mrkt			0.014			
			(0.020)			
Female * IT			0.032			
			(0.020)			
Accounting			-0.055**		-0.078***	-0.076***
			(0.028)		(0.025)	(0.025)
Marketing			-0.084***		-0.077***	-0.076***
			(0.026)		(0.025)	(0.024)
IT			-0.077***		-0.026	-0.024
			(0.027)		(0.035)	(0.035)
Total application size (100)				0.002	0.002	0.002
				(0.002)	(0.002)	(0.002)
Female * Istanbul Asia						0.064**
						(0.027)
Female * Ankara						-0.027
						(0.031)
Istanbul Asia						-0.051**
						(0.022)
Ankara						-0.008
						(0.029)
Constant	0.935**	0.939**	0.976**	0.896**	0.941**	0.972**
	(0.428)	(0.428)	(0.424)	(0.429)	(0.426)	(0.428)
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	3469	3469	3469	3469	3469	3469
R-squared	0.005	0.006	0.014	0.007	0.015	0.018

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupation clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Individual characteristics include experience in months, age in years, whether the candidate worked in one job only, and objective and subjective beauty score measures. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.11: Balance table for socioemotional skills treatment

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Istanbul Asia	0.311	0.311	0.000
	(0.463)	(0.463)	(0.009)
Istanbul EU	0.509	0.509	0.000
	(0.500)	(0.500)	(0.010)
Experience (months)	49.234	49.109	-0.125
	(5.563)	(5.673)	(0.108)
Age	26.411	26.399	-0.012
	(0.643)	(0.650)	(0.012)
Accounting	0.292	0.292	-0.000
	(0.455)	(0.455)	(0.009)
Marketing	0.276	0.276	0.000
	(0.447)	(0.447)	(0.009)
Sales	0.304	0.304	-0.000
	(0.460)	(0.460)	(0.009)
IT	0.128	0.128	-0.000
	(0.334)	(0.334)	(0.006)
Worked in one firm only	0.253	0.264	0.011
	(0.435)	(0.441)	(0.008)
Objective beauty	0.943	0.945	0.002
	(0.231)	(0.227)	(0.004)
Subjective beauty	0.506	0.493	-0.012
	(0.500)	(0.500)	(0.010)
Reading	4.582	4.573	-0.009
	(0.493)	(0.495)	(0.010)
Speaking	4.517	4.526	0.009
	(0.500)	(0.499)	(0.010)
Writing	4.514	4.512	-0.001
	(0.500)	(0.500)	(0.010)
Besiktas	0.460	0.460	-0.000
	(0.498)	(0.498)	(0.010)
Kadikoy	0.311	0.311	0.000
	(0.463)	(0.463)	(0.009)
Kagithane	0.050	0.050	-0.000
	(0.218)	(0.218)	(0.004)
Cankaya	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Observations	5,374	5,374	10,748

Notes: Standard errors are given in parentheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

socioemotional skill signal negatively when not asked for in the vacancy, although this effect is not robust. Including the signal when it is asked for in the vacancy increases the probability of receiving a callback: the coefficients of socioemotional skills treatment and its interaction with whether the signaled socioemotional skill is required in the vacancy is jointly significant at 10 percent level. Finally, Model 6 shows that, while the effect sizes may change according to cluster, results are qualitatively similar across all clusters.

Result 2. *Signaling a socioemotional skill decreases the probability of being invited for an interview if the skill is not specifically asked for in the vacancy, and it increases the probability of being invited for an interview if asked in the vacancy text.*

We finally investigate whether the probabilities of callback for out treatment CVs are different according to the applicant's gender.[13] Table 1.13 provides the results from OLS regressions conditional on the applicant's CV clicked, and with cluster-robust standard errors at the vacancy level. Results show that female candidates with socioemotional skill signals in their CVs are around 5% less likely to be invited for an interview when the vacancy text does not specifically ask for the socioemotional skill signaled. A joint significance test of the coefficient of *SE skills* with its interaction with *Male* shows that this particular negative effect only holds for women.[14]

Result 3. *Firms that do not ask for the signaled socioemotional skills in the vacancy text evaluate the skill signals negatively only for female applicants.*

[13] Balance tables for each gender is provided in Appendix 1.D.

[14] Note that the results from the reverse audit (see Appendix 1.B for details) show that women are not less likely to signal socioemotional skills in their CVs, indicating that this gender differerence cannot be attributed to our female candidates being outliers in signaling their socioemotional skills.

Table 1.12: The effect of socioemotional skills, conditional on applicant CV clicked

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SE skills	0.007	-0.027*	-0.027*	-0.026	-0.026	-0.051*
	(0.010)	(0.016)	(0.016)	(0.016)	(0.016)	(0.029)
Signaled SE skill required in vacancy		0.004	0.004	0.001	0.001	0.001
		(0.022)	(0.022)	(0.022)	(0.022)	(0.043)
SE skills * Signaled SE skill required in vacancy		0.049**	0.050**	0.049**	0.049**	0.092**
		(0.020)	(0.020)	(0.020)	(0.020)	(0.036)
SE skills * Acct						-0.010
						(0.042)
SE skills * Mrkt						0.036
						(0.044)
SE skills * IT						0.076*
						(0.045)
Signaled SE skill required in vacancy * Acct						0.035
						(0.061)
Signaled SE skill required in vacancy * Mrkt						-0.002
						(0.061)
Signaled SE skill required in vacancy * IT						-0.030
						(0.062)
SE skills * Signaled SE skill required in vacancy * Acct						-0.055
						(0.054)
SE skills * Signaled SE skill required in vacancy * Mrkt						-0.052
						(0.054)
SE skills * Signaled SE skill required in vacancy * IT						-0.080
						(0.056)
Constant	0.172***	0.169***	1.291***	0.164***	1.241***	1.280***
	(0.010)	(0.018)	(0.294)	(0.027)	(0.291)	(0.296)
Individual char.	No	No	Yes	No	Yes	Yes
Vacancy char.	No	No	No	Yes	Yes	Yes
N.obs.	3469	3469	3469	3469	3469	3469
R-squared	0.000	0.002	0.007	0.012	0.017	0.019

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *SE skills* takes on the value 1 for treatment CVs, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Individual characteristics include experience in months, age in years, whether the candidate worked in one job only, and objective and subjective beauty score measures. Vacancy characteristics include total number of applications for the vacancy, occupational clusters and location. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.13: The effect of socioemotional skills, conditional on applicant CV clicked

	Model 1	Model 2	Model 3	Model 4
SE skills	-0.050**	-0.049**	-0.048**	-0.048**
	(0.023)	(0.023)	(0.023)	(0.023)
Signaled SE skill required in vacancy	-0.004	-0.005	-0.007	-0.007
	(0.028)	(0.028)	(0.028)	(0.028)
SE skills * Signaled SE skill required in vacancy	0.071**	0.070**	0.069**	0.069**
	(0.029)	(0.029)	(0.028)	(0.029)
Male	-0.068***	-0.046	-0.064**	-0.043
	(0.025)	(0.029)	(0.025)	(0.029)
SE skills * Male	0.048	0.048	0.045	0.045
	(0.032)	(0.032)	(0.032)	(0.032)
Signaled SE skill required in vacancy * Male	0.018	0.018	0.016	0.017
	(0.031)	(0.031)	(0.031)	(0.031)
SE skills * Signaled SE skill required in vacancy * Male	-0.044	-0.044	-0.042	-0.042
	(0.039)	(0.040)	(0.040)	(0.040)
Constant	0.201***	0.960**	0.195***	0.916**
	(0.023)	(0.414)	(0.030)	(0.412)
Individual char.	No	Yes	No	Yes
Vacancy char.	No	No	Yes	Yes
N.obs.	3469	3469	3469	3469
R-squared	0.006	0.008	0.016	0.017

Notes: Models 1 to 4 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *SE skills* takes on the value 1 for treatment CVs, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Individual characteristics include experience in months, age in years, whether the candidate worked in one job only, and objective and subjective beauty score measures. Vacancy characteristics include total number of applications for the vacancy, occupational clusters and location. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

1.4 Conclusion

Economics literature has clearly demonstrated that socioemotional skills are important in determining earnings, but it is not obvious whether socioemotional skills matter in the hiring stage. Focusing on the hiring stage, this study answers whether and how these skills should be signaled for male and female candidates. Our results suggest that signaling a socioemotional skill increases the probability of receiving a callback only if the skill is specifically asked for in the vacancy text. There is also a penalty for female applicants: If they signal a skill not asked for, the probability of receiving a callback decreases for them.

Our unique dataset allows us to open the black box of candidate screening, and we investigate the importance of gender in all three stages of employer screening: making the long list, clicking on a candidate's CV, and inviting a candidate for an interview. We find that employers indicate a preference for women when making the long list, and that gender discrimination does not exist conditional on candidates making it to the long list. Interestingly, this result suggests that candidate's beauty does not play a role in gender preference of employers, since employers are simply not able to filter using beauty and the photos of applicants are not visible at this stage.[15]

Our results imply that for socioemotional skill signals to help in securing job interviews, one must be careful on when to include them in the CVs. A CV tailored only to the candidate's qualifications, at least in terms of socioemotional skill signals, may backfire in the job hunt even though the candidate may in fact have quite strong socioemotional skills. This is especially true for female applicants, which may be due to employer preferences. Previous literature suggests that women and men have different traits on risk-aversity, competition, negotiation, and tendency to overestimate themselves (Babcock and Laschever, 2009; Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Dohmen and Falk, 2011; Ludwig et al., 2017). Women are also less likely to be overconfident compared to men (Lundeberg et al., 1994; Barber and Odean, 2001). Employers may then expect female candidates to be less overconfident compared to the male candidates with similar characteristics. Arguably, a candidate that includes a socioemotional skill signal not specifically asked for in the vacancy may be evaluated as overconfident by the employer. If the candidate is female, employers may evaluate the signals negatively because they evaluate her overconfidence negatively, whereas male candidates are expected to show overconfidence in their CVs during application.

[15] Hamermesh and Biddle (1994); Barry (2000); Mobius and Rosenblat (2006); Scholz and Sicinski (2015); Doorley and Sierminska (2015) find beauty affects earnings, Deryugina and Shurchkov (2015) find that it does so only when beauty is expected to matter for performance, López Bóo et al. (2013) find that attractiveness increases invitations for interview.

While our results provide a detailed assessment of whether and how socioemotional skill signals may be useful (or detrimental) in the hiring stage, we can observe what happens only before the interview stage. It is plausible that employers test socioemotional skills of applicants during the interview through specific tests or questions. In this sense, it may be the case that socioemotional skill signals are valuable conditional on making it to the interview stage, or in other words, what we find as a positive effect for vacancies that ask for socioemotional skills we signal is a minimum effect. It may also be the case that employers value all socioemotional skill signals, but again, conditional on making it to the interview. These two aspects can unfortunately not be investigated using our design and methodology.

1.A Objective and subjective beauty scores

Photos are commonly used in the online job portals in Turkey. In order to reflect this aspect in our applications, we needed to use photos for the CVs of our fictitious candidates. Below is the procedure we generated the photos and how we made sure that male and female photos reflect similar beauty levels on average.

The photos used in the experiment are generated using volunteer face shots of Italian and Turkish males and females aged 22 to 30. All collected face shots were taken either by a photographer or the volunteers themselves, and each volunteer signed an informed consent form before sharing his/her photos with us.

The photos collected in this manner were handed over to a graphic designer, who created sets of new photos. None of the photos were exactly the same with the real versions, but pieces of several photos were used to create fictitious photos using Photoshop.

The photos obtained were then grouped according to their gender, and then two different measures of beauty and attractiveness were collected for each of the photos. The following parts explain the definition and measurement of the two different beauty scores, and the procedure used to eliminate potential biases resulting from differences in attractiveness.

Objective beauty scores

The first measure is the attractiveness score based on the face shape, distance between the eyes and lips, mouth size and face symmetry, using the golden ratio where appropriate. This type of measurement, which we call the objective beauty score, is from a scale of 0 to 100. The software at www.prettyscale.com was used for this part.

After the scores were collected, photos that had a rating that is too high (above 0.89) or too low (less than 0.45) were removed from the set, resulting in the removal of 7 photos. Then, the sets of male and female photos were compared in terms of the mean and the distribution. In order to make the minimum and maximum values similar for males and females, we deleted the male photos that had an objective beauty score above 0.82, and female photos that had an objective beauty score below 0.58, resulting in the deletion of 25 photos in total.

The objective beauty score depends solely on the placement of facial features without any reference to details such as hair color, color of the eyes and other features that may affect how beautiful the person in the photo is perceived. Moreover, whereas the objective beauty scores do not change according to country, individuals from different countries are known to have different conceptions of beauty.[16] This is why we also collected data on a second measure that

[16] For an example please see the Perceptions of Perfection Across Borders Project conducted by the UK pharmacy Superdrug: https://onlinedoctor.superdrug.com/perceptions-of-perfection/tab

we call the subjective beauty score, provided in the next part.

Subjective beauty scores

The scores for subjective beauty are the average beauty scores obtained from the ratings collected through an online survey. The online survey was conducted in Turkish and distributed through the Twitter accounts of the World Bank Turkey Office and the Economic Policy Research Foundation of Turkey (TEPAV).

The first page of the online survey included an informed consent form specifying information about the project and the task, and other details including contact details. Approving the informed consent, the participants then moved directly to rating the photos from a scale of 1 to 10, 10 being the highest beauty score. On each page, the software showed ten male and female photos in random order. Participants could leave at any moment, but were informed that every time they rate a total of 10 photos and click Next or End, their responses would be recorded. To leave in the middle of the page before rating all 10 photos, the participant would simply close the webpage.

The survey was conducted in April 2016 and 384 participants provided a total of 32,676 ratings. On average, a participant rated 85 photos.

Before running the analysis, we eliminated some of the observations:

- We dropped observations for all respondents under the age of 18, resulting in the deletion of 17 respondents and a total of 1724 ratings.

- We dropped observations for all respondents that provided the same rating for all photos they viewed, resulting in the deletion of 5 respondents and 91 observations.

Since our aim was to create a set of similar photos for males and females, we removed the photos that had too high or too low average subjective ratings, removing a total of 33 photos and 3130 observations that had an average subjective rating less than 3 or above 7.[17]

As a result of these stages, the regressions were run using observations from 361 respondents for 237 photos, and a total of 24,392 observations.

The main specification we use throughout the analysis is the following:

$$rating_{ij} = \beta_0 + \beta_1 femalephoto_i + \beta_2 respondent_j + \epsilon_1 \tag{1.1}$$

To control for objective beauty effects that may account for some of the gender difference in the subjective beauty scores, we also use the following specification where we control for the objective beauty scores:

[17] About two standard deviations around the mean.

$$rating_{ij} = \beta_0 + \beta_1 femalephoto_i + \beta_2 respondent_j + \beta_3 beautyscore_i + \epsilon_2 \qquad (1.2)$$

where $rating_{ij}$ denotes the subjective beauty rating for photo i from respondent j; $femalephoto_i$ is a dummy that takes the value 1 if photo i is of a female, and 0 otherwise; $respondent_j$ denotes the respondent-specific characteristics, and $beautyscore_i$ denotes the objective beauty score of photo i.

Both equations are estimated using OLS, and the results are shown in the first two columns of Table 1. According to the estimations, both specifications show a significantly higher rating for female photos in the sample. Given this result, we decide to select a subsample of the set so that the distribution of average subjective beauty scores for each gender is similar, and use that subsample in our experiment. In order to do that, we first need to find the influential observations, and remove the photos that cause these influential observations.

The measure we use is DFBETA, which measures how much impact a particular observation has in the regression coefficient of an explanatory variable. DFBETA computes the difference in β_2 for all observations when that particular observation is and is not included in the data, therefore computing the influence of that particular observation on $femalephoto$.

We generate the DFBETAs for each observation that contributes to the significance of $femalephoto$, using Model 1.2 above. We then get the average DFBETAs for each photo, and rank them in terms of the magnitude of the influence, and delete the most influential photos from our sample until we obtain an insignificant coefficient for the variable $femalephoto$ in the estimation of Model 1.2.

The final selection includes 99 female and 101 male photos. Models 1.1 and 1.2 run using the observations for this selected photos shows an insignificant coefficient for the variable $femalephoto$, as shown in the third and the fourth columns of Table 1.14.

Finally, we demonstrate that the unconditional means and the distributions of both the objective and the subjective measures of beauty are statistically the same between the male and female samples, using nonparametric tests. Table 1.15 outlines the results. The results show the tests fail to reject that the female and male objective and subjective beauty measures have the same means. Similarly, the Wilcoxon-Mann-Whitney test cannot reject the null that the distributions of the male and the female subjective and objective beauty scores are the same. Figure 1.3 provides four examples of photos used in the experiment, two each for two genders with low and high subjective and objective beauty scores.

Table 1.14: Regression results

	All photos		Photos selected for the experiment	
	(1)	(2)	(3)	(4)
femalephoto	0.143***	0.143***	0.031	0.028
	(0.023)	(0.023)	(0.025)	(0.025)
beautyscore		0.025		0.542***
		(0.156)		(0.168)
Constant	5.500***	5.483***	4.000***	3.615***
	(1.069)	(1.074)	0	-0.12
Observations	24,392	24,392	20,573	20,573
R-squared	0.37	0.37	0.377	0.377

Respondent-specific characteristics are included in all regressions.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.15: Tests for the unconditional means and distributions for the objective and subjective beauty measures

	Two-tailed t-test	Wilcoxon-Mann-Whitney test statistic
Subjective beauty scores	-0.3045	-0.527
	(0.7611)	(0.5985)
Objective beauty scores	-0.3984	0.296
	(0.6908)	(0.7673)

p-values are given in parenthesis.

Figure 1.3: Examples of male and female photos

(a) Female - lower score

(b) Female - higher score

(c) Male - lower score

(d) Male - higher score

1.B Determining the socioemotional skill signals

Step 1: Literature survey

Six occupational themes (i.e. RIASEC themes; Holland, 1959, 1997) form the basis of all occupational classifications. The RIASEC acronym stands for Realistic, Investigative, Artistic, Social, Enterprising, and Conventional occupations. This model specifies what common activities underlie each occupational theme and outlines corresponding personalities and interests that would fit each theme. Using the RIASEC themes vocational counselors and Human Resource specialists have been matching individuals to certain occupations or positions on grounds of person-occupation fit.

We first identified 52 occupational groups and 15 industries that can be described using these six themes. Based on the dominant activities and job requirements, each occupation can be summarized with a two-theme of three-theme code. For example, engineering occupations involve dealing with tools and machines and also researching and identifying the most optimum design, thus they typically have a Realistic-Investigative (RI) code. Codes reveal what interest and personality characteristics (including socioemotional skills) are most important to be successful and satisfied in that occupation. Hence, the occupational groups identified by the project team are first categorized into the RIASEC themes. This was accomplished using the Occupational Information Network (O*NET; www.onetonline.org); an online database compiling years of research and accumulated knowledge on work characteristics and related abilities, personality, and vocational interests based on the Dictionary of Occupational Titles (US Department of Labor, 1991) and the Dictionary of Holland Occupational Codes (Gottfredson & Holland, 1996). Occupations were then matched with the corresponding personality characteristics from the O*NET and also from norm studies of the 16 Personality Factor model (Conn & Rieke, 1994).

Step 2: The reverse audit study

In this step, we collaborated with a private company in Kocaeli, Turkey, which is outside, but extremely close, to the largest labor market we study in our experiment (Istanbul). The company was in the process of starting to collect applications for two positions, a Customer Relations Manager (CRM) and a Human Resources Specialist (HR). We added the socio-emotional skill descriptors we obtained from Step 1 above, and asked to collect anonymized CV information from the company, as well as which one of the CVs they invited for an interview in the end.

CVs of applicants were analyzed and coded in terms of the socioemotional skills mentioned. Specifically, which socioemotional skill construct was signaled (e.g. leadership), how it was signaled, the type of signal used (adjective, activity or ambiguous), and the section of the CV it was signaled (e.g. abilities) was coded. In coding the type of signal, signals were categorized as "adjective" if the applicant explicitly used adjectives to describe self. Signals were coded as "activity" as long as the applicant provided an experience or an activity that demonstrates the utilization of the signaled skills. The "ambiguous" category was used to refer to completed seminars or certificates related to developing a specific socioemotional skill. In such cases the applicant is not claiming to have developed the skill (unless indicated elsewhere) and there is no experiential indication of such.

The analyses of coded data included how many of the socioemotional skill signals were mentioned broken down by the open position, signal type, CV section, and gender. Counts were obtained based on the number of data points including multiple entries by one person, and also based on the number of CVs. Here, results based on the number of CVs are summarized.

CRM Position Applicants

The CRM position ad was soliciting for applicants with the socioemotional skills of strong communication, teamwork orientation, open to continuous self-development and novel approaches, adaptability to dynamic work contexts, strong persuasion skills, and leadership skills (even though the ad only specified leadership skills, managerial skills were also coded as relevant for the job). Of the 184 applicants, 91 (49.5%) did signal at least one socioemotional skill with 44 men and 47 women. 93 did not include any socioemotional skill signal with 45 men and 48 women. 69 out of 91 (76%) applicants mentioned an ambiguous signal (45% men and 55% women), 25 out of 91 (27.5%) mentioned an adjective (40% men and 60% women), and 20 out of 91 (22%) mentioned an activity (55% men and 45% women). Out of the 69 who mentioned an ambiguous socioemotional skill signal (certificates and seminars), 54 applicants (78%) mentioned a solicited socioemotional skill, with 44% men and 56% women. Out of the 25 applicants who mentioned an adjective type signal, 10 applicants (40%) included a solicited socioemotional skill, with all of them women. Out of the 20 applicants with an activity signal, all mentioned the solicited socioemotional skill signals, with 55% men and 45% women. Altogether 84 applicants signaled a solicited socioemotional signal (92.3% of those who signaled any socioemotional skill and 45.57 of total applicants). Of those who mentioned solicited socioemotional skills, 49 (58%) were women and 35 were men (42%). Activity-type signals were mostly indicative of leadership/managerial signals. Adjective-type signals were mostly indicative of being open to self-development and teamwork orientation. Information on certificates and seminars (i.e. ambiguous-type signals) were mostly about communication and leadership. Of those who mentioned solicited socioemotional skills, only 9 mentioned both an adjective and an activity.

HR Specialist Position Applicants

The HR position ad was soliciting for applicants with the socioemotional skills of communication, teamwork, openness to continuous self-development, planning/organization, following through (goal-orientation), detail-oriented, sense of responsibility, and adaptability. A total of 535 applicants CV information was analyzed. These included the first 200 applicants (one of which received an interview call), 10 applicants who received an interview call, 225 applicants with English speaking, writing, and listening skill scores of 5 and 6, and 100 applicants selected randomly from the list of applicants with an English score of 4. Of the 535 applicants, 248 (46%) did signal at least one socioemotional skill with 76 men and 172 women. 286 did not include any socioemotional signal with 110 men and 176 women. 159 out of 248 (64%) applicants mentioned an ambiguous signal (26% men and 74% women), 88 out of 245 (35%) mentioned an adjective (40% men and 60% women), and 51 out of 248 (21%) mentioned an activity (20% men and 80% women).

Out of the 159 who mentioned an ambiguous socioemotional signal (certificates and seminars), 63 applicants (40%) mentioned a solicited socioemotional skill, with 21% men and 79% women. Out of the 88 applicants who mentioned an adjective type signal, 79 applicants (90%) included a solicited socioemotional skill, with 40% men and 60% women. Out of the 51 applicants with an activity signal, 25 applicants (49%) mentioned the solicited socioemotional skill signals, with 16% men and 84% women. Altogether 167 applicants (29.3% men and 70.7% women) signaled a solicited socioemotional skill signal (67.3% of those who signaled any socioemotional skill and 31.2% of total applicants).

Activity-type signals were mostly indicative of leadership/managerial signals (not solicited in the ad), organization skills, teamwork and adaptability. The solicited socioemotional skills were the mostly appearing adjectives. Information on certificates and seminars (i.e. ambiguous-type signals) were mostly about communication and leadership (not a solicited skill for HR). Of those who mentioned solicited socioemotional skills, only 9 mentioned both an adjective and an activity.

Analyses by gender

CVs of 89 men and 95 women applicants were analyzed for the CRM position and 188 men and 347 women applicants were analyzed for the HR position. Table 1.16 displays the percentage of men and women in terms of providing the solicited signals.

Table 1.16: Socioemotional signals by candidates

	Ambiguous	Adjective	Activity	Any
Customer Relations				
Women (N = 95)	31.6%	10.5%	9.5%	51.6%
Men (N = 89)	27%	0%	12.4%	39.3%
Total (N = 184)	29.3%	5.4%	10.9%	45.7%
Human Resources				
Women (N = 347)	14.4%	13.5%	6.1%	34%
Men (N = 188)	6.9%	17%	2.1%	26.1%
Total (N = 535)	11.8%	14.8%	4.7%	31.2%

1.C Examples of socioemotional skill signals used

Table 1.17: Socioemotional skill signals used in the experiment

Accounting	detail orientation, organization, communication	Accountant with more than XX years of experience Have reliable and sufficient knowledge on preparing accounting tables and memorandums.	Detail-oriented in preparing accounting tables and memos. Accountant who can maintain continuous communication and get the assigned tasks done in an organized and timely manner.	Recording day-to-day financial transactions in the system using the uniform chart of accounts. Prepared the reports on accounting records, profit and loss statement. Presented financial reports and specific budgets. Processing the ledger entries to ensure all business transactions are recorded.	Effectively communicated with clients to determine payment schedules with them that were in line with the companys needs. Preparation of financial sheets and statements according to the legislation and accounting and financial guidelines. Closing the accounting records in the first five days of the month by organizing the required documents for records. Detailed and careful current account settlements with customers and suppliers.	Worked on accurately recording hundreds of students' contact information during the university's open house.

Occupational cluster	Socioemotional skill	Taglines		Job descriptions		Extracurricular activity for treatment
		Control	Treatment	Control	Treatment	
Marketing	dynamic, teamwork, persuasion	I am a marketing specialist, graduated from the Business Administration Department of XX University, who can effectively determine the market needs and develop strategies accordingly.	I am a specialist who has developed effective marketing strategies by using my dynamism and persuasion skills through my work experience. I have teamwork experience in the tasks I took part in since my undergraduate education.	Identifying new market opportunities based on market analyses. Experienced in working on preparing online marketing materials. Participation in the development of marketing campaigns for a variety of products and services. Experienced in using the reporting and analysis tools.	As an active member of a team of specialists from related departments, preparing new brands, identifying regional marketing activities and campaigns/sales. Took part in the preparation of written and visual materials for media campaigns. Conducting marketing campaigns by having frequent meetings with press organs, organizing all related processes. By carrying out marketing analytics and persuading the team to include new media strategies based on target demographics, I contributed to the social media outreach.	Volunteered in a team of 10 at the XX National Youth Work Camp.

Occupational cluster	Socioemotional skill	Taglines		Job descriptions		Extracurricular activity for treatment
		Control	Treatment	Control	Treatment	
Sales	persuasion, networking, teamwork	I am a sales representative who can successfully transfer the technical knowledge and skills to have the firm meet its sales goals.	Able to form networks and use persuasion skills to the extent of improving firm's sales.	Identifying customer demands and present ways to improve sales volume.	Persuaded current customers to try new products, thus enabled surpassing targeted sales volume and profit.	Participated in regional debate tournaments.
			A good team member who strives to determine the customer needs accurately.	Including new customers in the customer portfolio to meet sales targets.	I was selected for explaining new staff members on how to effectively communicate with clients during the initial orientation.	
		With an experience of more than XX years.		Meeting with customers to enable the coordination and cooperation between the company and the customers.	Making offers to customers for sales by meeting them.	
				Worked on preparing timely sales reports.	I worked in close coordination with the marketing team and provided timely feedback about customer preferences.	

Occupational cluster	Socioemotional skill	Taglines: Control	Taglines: Treatment	Job descriptions: Control	Job descriptions: Treatment	Extracurricular activity for treatment
IT	detail orientation, perseverance, teamwork	IT specialist who has an experience of XX years in problems in software, hardware, internet or servers	A determined IT specialist who can coordinate with team members to provide detailed solutions to server, internet, software or hardware problems.	Maintenance and control of internet servers for secure and reliable performance.	Persevered to identify unknown sources of server failures by searching for new technological updates.	Worked on complete (accurate) entry of university personnel information into the database.
				Configuration of system network components, installation and monitoring routers and the LAN/WAN network environment.	Installed and configured secured networks.	
				Maintenance and update of company web page and software and applications used.	Analysis of company software in detail and identification of errors and providing solutions.	
				Providing support for technical failures with equipment such as PC, printer or scanners.	Working as a team in coordination and identifying deficiencies and supplying the necessary hardware.	

Note: The CVs were constructed in Turkish. The translations included here are for information purposes.

1.D Conditional balance tables

Table 1.18: Balance table for gender treatment, conditional on applicant being in the long list

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.185	0.183	-0.002
	(0.388)	(0.387)	(0.009)
Istanbul Asia	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Istanbul EU	0.506	0.509	0.003
	(0.500)	(0.500)	(0.011)
Experience (months)	49.041	49.498	0.457
	(5.588)	(5.664)	(0.129)***
Age	26.786	26.053	-0.733
	(0.561)	(0.506)	(0.012)***
Accounting	0.259	0.261	0.002
	(0.438)	(0.439)	(0.010)
Marketing	0.286	0.286	-0.000
	(0.452)	(0.452)	(0.010)
Sales	0.315	0.313	-0.001
	(0.464)	(0.464)	(0.011)
IT	0.140	0.140	0.000
	(0.347)	(0.347)	(0.008)
Worked in one firm only	0.278	0.247	-0.031
	(0.448)	(0.431)	(0.010)***
Objective beauty	0.928	0.965	0.037
	(0.259)	(0.185)	(0.005)***
Subjective beauty	0.451	0.550	0.099
	(0.498)	(0.498)	(0.011)***
Reading	4.575	4.562	-0.013
	(0.494)	(0.496)	(0.011)
Speaking	4.519	4.525	0.006
	(0.500)	(0.499)	(0.011)
Writing	4.522	4.499	-0.023
	(0.500)	(0.500)	(0.011)**
Besiktas	0.452	0.456	0.003
	(0.498)	(0.498)	(0.011)
Kadikoy	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Kagithane	0.054	0.054	-0.000
	(0.226)	(0.225)	(0.005)
Cankaya	0.185	0.183	-0.002
	(0.388)	(0.387)	(0.009)
Observations	3,845	3,809	7,654

Notes: Standard errors are given in parantheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.19: Balance table for gender treatment, conditional on applicant's CV clicked

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.200	0.197	-0.003
	(0.400)	(0.398)	(0.014)
Istanbul Asia	0.316	0.308	-0.008
	(0.465)	(0.462)	(0.016)
Istanbul EU	0.484	0.495	0.011
	(0.500)	(0.500)	(0.017)
Experience (months)	48.816	49.577	0.761
	(5.575)	(5.585)	(0.190)***
Age	26.756	26.052	-0.704
	(0.568)	(0.502)	(0.018)***
Accounting	0.209	0.204	-0.005
	(0.407)	(0.403)	(0.014)
Marketing	0.239	0.243	0.004
	(0.427)	(0.429)	(0.015)
Sales	0.317	0.350	0.033
	(0.465)	(0.477)	(0.016)**
IT	0.235	0.203	-0.032
	(0.424)	(0.402)	(0.014)**
Worked in one firm only	0.275	0.269	-0.006
	(0.447)	(0.444)	(0.015)
Objective beauty	0.938	0.961	0.024
	(0.242)	(0.193)	(0.007)***
Subjective beauty	0.462	0.538	0.076
	(0.499)	(0.499)	(0.017)***
Reading	4.550	4.559	0.010
	(0.498)	(0.497)	(0.017)
Speaking	4.505	4.530	0.025
	(0.500)	(0.499)	(0.017)
Writing	4.520	4.500	-0.020
	(0.500)	(0.500)	(0.017)
Besiktas	0.389	0.415	0.025
	(0.488)	(0.493)	(0.017)
Kadikoy	0.316	0.308	-0.008
	(0.465)	(0.462)	(0.016)
Kagithane	0.095	0.081	-0.014
	(0.293)	(0.272)	(0.010)
Cankaya	0.200	0.197	-0.003
	(0.400)	(0.398)	(0.014)
Observations	1,656	1,813	3,469

Notes: Standard errors are given in parantheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.20: Balance table for socioemotional skills treatment, conditional on applicant being in the long list

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.185	0.183	-0.002
	(0.388)	(0.386)	(0.009)
Istanbul Asia	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Istanbul EU	0.506	0.510	0.004
	(0.500)	(0.500)	(0.011)
Experience (months)	49.296	49.240	-0.056
	(5.548)	(5.711)	(0.129)
Age	26.422	26.420	-0.002
	(0.642)	(0.654)	(0.015)
Accounting	0.259	0.261	0.002
	(0.438)	(0.439)	(0.010)
Marketing	0.287	0.285	-0.002
	(0.452)	(0.452)	(0.010)
Sales	0.314	0.314	-0.001
	(0.464)	(0.464)	(0.011)
IT	0.140	0.140	0.000
	(0.347)	(0.347)	(0.008)
Worked in one firm only	0.255	0.270	0.015
	(0.436)	(0.444)	(0.010)
Objective beauty	0.944	0.948	0.004
	(0.230)	(0.222)	(0.005)
Subjective beauty	0.508	0.493	-0.015
	(0.500)	(0.500)	(0.011)
Reading	4.576	4.561	-0.015
	(0.494)	(0.496)	(0.011)
Speaking	4.510	4.534	0.025
	(0.500)	(0.499)	(0.011)**
Writing	4.515	4.506	-0.008
	(0.500)	(0.500)	(0.011)
Besiktas	0.452	0.456	0.004
	(0.498)	(0.498)	(0.011)
Kadikoy	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Kagithane	0.054	0.054	-0.000
	(0.226)	(0.225)	(0.005)
Cankaya	0.185	0.183	-0.002
	(0.388)	(0.386)	(0.009)
Observations	3,831	3,823	7,654

Notes: Standard errors are given in parantheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 1.21: Balance table for socioemotional skills treatment, conditional on applicant's CV clicked

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.194	0.203	0.009
	(0.395)	(0.402)	(0.014)
Istanbul Asia	0.315	0.309	-0.006
	(0.464)	(0.462)	(0.016)
Istanbul EU	0.492	0.488	-0.003
	(0.500)	(0.500)	(0.017)
Experience (months)	49.322	49.101	-0.220
	(5.512)	(5.674)	(0.190)
Age	26.388	26.388	-0.001
	(0.632)	(0.648)	(0.022)
Accounting	0.202	0.211	0.008
	(0.402)	(0.408)	(0.014)
Marketing	0.244	0.238	-0.005
	(0.429)	(0.426)	(0.015)
Sales	0.336	0.333	-0.003
	(0.472)	(0.471)	(0.016)
IT	0.218	0.218	0.000
	(0.413)	(0.413)	(0.014)
Worked in one firm only	0.267	0.278	0.011
	(0.442)	(0.448)	(0.015)
Objective beauty	0.949	0.952	0.003
	(0.221)	(0.215)	(0.007)
Subjective beauty	0.516	0.487	-0.030
	(0.500)	(0.500)	(0.017)*
Reading	4.549	4.560	0.011
	(0.498)	(0.496)	(0.017)
Speaking	4.505	4.531	0.026
	(0.500)	(0.499)	(0.017)
Writing	4.510	4.509	-0.000
	(0.500)	(0.500)	(0.017)
Besiktas	0.403	0.402	-0.001
	(0.491)	(0.491)	(0.017)
Kadikoy	0.315	0.309	-0.006
	(0.464)	(0.462)	(0.016)
Kagithane	0.089	0.086	-0.002
	(0.284)	(0.281)	(0.010)
Cankaya	0.194	0.203	0.009
	(0.395)	(0.402)	(0.014)
Observations	1,774	1,695	3,469

Notes: Standard errors are given in parantheses. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Chapter 2

Signaling Socioemotional Skills

This chapter consists of a prior study for a larger research project with coauthors Stefan Hut, Victoria Levin and Ana Maria Munoz Boudet and includes only the work I conducted.[1]

Many sources from career support centers to online job application portals suggest that the candidate should signal different types of skills, such as hard skills, socioemotional skills, and technical skills, in their CV as they are valuable for companies in their assessment of the candidates. However, signalling socioemotional skills may not be trivial. Using an online randomized discrete choice experiment, this study aims to find how to signal socioemotional skills effectively. Randomly assigned socioemotional skill signals are shown to potential future human resources personnel, and information on how well they remember each CV characteristic as well as which candidate they would potentially invite for an interview are collected.The results suggest that socioemotional skills are at least as well remembered as other skills, such as cognitive skills, on the CV, implying the importance attributed to them. This is especially true when the skills are listed as activity-based signals. Supporting this finding, socioemotional skills signaled through costly activities are considered valuable when inviting candidates for an interview, while adjectives as socioemotional skills do not make a significant difference than a CV without any socioemotional skill signal.

JEL classification: *C99, J24*

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2.1 Introduction

Many sources from career support centers to online job application portals' sources on how to write a good CV suggest the potential candidate to signal different types of skills, such as hard skills, socioemotional skills, and technical skills, in their CV as they are valuable for companies in their assessment of the candidates. In fact, it is quite common to see specific socioemotional skills requirements listed in the vacancy ad texts, for example, in the form of leadership or communication skills, depending on the characteristics of the occupation.

Economics literature has also firmly established that socioemotional skills are a form of human capital and the posession of socioemotional skills has a positive impact on lifetime earnings (see for example, Cunha and Heckman, 2007, 2008; Cunha et al., 2006; Bowles et al., 2001a). However, while earnings over the lifetime seem to be positively affected by socioemotional skills, whether these skills are a significant factor in employers' *hiring* decisions has not been analysed in economics until very recently. It is important to distinguish between the value of socioemotional skills for lifetime earnings and at the stage of hiring, because if employers in fact do not consider socioemotional skills important in their hiring decisions, then it is not optimal for job seekers to signal them at all in their CVs, or invest time and money on developing these skills through experience if the sole purpose is to signal them in their job applications.

In a recent working paper, Piopiunik et al. (2018) implement an online survey to a representative sample of German human resources managers and show that socioemotional skills are considered to be important by employers, providing the first evidence that socioemotional skills matter at the hiring stage. However, the problem of signaling is not solved even when socioemotional skills are known to be valuable for employers for hiring decisions: The candidate must still know how best to signal these skills when applying for a job. While education and labor economics as well as the literature on signaling have established that the candidate should signal her cognitive skills through her education, it is far from clear what advice to give to the candidate in terms of signaling socioemotional skills. To see what options are available, consider a young professional with a few years of job experience. Upon the finding that socioemotional skills are valuable at the hiring stage, the candidate may decide to include a signal in her CV that shows she has, say, strong negotiation skills. Searching for some example signals online, she would realize that there are different possible ways to include these skill signals in the CV. The first alternative is to list her socioemotional skills as an adjective in the section where she lists her other skills, such as her technical skills. She can do that by adding a text in the form of, e.g., "strong negotiation skills". Signals of this type do include the skill, but they may not be credible since the candidate has not incurred any costs - time or money - to be able to signal these skills. Another alternative then is to include them through presumably some costly activities, such as tasks at work or extracurricular activities during education, e.g., by adding “participated in debate tournaments as an undergraduate student”, where she has devoted time and possibly some money while doing these tasks. I consider the first type an *adjective-based* socioemotional skill signal following the fact that it is just the statement of an adjective by oneself about herself, and the second type as an *activity-based* skill signal since it attempts to demonstrate the possession of the skill through some sort of (costly) activity.

This paper is concerned with whether potential employers consider socioemotional skills important in evaluating candidates, and what kind of signals receive a higher evaluation. In particular, the purpose of this paper is to investigate the following questions:

1. During the job recruitment process, are socioemotional skills valued above and beyond other factors, such as education and experience?
2. During the job recruitment process, are either one of activity-based social skill signals or adjective-based social skill signals valued higher compared to the other?

An important drawback that limits the studies on socioemotional skills is their measurement. It is not possible to directly observe or measure socioemotional skills. The conventional method is to use performance in tests such as the Big-5 Personality Test, but performance in any test depends on effort, socioemotional skills, cognitive ability, and incentives, causing biased estimations of the effect of any particular variable such as socioemotional skills (Heckman and Kautz, 2012). For example, studies show that incentives in the form of rewards affect performance in IQ tests, and this effect varies with the level of socioemotional skills (Borghans et al., 2008; Segal, 2012). Moreover, as argued by (Heckman and Kautz, 2012, p.455), it is not clear whether the measured traits “are the manifestation of a deeper set of preferences or goals. Achieving certain goals requires certain traits, e.g., a surgeon has to be careful and intelligent; a salesman has to be outgoing and engaging and so forth,etc. Under this view, traits are developed through practice, investment, and habituation.” It follows from this argument that at least some aspects of socioemotional skills that are valuable for the individual’s job might change with work experience, causing an endogeneity problem in the identification of socioemotional skill effects in the labor market.

The literature is not clear even on which name to use. In their review, (Heckman and Kautz, 2012, p.452) state that the terms “soft skills”, “personality traits”, “non-cognitive skills”, “non-cognitive abilities”, “character”, and “socioemotional skills” are all used to identify the personality attributes. The key difference between skills and traits are that skills indicate properties that can be learned, whereas traits imply permanence. The authors argue both skills and traits can change over time and across the life cycle, but the mechanisms through which they change may be different. Heckman (2008) identifies socioemotional skills as motivation, socioemotional regulation, time preference, personality factors and the ability to work with others; although in practice the use of certain socioemotional skills in research in labor economics depends heavily on data availability (Brunello and Schlotter, 2011). This unavailability of data on different dimensions of socioemotional skills makes it difficult to establish the true extent of the importance of these skills, because the relative importance of different socioemotional skills are different depending on occupation. For example, a sales assistant practices tasks that require extraversion, persuasion and negotiation skills, whereas detail-orientation is valued to a higher degree for an accountant. These different necessities of socioemotional skills are stated first through the O*NET classifications that are widely used in labor market research. O*NET categorizes occupations using one or more of the categories 'Realistic, Investigative, Artistics, Social, Enterprising, Conventional', based on the daily tasks involved in the occupation.[2] According to this classification, important socioemotional skills for each category is different (Conn and Rieke, 1994). In addition to these classifications, conventional job ads also specifically state the required socioemotional skills along with the tasks expected from the candidate.[3]

This study solves the problems of definition through gathering information from the O*NET descriptions and the organizational psychology literature. Socioemotional skill used for each occupation selected for the study are taken using these two sources. The problems of measurement and identification are solved through the random assignment of socioemotional skill signals. The methodology used in this study is a discrete choice experiment in which alternative CVs that include adjective-based, activity-based, or no socioemotional skill signals are presented as pairs, and the subject selects which one to (hypothetically) invite for an interview. After selection, CV characteristics are no longer visible, and the subject is asked to state various CV characteristics for both CVs. The two variables of interest are the type of the CV selected for an interview, and the rates of different CV characteristics that are correctly remembered.

The results suggest that socioemotional skills are at least as correctly recalled as the other

[2]Definitions for these categories are as follows. *Realistic*: Realistic occupations frequently involve work activities that include practical, hands-on problems and solutions. They often deal with plants, animals, and real-world materials like wood, tools, and machinery. Many of the occupations require working outside, and do not involve a lot of paperwork or working closely with others. *Investigative:* Investigative occupations frequently involve working with ideas, and require an extensive amount of thinking. These occupations can involve searching for facts and figuring out problems mentally. *Artistic:* Artistic occupations frequently involve working with forms, designs and patterns. They often require self-expression and the work can be done without following a clear set of rules. *Social:* Social occupations frequently involve working with, communicating with, and teaching people. These occupations often involve helping or providing service to others. *Enterprising:* Enterprising occupations frequently involve starting up and carrying out projects. These occupations can involve leading people and making many decisions. Sometimes they require risk taking and often deal with business. *Conventional:* Conventional occupations frequently involve following set procedures and routines. These occupations can include working with data and details more than with ideas. Usually there is a clear line of authority to follow.

[3]Job ads used in this experiment are given in Appendix 2.A.

skills listed in the CVs, but activity-based signals are remembered better than the adjective-based ones, suggesting a higher degree of importance assigned to the former compared to the latter. This finding is further reinforced by the fact that CVs with activity-based socioemotional skill signals are chosen more frequently compared to both CVs with adjective-based signals and CVs with no socioemotional skill signals, and regression analyses show a significant effect of activity-based signals on the selection of the CV for an interview. In line with the insights from the signaling literature, the findings suggest that signaling socioemotional skills only through adjectives is not useful when looking for a job. Instead, job seekers should focus on gathering experiences that will later ensure them to signal their socioemotional skills in a more credible way.

The experiment is not incentivized and the selection for an interview is hypothetical, leading to a potential drawback that participants may have not paid attention to the experiment. However, three elements of the study are relevant in providing the validity of the results. First, the subject pool includes senior undergraduates and masters students of pscyhology and business administration, selected in order to provide a subject pool closer to potential human resources personnel. The subject pool is thus arguably more interested than the general student sample in attempting to select the best candidate for the task given. Furthermore, subjects tend to remember CV elements correctly with a very high percentage, implying that they did in fact pay attention to the CVs in making their decision. Finally, the fact that there is a significant difference between which types of CVs are invited for an interview shows that the selection on average was not made at random.

The following section explains the context in which socioemotional skills signaling is relevant and distinguishes between types of signals, Section 2.3 outlines the methodology and the design, Section 2.4 presents the results. The final section concludes.

2.2 Socioemotional skills and signaling: theoretical context

The theoretical intuition follows from the signaling model that is pioneered in Spence (1973). Rather than building a formal model, this section explains the intuition behind the difference between activity- and adjective-based socioemotional skill signals using the framework in Sobel (2012).

Consider the case with a job seeker (S) and a potential employer (R), where the job seeker is either a high- or a low-productivity candidate for the position the employer aims to fill. If the job seeker has a high productivity, her type is θ_H, if low, then her type is θ_L, where $\theta_H > \theta_L$. The type is observable to the job-seeker herself, but not to the employer, although the job seeker may signal her type through signaling her socioemotional skills to the potential employer.

In the beginning, the job seeker finds out about her type, θ_H or θ_L. She can then choose whether to signal (s) an adjective-based (m) or an activity-based (c) signal, or nothing, where $c > m$. An adjective-based signal (m) may be considered as cheap talk since it is not costly. On the other hand, an activity-based signal (c) provides verifiable information about a previous activity that demonstrates the socioemotional skill, and is therefore costly. The employer receives the signal and the employer decides on the action a. The action is either to invite the job seeker for an interview, or do nothing.

The payoff to player i in this setting is given by the payoff function u^i, where u^S is strictly increasing in a and strictly decreasing in the signal. u^S also satisfies the single-crossing condition such that if $u^S(\theta_L, s, a) \leqslant u^S(\theta_L, s', a')$ for $s' > s$, then $u^S(\theta_H, s, a) < u^S(\theta_H, s', a')$. Employer's utility function u^R is independent of the signal and increasing in the type of worker, such that the high type is more likely to be employed. These assumptions imply that the high type is able to send a higher signal, and that in equilibrium high type will send a weakly higher signal. Also, high type induces a higher action by the employer.

Given this structure, it is trivial to see that there is a separating equilibrium in which only the high type sends a costly (activity-based) signal, and that the signal is valuable for the employer. On the other hand, the costless signal does not carry a meaningful message since the job seeker's utility is monotonic in the employer's action, and so all job seekers would like to send the highest possible signal. This implies that, upon receiving the signal m, employers can identify the low type.

2.3 Experimental design

The design of the experiment follows the design used in the salience test in Kroft et al. (2013), with some revisions to fit the current study.

Job and skills selection and creation of job ads

We select two occupations with different socioemotional skill necessities: financial analysts and sales supervisors. We select an occupation-specific sociemotional skill based on the skills listed in the O*NET description for the sales supervisor job. For the financial analyst position, we select a socioemotional skill that is relevant for all occupations, namely teamwork. We base this decision on the personnel selection in organizational psychology literature (Campbell et al., 1993) and due to the fact that many financial analyst position job ads in practice especially ask for teamwork skills.[4]

The CVs were presented in the Europass format that is widely used in Europe, and the socioemotional skill signal treatments were included in the section "Job-related skills" as shown in Table 2.1. The exact job ad texts that we have provided to the subjects are given in Table 2.2.

Table 2.1: Socioemotional skill signals for adjective- and activity-based treatments according to occupation

	Sales assistant	**Financial analyst**
Adjective-based SE	Persuasion skills, assertiveness, strong interpersonal/communication skills.	Adaptability to new and multicultural contexts, familiarity with teamwork
Activity-based SE	Participation in 8 debate tournaments held locally and at the national level 2008-2011; Organizing the invitation of two CEOs from the Aegean region as key speakers at the Debate Council meeting (2012)	Member of Rotaract 2440 International Commitee (2010-), participated in the International Youth Camp, Arthez, France and worked in 10-member multicultural teams (2012)

CV types and treatments

For each job type (sales supervisor or financial analyst), there are three types of CVs:

1. *No socioemotional skill:* This type of CV does not have any socioemotional skills listed in the CV.

2. *Adjective-based socioemotional skill:* This type of CV has socioemotional skills listed as an adjective only, such as "Persuasion skills".

3. *Activity-based socioemotional skill:* This type of CV has socioemotional skills listed as an activity, such as "Participation in 8 debate tournaments held locally and at the national level 2008-2011".

Table 2.3 summarizes the distribution of CVs for each CV type. From a total of 180 CVs, 88 are for sales supervisor and 92 are for the financial analyst. 61 CVs each are control and activity, and 58 are adjective-based CVs.

[4]Based on job search done on the largest online job portal in Turkey where the experiment is conducted.

Table 2.2: Vacancy ad texts

Sales assistant ad	Financial analyst ad
Description: We are searching for a **Senior Sales Assistant** for our world leader client in clinical laboratory testing of blood, urine and other specimens. In this job you are expected to: • Formulate and administer a Territory Plan (Aegean region) with appropriate sales strategies; • Find new customers and business opportunities in the specified market and product range, • Execute the sales process including demonstrations, proposal presentation, negotiation and closing, • Present company products to customers to position the product's technological superiority and benefits over competitors, • Perform and participate in customer meetings to promote the product lines. **Requirements:** The ideal candidate will possess: • University degree in related departments (Business preferred) • 2 years of sales experience • Computer Skills: MS Office (Word, Excel, Powerpoint) • Fluent level of English • Strong interpersonal and communication skills • Strong negotiation skills, assertiveness	**Description:** We are seeking a **Financial Analyst** for our multinational client in the IT & Technology sector. In this job you are expected to: • Check financial tables to ensure the monthly financial reports prepared by the accounting team are accurate, • Analyze data and compare forecasts with actual results, • Prepare accurate, relevant and timely management reports to accurately reflect the status of the business, • Identify trends and recommending actions to improve financial status. **Requirements:** The ideal candidate will possess: • University degree in Business Administration, Economics or related area, • At least 2 years working experience as accounting & finance positions, • Strong MS Office Applications, particularly in Excel, • International accounting knowledge (IFRS) would be an asset, • SAP knowledge is an asset, • Fluent in spoken and written English • Adaptability to a multinational environment, • Teamworking skills

Table 2.3: Distribution of jobs and CVs

	Financial analyst	Sales assistant	Total
Control	33	28	61
Adjective	30	28	58
Activity	29	32	61
Total	92	88	180

Procedures

The discrete choice experiment was conducted between May and December 2015. Links for the online survey were sent to 320 senior undergraduates and masters students of psychology and business administration departments of two universities in Ankara and one university in Izmir, Turkey; and 90 respondents replied. Psychology and business administration departments were chosen in order to reflect the educational background composition of the human resources (HR) personnel in Turkey.[5] The participants did not receive any compensation for filling out the survey.

The experiment itself consisted of three steps:

Step 1. In the first step of the discrete choice experiment, respondents are asked to read a job ad and CVs of two potential applicants for the advertised position. Both the text of the ad and the individual profiles are composed to closely mirror the ads and CVs found on the most popular job search engine in Turkey, and LinkedIn. The content of the CVs are representative of an average CV for two fictitious individuals of similar characteristics: Candidates are both female, and are the same age. Names are constructed using the list of most common names and surnames in Turkey. Education history, and other information are constructed by using the information from actual CVs available online. CVs constructed in this way (two for each job) are later assigned the treatments, such that all CVs have Control, Adjective and Activity versions, so that there are a total of two versions for each of control and treatment, and a total of six CVs for each job. Participants are informed that they are asked to put themselves in the hypothetical situation of a Human Resources Manager and are asked to select the best of the two candidates for an in-person interview. In this stage, both the CVs and the job ad are visible to the participant and the participant would be able compare the CVs side by side.

Step 2. Following their choice of the best candidate for the advertised position, the ad and the CVs are removed from the screen, and the participants are not allowed to go back: If they click on the back button of their browser, they receive a warning and we collect this information as a separate variable.[6] The participants are then asked a series of questions trying to recall

[5]Based on interviews with the HR departments

[6]They can return to the previous screen after they see the warning, but we mark them as 'cheaters' and control

the CV characteristics including age, education, experience, and whether socioemiotional skills were mentioned (either as a tagline or as hobbies/activities) and if so, what they were. They are also asked to state the two most important attributes that led them to select the CV for the in-person interview.

Step 3. Finally, the respondent is asked a few demographic questions, including gender, age, level of experience reviewing CVs, work experience in HR.

The sequence of screens are given in Appendix 2.A. For each participant, the job ad is randomly selected from two alternatives: ad for a sales supervisor or a financial analyst. The algorithm then selects two random CVs for two females for the selected job ad. The randomization is constructed such that same types of CVs never appear side by side, so that the participant always selects between two types and never among each type. Note that which side of the screen each CV is shown is also randomized to avoid any selection effect based on reading habits.

2.4 Results

The main interest is to see whether socioemotional skills were an important dimension in the selection of candidates for an interview. In order to see this, we first compare the frequency with which the candidates correctly remember socioemotional skills with other types of skills listed in the CV. When making this comparison, we only consider data from participants who did not cheat (14 out of 90 cheated in total) in order to go back to the previous page where the CVs were shown. We then investigate which candidates are more likely to be selected for an interview, and whether socioemotional skills signals play a role in this decision.

Table 2.4 provides the number of subjects by treatment pairs and by job type. Out of a total of 90, 46 were for the finance and 44 were for the sales job ad. Comparing the treatments, 29 subjects saw a control CV and a CV with an adjective-based signal side by side; 32 saw a control CV and a CV with an activity-based signal side by side; and another 29 saw a CV with an adjective-based signal and a CV with an activity-based signal side by side.

Looking at how well the characteristics are correctly recalled for each applicant, i.e., the salience of CV characteristics, the first observation to note is that socioemotional skills are remembered better than some of the CV characteristics, such as the job experience of the candidate. Table 2.5 shows the percentage of subjects who correctly remembered different CV characteristics, computed as the average percentage of subjects that remembered each category

for this information.

Table 2.4: Number of subjects by treatment couples and the frequency of types selected for interview

	All	**By Job**	
		Finance	**Sales**
Adj in Control-Adj	51.7%	41.2%	66.7%
Total Control-Adj	29	17	12
Act in Control-Act	71.9%	50.0%	93.8%
Total Control-Act	32	16	16
Act in Adj-Act	72.4%	92.3%	56.3%
Total Adj-Act	29	13	16
TOTAL	90	46	44

correctly by either selecting a characteristic that is signaled in CV, or not selecting one that is not signaled in CV. Overall, quantitative/analytical skills are remembered correctly 96%, and experience 47%. On the other hand, activity-based socioemotional skill signals are remembered correctly 85% of the times, whereas adjective-based ones are remembered correctly in 75% of the times. Out of the 13 different socioemotional skill signals listed, the median number of correctly remembered socioemotional skill is 11.

Subjects especially remember socioemotional skill signals when signaled through activities. Nonparametric tests provide a clearer picture, although more precise estimates using regressions are provided in the following pages. To do this, we first create two variables that capture the mean correct recall rates for socioemotional skills and other signals. All CVs have a total of 13 socioemotional skill signals included in the questions, in the form of adjectives or activities. Adjectives include adaptability to multicultural environments, attention to detail, assertiveness, communication skills, motivation, persuasion skills and teamwork skills, whereas activities include participation in international youth organization, participation in debate tournaments, student club leadership, experience in organizing meetings, membership in international organizations, and teamwork. For each subject, we create a variable that records the mean recall rate for these skill signals, and another mean recall rate for the other signals in the CV.[7] We then run the nonparametric test based on these two variables that record the mean recall rates for socioemotional skills signals and other signals in the CV. Based on a total of 76 observations for each subject that did not try to cheat by going back to the previous page, socioemotional skills are correctly recalled 80% of the times on average, whereas the other skills 86%, and a paired t-test suggests that this difference is statistically significant (p-value=0.0031). Comparing all cases where an activity-based CV was shown to subjects and the subject did not cheat (57 observations), however, activity-based socioemotional skill signals are correctly re-

[7] All signals are provided in the screenshots provided in Appendix 2.A.

called 85% of the times compared, not significantly different compared to correct recall rate for other skills (86%).[8] Furthermore, comparing the 27 cases where activity-based socioemotional skills are shown together with an adjective-based CV, activity-based CVs are correctly recalled with a frequency of 88% compared to 66% for the adjective-based ones, and this difference is statistically significant.[9]

Result 1. *Socioemotional skills are as correctly remembered as other skills in the CV, but this is true only when they are signaled as activities.*

Table 2.5: Percent correctly remembered for various CV characteristics (non-cheaters only)

	All	**By Job**	
		Finance	**Sales**
Quantitative/analytical skills	96.1%	94.6%	97.4%
Language skills (French, Italian, English)	95.0%	93.2%	96.6%
What is the education level of the candidate?	92.8%	93.2%	92.3%
Is the candidate currently employed?	84.9%	83.8%	85.9%
Socioemotional skills (activity-based)	84.5%	84.2%	84.8%
Computer skills (MS Office, Stata, SAP, IFRS)	79.4%	60.5%	97.4%
Socioemotional skills (adjective-based)	75.3%	84.4%	66.7%
Experience level of the candidate (year and months)	46.7%	50.0%	43.6%

Note: Statistics derived for the 76 subjects who did not cheat. Subject is assumed to have correctly remembered any signal if they correctly selected a characteristic signaled in the CV, or correctly not selected a characteristic not signaled in the CV. Percent correctly recalled for language skills, computer skills and socioemotional skills are averages across various skills under one category. For example, language skills include the average correct recall for aggregated data on French, Italian and English language skills, and so on. Experience level of the candidate is assumed to be correctly guessed if guessed within a 5-month interval.

The second variable of interest is observing which candidates are more likely to be selected for an interview, and whether socioemotional skills signals play a role in this decision. The raw tabulations given in Table 2.4 clearly show a preference towards candidates with activity-based socioemotional skills over both the control group (72% selects the activity-based treatment CV over the control CV) and the candidates with adjective-based socioemotional skills (73% selects the adjective-based treatment CV over the control CV); but no such pattern is apparent for the selection of adjective-based socioemotional skills over the control CV (52% selects the adjective-based treatment CV over the control CV). To corroborate this finding, we conduct a regression analysis. The main model we consider in this case is as follows:

$$\mathrm{y}_i = \alpha_0 + \beta_1 Adj_{1i} + \beta_2 Act_{1i} + \gamma_1 Adj_{2i} + \gamma_2 Act_{2i} + \\ \delta_1 Finance_i + \delta_2 Sales_i + \theta \mathbf{X_i} + \delta_1 jobtype_i + \epsilon_i \quad (2.1)$$

[8] $N = 57$, p-value=0.7573.
[9] $N = 27$, p=0.000.

where y_i is a binary variable that takes on the value 1 if CV 1 (CV on the left) is selected; Adj_{1i} (Adj_{2i}) is a dummy variable that takes on the value 1 if CV 1 (CV 2) has adjective-based non-cognitive skills; Act_{1i} (Act_{2i}) is a dummy variable that takes on the value 1 if CV 1 (CV 2) has activity-based non-cognitive skills; $Finance_{1i}$ and ($Sales_{1i}$) is a dummy variable that takes on the value 1 if CV1 is the first type of CV constructed for the financial analyst (sales supervisor) job ad and captures CV characteristics other than our treatments within the financial analyst (sales supervisor) job applications; $jobtype_i$ controls for the type of job (sales supervisor or financial analyst); and X_i covers the individual characteristics of the subjects such as gender, undergraduate degree, experience in HR etc. Note that, since the position of the CVs on the screen is allocated randomly for each CV couple, the terms CV 1 and CV 2 do not denote any specific characteristic other than the random position of the CVs on the screen.

Model 1 in Table 2.6 gives the results of the model in (2.1). Note that we expect high collinearity in this model since by the design of the experiment participants do not see two CVs of the same type. For example, if CV 1 has the adjective-based non-cognitive skills treatment, CV 2 either has no non-cognitive skills in the CV or had the activity-based one. Therefore if $Adj_1 = 1$, then $Act_1 = 0$ and $Adj_2 = 0$ must hold. This is why we try the specification in Model 2 to avoid this type of collinearity effects. Model 2 uses the differences of the treatments for each treatment, so that $\Delta Act = Act_1 - Act_2$ and $\Delta Adj = Adj_1 - Adj_2$. Both specifications clearly show a significant effect of the activity-based treatment and an insignificant effect of the adjective-based treatment on CV selection.

Result 2. *Activity-based socioemotional skill signals play a significant role in CV selection, whereas adjective-based socioemotional signals do not have a significant effect.*

A similar picture emerges also looking at the ranking of attributes the participants stated for the selection that they made. This part of the analysis is based on a question in the survey that asks each participant how they rank the characteristics they consider the most important in selecting a CV for an interview. They could select up to 6 CV qualities, and had to type their ranking by giving each characteristic a number from 1 (highest ranked) to 6 (lowest ranked). We then compute an average score for each of the characteristic using these rankings, by reordering them from 6 (highest ranked) to 1 (lowest ranked), and calculating the average scores weighted by the number of subjects that gave the characteristic that particular score. Finally, we recalculate the scores on a scale of 0 to 1, for easier interpretation. The results are given in Table 2.7, and they show that socioemotional skill signals are ranked quite high as attributes considered to be important in CV selection for an interview. In particular, communication skills are ranked the second in the list right after job experience, and persuasion skills are ranked the fourth and above, for example, foreign language skills and technical skills.

Table 2.6: Marginal effects from the logit regression of CV1 and CV2 characteristics on selection of CV1

	Model 1	Model 2
CV1 is adjective-based	0.157	
	(0.113)	
CV1 is activity-based	0.243*	
	(0.125)	
CV2 is adjective-based	0.054	
	(0.125)	
CV2 is activity-based	-0.253**	
	(0.104)	
Other finance CV characteristics	0.305***	0.318***
	(0.108)	(0.111)
Other sales CV characteristics	0.441***	0.422***
	(0.104)	(0.101)
ΔAct		0.243***
		(0.060)
ΔAdj		0.058
		(0.065)
Subject characteristics	Yes	Yes
Job type	Yes	Yes
N.obs.	90	90
Pseudo R-squared	0.307	0.296

Note: Models 1 and 2 provide the marginal effects from logit regressions in which the dependent variable is a dummy that takes on the value 1 if CV1 (CV displayed on the left) is selected. Note that the display order for the CV is randomized. $\Delta Act = Act_1 - Act_2$ and $\Delta Adj = Adj_1 - Adj_2$. Other finance CV characteristics and other sales characteristics each are dummy variables to denote the type of finance or sales CV (there are two types of CVs for each job). Job type includes a dummy variable for type of job (finance or sales), and subject characteristics include type of undergraduate degree, gender, age, experience in HR. Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 2.7: Ranking of attributes for CV selection (scale:0-1)

	All	**By Job**	
		Finance	**Sales**
Job experience	0.71	0.72	0.71
Communication skills	0.68	0.61	0.72
Education level	0.68	0.65	0.70
Persuasion skills	0.67	0.56	0.72
Foreign language skills	0.62	0.63	0.61
Participation to debate tournaments	0.61	0.59	0.63
Quantitative/analytical skills	0.61	0.68	0.48
Data entry experience	0.58	0.61	0.33
Assertiveness	0.56	0.57	0.56
Participation in youth organizations	0.56	0.53	0.67
Motivation	0.55	0.57	0.53
Technical skills	0.55	0.62	0.35
Attention to detail	0.54	0.60	0.46
Teamwork	0.54	0.54	0.53
Adaptability to multicultural environments	0.54	0.54	0.53
Organizational skills	0.53	0.57	0.51
Membership for international organizations	0.52	0.52	0.54
Student club presidency	0.47	0.45	0.58

Note: Statistics derived for all 90 subjects. Subjects rated the importance of characteristics on a scale of 1 to 6, which were later used to produce weighted averages, and subsequently to rankings on a scale of 0 to 1 for convenience.

2.5 Conclusion

This study attempted to identify whether and how including socioemotional skills in CVs might have an impact on selection of the CV for an interview. The results suggest that socioemotional skills are at least as correctly recalled as the other skills listed in the CVs, but activity-based signals are remembered better than the adjective-based ones, suggesting a higher degree of importance assigned to the former compared to the latter. This finding is further reinforced by the fact that CVs with activity-based socioemotional skill signals are chosen more frequently compared to both CVs with adjective-based signals and CVs with no socioemotional skill signals, and regression analyses show a significant effect of activity-based signals on the selection of the CV for an interview.

The results have implications for job seekers as well as the institutions that help job seekers in preparing their CVs. The findings suggest that the signaling of socioemotional skills matter in the CV. However, the currently popular way of signaling socioemotional skills through adjectives, for example in the taglines or summaries of CVs or LinkedIn profiles, does not seem to be an effective way of signaling skills to potential employers. Instead, job seekers should focus on gathering experiences that will later ensure them to signal their socioemotional skills in a more credible way.

2.A Screenshots

You are invited to participate in a survey conducted as part of a study on the labor market by the Economic Policy Research Foundation of Turkey (TEPAV).

This survey is entirely voluntary and is not part of any class assignment; it is solely for research purposes. Even if you agree to take part in the survey right now, you may discontinue participation at any time for any reason by navigating away from the survey website.

It is not possible for the researchers to link your responses to this survey with your identity. The survey software strips away and identifying information before saving your responses. You will never be asked to insert your name at any point in the survey. Your answers will remain strictly confiential: We plan to publish the results of this survey; but no identifying information will ever be used in this research. If you have any questions about this study, please contact .

Your opinions about a hiring process will be asked in this survey, and the survey lasts for about 5-10 minutes. There is no compensation to participate in the survey, but we hope your contribution will help us gain important information about hiring decisions.

I participate in this research completely voluntary, and I know I can leave the survey at any point. I agree to have my responses used in scientific publications.

YES NO

Survey Instructions
We would like you to put yourself in the situation of a human resources manager. In this study, you are making a personnel selection for the **Financial analyst** position. Two CVs submitted today are shown below.

Please examine the job ad and the two CVs below, and decide which one of the below candidates you would like to invite for an interview.

In the next part, you will be asked to answer some questions about the candidates who applied fo this job. **We ask you not to try to come back to this screen while you answer those questions: in this case, your responses will not be useable in our research.**

Job description

We are seeking a **'Financial Analyst'** for our multinational client in the IT & Technology sector. In this job you are expected to:

- Check financial tables to ensure the monthly financial reports prepared by the accounting team are accurate,
- Analyze data and compare forecasts with actual results,
- Prepare accurate, relevant and timely management reports to accurately reflect the status of the business,
- Identify trends and recommending actions to improve financial status.

Requirements:

- University degree in Business Administration, Economy or related area,
- At least 2 years working experience as accounting & finance positions,
- Strong MS Office Applications, particularly in Excel,
- International accounting knowledge (IFRS) would be an asset,
- SAP knowledge is an asset,
- Fluent in spoken and written English
- Adaptability to a multinational environment,
- Teamwork skills

CV #1: Elif Demir

europass

PERSONAL INFORMATION

Name- Surname Elif DEMIR
Sex Female
Date of birth 10/06/1992
Nationality Turkish

WORK EXPERIENCE

Date October 2014- going on
Position Financial Analyst Assistant
Company Name Uniteks Tekstil ve Ticaret A.Ş
The main field of activity and responsibility Analysis of financial balance sheet and transaction reports by data comparison and correction. Preparation of periodic reports on internal financial situation for managers

Date September 2013 - October 2014
Position Department of Treasury Manager Intern
Company Name Finansbank

EDUCATION AND TRAINING

Date 2009-2013
Education and Training Institution Ege University , Izmir, Turkey
Department Business Administration
Degree Undergraduate

Mother tongue(s) Turkish

Other language(s)	UNDERSTANDING		SPEAKING		WRITING
	Listening	Reading	Spoken interaction	Spoken production	
English	B2	C2	C1	C1	C1

Computer Skills MS Office, SAP,UFRS
Business Skills Able to adapt to new and multicultural environments, familiar working with the team

CV #2: Ayşe Yıldırım

europass

PERSONAL INFORMATION

Name- Surname Ayşe YILDIRIM
Sex Female
Date of birth 01/08/1992
Nationality Turkish

WORK EXPERIENCE

Date June 2014- going on
Position Financial Analyst Assistant
Company Name Pamir Gıda A.Ş
The main field of activity and responsibility Profit sharing based on cost and budget balance and estimation processes, prepare quarterly / annual financial information notes for decision makers

Date September 2013-May 2014
Position Assistant Inspector
Company Name TEB

EDUCATION AND TRAINING

Date 2009-2013
Education and Training Institution Dokuz Eylül University , Izmir, Turkey
Department Business Administration
Degree Undergraduate

Mother tongue(s) Turkish

Other language(s)	UNDERSTANDING		SPEAKING		WRITING
	Listening	Reading	Spoken interaction	Spoken production	
English	C1	C2	B2	C1	C1

Computer Skills MS Office,(Excel, Powerpoint, Word)
Business Skills Rotaract 2440 International Committee Member(2010-going on)
Working with teams of 10 people from different countries at the International Youth Camp in Arthez, France(2012

Please select which candidate you would like to invite for an interview:

○ **CV #1: Elif Demir**

○ **CV #2: Ayşe Yıldırım**

Continue

	#1:	#2:
S1: What is the total job experience of the candidate?	Year, Month	Year, Month
S2: What is the education level of the candidate?	High school Undergraduate Masters PhD	High school Undergraduate Masters PhD
S3: Which qualities has the candidate mentioned in her CV? (**Select all that apply**)	MS Office Stata SAP IFRS French Italian English Persuasion skills Motivation Adaptability to multicultural environments Quantitative/analytical skills Attention to detail Communication skills Teamwork skills Assertiveness Driving license	MS Office Stata SAP IFRS French Italian English Persuasion skills Motivation Adaptability to multicultural environments Quantitative/analytical skills Attention to detail Communication skills Teamwork skills Assertiveness Driving license
S4: Is the candidate currently employed?	Yes No	Yes No
S5: Which activities has the candidate mentioned in her CV? (**Select all that apply**)	Editing Participation in international youth organizations Participation in debate tournaments Experience in data entry Sailing Reading Student club leadership Experience in organizing meetings Membership in international societies Teamwork	Editing Participation in international youth organizations Participation in debate tournaments Experience in data entry Sailing Reading Student club leadership Experience in organizing meetings Membership in international societies Teamwork

Please rank the first 6 qualities that you consider the most important in selecting the CV for this exercise.
1: most important, 2: second most important, 3: third most important ...... 6: sixth most important

- Communication skills
- Experience in organizing meetings
- Education
- Attention to detail
- Motivation
- Technical/computer skills
- Adaptability to multicultural environments
- Quantitative/analytical skills
- Work experience
- Membership in international societies
- Foreign language skills
- Participation in debate tournaments
- Student club leadership
- Experience in data entry
- Persuasion skills
- Assertiveness
- Participation in international youth organizations
- Teamwork skills

Continue

In general, what are the 3 most important criteria in evaluating the applicants? Please rank by putting 1, 2 and 3 accordingly.
1: most important, 2: second most important, 3: third most important

- Level of education
- General work experience
- Work experience in a related job
- Work experience in a related sector
- Cognitive skills
- Communication skills
- Leadership skills
- Negotiation skills
- Analytical/quantitative skills
- Foreign language skills
- CGPA at graduation 1
- Age
- Civil status
- Gender
- Hobbies
- Extracurricular activities
- Other

In general, are there any other characteristics that you consider important but are not included in the ranking list?

- Yes
- No

Continue

Concluding questions

Please indicate your experience level in evaluating CVs:
(no experience) ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 (a lot of experience)

Have you ever worked in human resources?
○ Yes ○ No

What is your gender?
○ Male ○ Female

When were you born?
2017

Are you currently working?
○ Yes ○ No

What is the subject of your undergraduate education?
○ Economics/Administrative Sciences
○ Engineering
○ Psychology
○ Sociology
○ Other

Continue

This study is related the saliency of different skills on the CV, and the CVs and the job ad are created by the research team. To get more information about the study, please enter your e-mail address:

Do you have any other suggestions to make some CV characteristics more salient on the CV?

Send!

Your responses are recorded.

Thank you for taking part in this survey!

Chapter 3

Hope and Anger: An Experiment on Inequality and Disruptive Behavior

This chapter is based on joint work with Maria Bigoni and Stefania Bortolotti.[1]

The extent of inequality is a decisive factor in fueling social unrest, but not all inequalities are born alike. By means of a laboratory experiment, we investigate how the unequal distribution of monetary payoffs can trigger disruptive behavior against people with whom there is no previous or expected future contact. In particular, we study whether disruptive behavior depends on the levels of inequality only, or the conditions through which inequality occurs play a role. To do so, we compare an environment in which reducing inequality is safe for the rich with one in which reducing inequality puts the rich in a vulnerable position. We find that inequality triggers the poor's disruptive behavior towards rich strangers Moreover, the experience of the same level of inequality leads to a higher degree of frustration and disruptive behavior among the poor, when the rich can safely reduce inequality. This behavioral change appears to be driven by a change in the poor's expectations on the behavior of the rich, which are more optimistic compared to the case in which the rich are in a vulnerable position.

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3.1 Introduction

Tensions between social classes have gained a prominent role in the public arena and are often at the center of heated political debates. The media and the rise of popular movements such as Occupy Wall Street have increasingly given voice to these tensions. While the extent of

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inequality is of course a decisive factor in fueling social unrest (Stiglitz, 2012), not all inequalities are born alike. What is deemed fair and acceptable can greatly depend on the process that led to inequality (Alesina and Angeletos, 2005; Cappelen et al., 2010; Mollerstrom et al., 2015; Cappelen et al., 2017).

Here we study the rise of social tensions which translates into socially disruptive behavior, under two different scenarios. In the first scenario, a reduction in inequality is difficult to achieve, because the poor can take advantage of a generous act by the rich, whose kindness exposes them to exploitation. This can happen, for instance, in societies where the institutional environment does not grant sufficient protection to individuals. Even the most altruistic among the rich may be reluctant to show any sign of generosity in such a context, as this would make them too vulnerable. This in turn may induce the poor to have pessimistic expectations on the likelihood of a reduction of inequality, and not to attribute the responsibility of inequality fully on the rich. In the second scenario instead, effective mechanisms to prevent exploitation are in place, and inequality can be unilaterally reduced by the rich without any risk of being abused. If disparities prevail in this scenario, the responsibility is solely on the shoulders of the rich. In such a scenario, the poor might have some legitimate aspirations to improve their economic position.

Suppose for a moment that the two scenarios were characterized by the same level of inequality: would this give rise to the same level of socially disruptive behavior – in the form of protests, vandalism, and violence? If social unrest is simply triggered by the degree of absolute or relative poverty, we should not observe any difference. However, evidence from the psychological literature would suggest otherwise. Anger is often rooted in frustration stemming from disappointment of expectations (Potegal et al., 2010, Chapter 5). In our first example, we should not observe much disruptive behavior as the poor do not quite expect a brighter future and cannot be disappointed. Conversely, in the second scenario, the poor might have more optimistic expectations on the possibility of an improvement in their condition. If such a prospect is not realized they can feel disappointed and frustrated and hence more prone to burst with anger and engage in aggressive behavior.

While frustration of optimistic expectations might have an important role in explaining relevant and potentially distressful real-world situations, it is hard to collect clean evidence on this phenomenon in the field. Individual responsibilities are difficult to attribute, and the institutional framework cannot be easily controlled. Keeping inequality constant across contexts can also prove challenging. In addition, it would also be difficult to control for strategic and monetary motives triggering socially disruptive behavior. For these reasons, we move to a tightly controlled laboratory environment.

We develop a new zero-sum two-by-two game, the *Inequality Game*. The game has a unique Nash Equilibrium, in which a "Strong" player earns 90% of the pie, leaving the "Weak" player with a very low profit. The fundamental characteristic of the *Inequality Game* is that there exists a fully equitable outcome, where players share the pie equally, which can be achieved only if the Strong player deviates from equilibrium and chooses a strictly dominated action. Inequality is therefore ingrained in the structure of the game and arises endogenously, as only the Strong player has a chance of choosing between a favorable but inequitable outcome and a perfectly even distribution.

In Experiment 1, we consider two versions of the game, aimed at capturing the essence of the scenarios we just described. In the *Simultaneous* version, by choosing the dominated action, the Strong player faces the risk of earning only 10% of the pie, if the Weak player also chooses the off-equilibrium action. Hence, the choice of the dominant action might be driven by the fear of exploitation, and not only by a greedy ambition. In the *Sequential* game, instead, this form of strategic uncertainty is completely removed, because the Weak player moves first, hence the Strong player can harshly punish a deviation from the Nash equilibrium. On the equilibrium path, the Strong player can choose between a perfectly equal and a highly unequal distribution of resources, without facing any risk of exploitation. In this sense, the *Sequential* game makes it very easy for the Strong player to reduce inequality, and at the same time puts all the responsibility for the final outcome on him/her. This might generate more optimistic expectations among the Weak players. To allow players to gain experience with the game, without affecting its one-shot nature, we let players interact repeatedly for ten rounds, with fixed roles and perfect stranger matching.

To study the extent of disruptive behavior in these scenarios, in two additional treatments, we introduce the possibility to "exit" the game before it starts. Exit is socially costly as it destroys all the money at stake in the game. In addition, a self-interested player should never exit, as it is always costly to do so. It is important to stress that the choice to exit must be taken at the beginning of each round, before playing the game, and hence before knowing the action taken by the counterpart. Differently from other forms of direct and indirect punishment – which have been extensively studied in the literature[2] – exit is thus directed towards someone whose past behavior is completely unknown, and can only be guessed based on the behavior of other players in the same role. As such, exit cannot provide any motive for the Strong players to share the resources more equally, not even off the equilibrium path.[3] Here the idea is

[2]See for instance Güth et al. (1982); Fehr and Gächter (2000); Fehr and Fischbacher (2004); Nikiforakis (2008); Ule et al. (2009); Balafoutas et al. (2014); Güth and Kocher (2014).

[3]For example, while in the Ultimatum Game proposers have an incentive to increase offer to the responders if

that frustration grows over time: one enters the first round with some hope, but then observes that the unequal outcome is realized over and over again. This frustration cannot be unleashed against a previous partner, whose actions are known, as exit can only affect the outcome of the current round, where the player faces a new, completely unknown counterpart. In this sense, we consider a form of socially disruptive behavior that is directed towards a category of people – e.g. a "social class" or part of it – and not toward someone who is directly responsible for the suffered harm. Under this respect, the situation we analyze is also different from the one modeled by Bartling and Fischbacher (2012) and Bartling et al. (2015), where the direct attribution of responsibility is the main driver of punishment. Our framework is closer to the one described in Battigalli et al. (2017), where an individual's tendency to hurt others depends on the degree of frustration of his expectations.[4]

To directly assess whether the two scenarios under analysis – *Simultaneous* and *Sequential* – in fact induce different expectations on the Strong players' behavior, and on the realized degree of inequality, in Experiment 2 we elicit beliefs by means of an incentivized procedure. Experiment 2 involved a new set of participants, who never actually took part in the Inequality Game but had to read the instructions and guess the actual choice made in the first round by the participants in Experiment 1. This experiment is meant to test if the two versions of the game – *Simultaneous* and *Sequential* – generate different expectations about the Strong players' behavior and inequality.

We report three main results. First, data from Experiment 1 reveal that exit emerges only after some experience of the game, and takes place more often in the *Sequential* than in the *Simultaneous* treatment. This is true even though the level of realized inequality and Strong players' behavior is not significantly different across treatments. Second, we look at individual experiences and the choice to exit the game. Weak players' decision to exit in one round is strongly correlated with their experience in previous rounds. In particular, being repeatedly matched with Strong players who never act generously is positively associated with the use of exit. Interestingly, this effect is much more pronounced in the *Sequential* treatment where the Strong players have an easy option to equalize the payoffs. This finding suggests that there is more to exit than just the absolute level of inequality. Third, we find support for the idea that the mismatch between expectations and realized outcomes is a major contributor for the decision to engage in costly punishment against an individual with unknown history. Results from Experiment 2 indicate that subjects expect the Strong players to choose the generous action more often in the *Sequential* treatment. Since subjects in the two experiments are drawn from

they fear that they will reject, such a strategic incentive is not present in our set-up.

[4] Persson (2018) and Aina et al. (2018) provide the first experimental tests of the theory in Battigalli et al. (2017).

the same pool of participants, that suggest that participants in Experiment 1 also had higher hopes for a more equal distribution of earnings in *Sequential* than *Simultaneous*. An implication of our study is that initial expectations about the likelihood of an equal outcome plays a strong role in reaction to inequality, and that if the difference between expectations and reality is wider, then we might expect much stronger reactions to inequality than what the absolute inequality level itself might suggest.

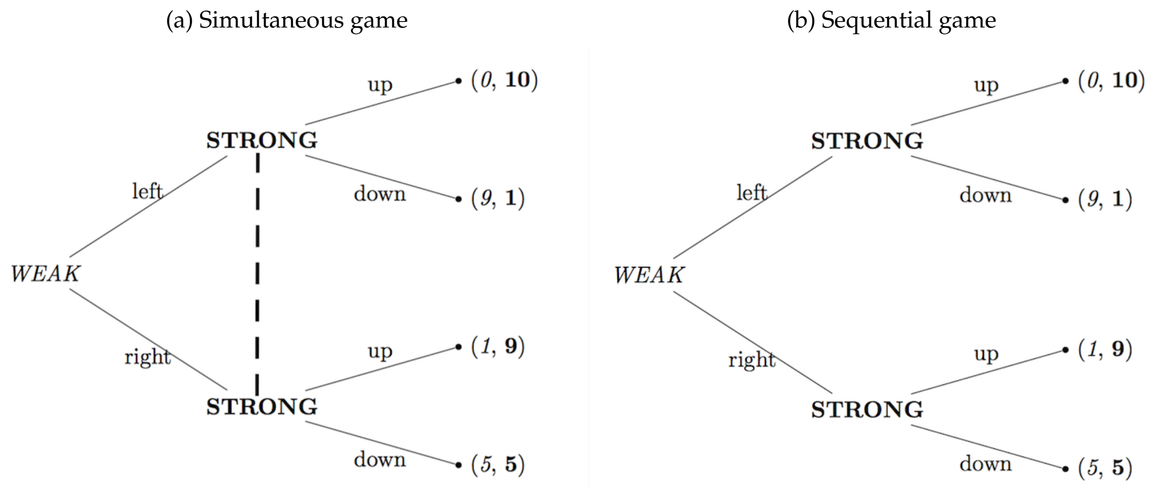
Our design allows us to investigate an overlooked form of reaction to inequality. Previous literature suggests that inequality leads to conflict, vendetta behavior, riots, and extreme forms of intergroup punishment (Abbink et al., 2011; Abbink, 2012; Bolle et al., 2014; Eckel et al., 2016), and that intentions and the source of inequality are important in punishment and money burning (Zizzo and Oswald, 2001; Zizzo, 2003; Fehr, 2015). The defining feature of the form of disruptive behavior we investigate in this study is the fact that it is directed towards individuals whom the subject has no information about. In this sense, the only study close to ours is Lacomba et al. (2014), which investigates post-conflict behavior where conflict is created through a Tullock contest. The study includes one treatment in which losers of the contest can decide to burn money before knowing how much the winner of the contest will appropriate. The primary difference between Lacomba et al. (2014) and our study lies in the research question we answer. While Lacomba et al. (2014) design is not suited to see how expectations affect disruptive behavior, we explicitly manipulate the expectations of Weak player on Strong player behavior. In addition, when they decide whether to burn money, the losers in Lacomba et al. (2014) know they will inevitably be poorer than the winners, whereas the players in our design make their decision in a position where an equitable outcome is possible.

The paper is organized as follows. Section 3.2 explains our novel game, the exit option, and the experimental procedures. Section 3.3 presents the results of the experiment. Section 3.4 details the design and results of Experiment 2. Section 3.5 discusses the implications of our findings and concludes.

3.2 Inequality game and exit: design

In the first experiment, we implemented a 2×2 between-subject design. We exogenously manipulated two dimensions: the sequence of play – *Simultaneous* vs. *Sequential* – and the availability of an exit option – *Control* vs. *Exit*. In the remainder of this section, we first describe the two variants of the *Inequality Game*. We then move to the exit option and finally we turn to the matching protocol, feedback, and procedures.

Figure 3.1: The Inequality Game



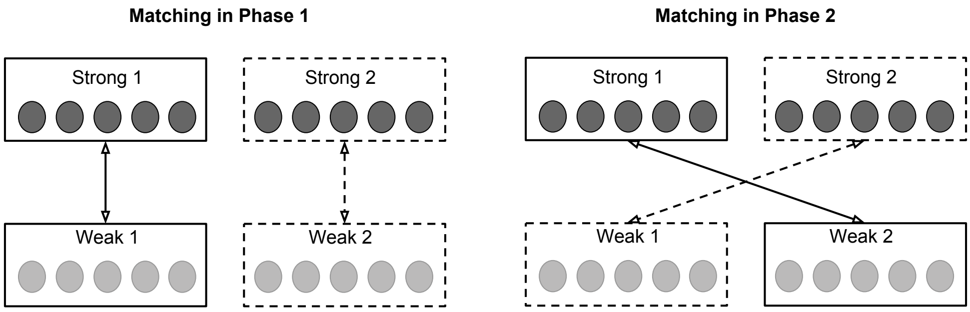
The Inequality Game. To endogenously generate inequality, we developed a novel 2-by-2 asymmetric zero-sum game that we dub the *Inequality Game*. The game involves a Strong and a Weak player.[5] The Strong player can choose between Up and Down and the Weak one between Left and Right: the payoffs (expressed in €) are reported in Figure 3.1. In the *Simultaneous* treatment, both players decide at the same time, while in the *Sequential*, the Weak player decides first. In the latter treatment, we used the contingent method for Strong players, so that they had to make a decision for both nodes.

To allow subjects to gain experience, the inequality game is repeated for a total of 10 periods divided in two phases of equal length. At the end of each period, participants received feedback about the action adopted by their counterpart, and the payoffs in the pair. Roles were fixed over the entire duration of the experiment and there were exactly 10 Strong and 10 Weak players in each session. We used a perfect-strangers matching protocol and players were never matched together more than once.

Feedback and matching were designed so to strip away any possibility of forming an individual reputation, and hence, to rule out any form of direct or indirect reciprocity. Four sets of 5 players were formed at the beginning of the experiment: two sets of Strong players and two sets of Weak players. In Phase 1, each set of Strong players was matched with a set of Weak players, to form a 10-player "matching-group". In the five periods of Phase 1, each Strong player was paired once and only once with each Weak player in his/her matching group. At the end of Phase 1, participants were informed about the average earnings for the Strong and the Weak players in their matching group, but they did not receive any feedback on the out-

[5]The instructions were framed neutrally and the players were referred to as Red and Blue.

Figure 3.2: Matching in Phase 1 and Phase 2



comes realized in the other matching group. In Phase 2, each set of Strong players was matched with the set of Weak players they had not met in Phase 1 (Figure 3.2). This implies that, at the beginning of Phase 2, subjects had some aggregate information on the history of play of the other players in their own set in Phase 1, but no information on the set of players they would be matched with in the next five periods.

The exit option. In the *Exit* treatments, all participants – regardless of their role – were given the chance to exit the game before making any decision for the current round. If at least one of the two participants in the pair decided to exit, both players earned €0. Hence, the exit option is *harmful for both players* and *socially costly* as it generates a Pareto-dominated outcome. The choice to exit could only be taken before playing the game and, therefore, before having any information about the action taken by the other player: when they decided whether to exit or not, participants had no information on the history of play of their counterpart, and they could only rely on their own previous experiences with different counterparts. At the end of each period, subjects were informed whether their counterpart chose to exit, but participants that implemented the exit option could not see the choices made by their counterpart, in terms of either exit or actions. At the end of Phase 1, that is after the first 5 periods, participants were also informed about the total number of exits by the Strong and by the Weak players in their matching-group.

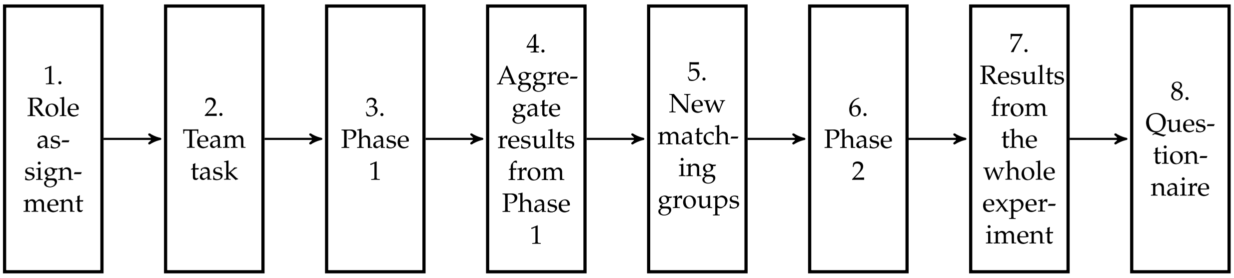
Procedures. 240 subjects equally divided into 12 sessions – 3 for each treatment – participated in the experiment that was conducted at Cologne Laboratory for Economic Research (CLER) in May 2017. Participants were recruited via ORSEE (Greiner, 2015) and the experiment was programmed with zTree (Fischbacher, 2007). Figure 3.3 provides the sequence of events in the experiment. Upon arrival, participants were randomly seated in a cubicle. Instructions were read aloud to ensure common knowledge and a paper copy of the instructions was distributed to participants.[6] An alphanumeric code was distributed together with the instructions and

[6]The experiment was run in English and that was announced in the recruitment message.

participants were asked to enter it on their computer at the beginning of the experiment. The code revealed the role – Strong or Weak player – assigned to the participant. In all sessions and before the *Inequality Game*, there was a team task meant to foster a sense of "group identity". In the team task, participants interacted only with other participants of their same color; hence two teams of ten were formed.[7]

Figure 3.3 summarizes the eight steps of the experiment. In the first two steps, the role was assigned and the team task was performed. Step 3 included five periods of the stage game (Phase 1) and was followed by aggregate results at the matching-group level. In step 5, subjects were moved to a new matching-group and in step 6 five more periods of the *Inequality Game* were played (Phase 2). Aggregate results about Phase 2 were then provided and as a final step a computerized questionnaire was administered.

Figure 3.3: Timeline of the experiment



At the end of the experiment, a computerized questionnaire was administrated. The questionnaire included some socio-demographic questions and a personality test (Ashton and Lee, 2009). To reduce any hedging problem, we paid only two periods. At the end of the experiments, one period from phase 1 and another period from phase 2 were selected at random for payment. Payments ranged from €6 to €26, with an average of €15.50, including a €4 show-up fee. A session lasted 50 minutes on average.

3.2.1 Theoretical predictions

The Inequality Game is dominance-solvable and has the same, unique Nash Equilibrium outcome (Right, Up) in the *Sequential* and the *Simultaneous* versions. The equilibrium payoffs are €9 for the Strong and €1 for the Weak player. In addition, self-interested profit maximizer players – both Strong and Weak – should never use the exit option as it always implies some cost and can bring no material benefit. So, according to a standard game-theoretical approach,

[7]The task consisted of solving math problems to reveal a picture hidden on the subjects' screen. Participants were asked to add up three two-digit numbers and every time a member of the team submitted a correct answer, one more piece of the picture behind the box was revealed. If the team task was successfully completed within 150 seconds, each team member earned €2; all teams succeeded.

we should not observe any behavioral difference across treatments.

Even though the payoffs in equilibrium are highly unequal, it is important to notice that a perfectly equitable outcome exists. The equal split, however, can be achieved only if the Strong player chooses a strictly dominated action. The two treatments – *Simultaneous* and *Sequential* – fundamentally differ in the way the equitable outcome can be reached. A fair-minded Strong player can play Down in the *Simultaneous* game in the hope to reach the equal split (Down-Right). However, a self-interested Weak player could anticipate that and play Left, hence leaving the Strong player with only 10% of the total wealth (Down-Left). Strong players can thus choose Up not only because they are self-interested but also out of strategic concerns. Such a tension is not present in the *Sequential* version of the game where the equitable outcome can be safely chosen.

To capture this difference, we derive alternative predictions based on the assumption of inequality aversion à la Fehr and Schmidt (1999), assuming that the utility is a function of own payoffs and the distance between own and others' material payoffs. We denote by α and β the parameters that capture an individual's sensitivity toward disadvantageous and advantageous inequality, respectively. For the sake of brevity, we relegate all proofs to Appendix 3.B.

Control treatments. We first characterize the predictions for the Strong players. In both variants of the game, Strong players who do not care much about inequality ($\beta \leq 1/2$) always play Nash (Up), while those who are averse to favorable inequality ($\alpha \geq \beta > 1/2$) might play out-of-equilibrium (Down). More specifically, in the *Sequential* treatment, a Strong player with $\alpha \geq \beta > 1/2$ always plays Down in response to Right, as the sub-game corresponds to a mini Dictator Game.[8] However, in the *Simultaneous* treatment, a player with $\alpha \geq \beta > 1/2$ plays Down only if he/she expects the Weak player to choose Right with a sufficiently high probability. In this sense, the model captures the tension between equalizing payoffs and strategic uncertainty in the *Simultaneous* treatment well: inequality averse Strong players might decide not to act kindly simply because they are afraid of being exploited by their counterpart. This tension is not present in the *Sequential* treatment.

It is straightforward to see that Weak players should always play Nash (Right) in the *Sequential* treatment, regardless of their degree of inequality aversion. On the other hand, in the *Simultaneous* treatment the Weak players who do not care much about advantageous inequality (low β) and who attach a sufficiently large probability to the event that Strong chooses out-of-equilibrium (Down) will play Left in the attempt to exploit the Strong player.

[8]Strong players will always play Up in response to Left, for any $\alpha \geq \beta \geq 0$.

Exit treatments. The introduction of the exit option should not affect the behavior of the Strong players, who should never exit the game, and play as they would do in the *Control* treatments. However, the exit option can be rationalized for inequality-averse Weak players having preferences that are compatible with the model by Fehr and Schmidt (1999). More specifically, players with a sufficiently large β may choose to exit both in the *Sequential* and in the *Simultaneous* version of the game, if they have pessimistic expectations about the behavior of the Strong player – i.e., they expect their counterpart to play Up. Instead, for Weak players who are less pessimistic, and very sensitive to disadvantageous but not to advantageous inequality, there may be a substitution effect between the exit option and Left in the *Simultaneous* treatment, where Weak players can try to escape the unequal outcome by playing Left, rather than exiting. This cannot happen in the *Sequential* treatment. To sum up, if expectations on the behavior of the Strong players are the same under the *Simultaneous* and *Sequential* versions of the game, exit should take place less often in the *Simultaneous* treatment. However, the predicted treatment effect on Exit can go in either direction, depending on the players' expectations on their counterparts' actions. If Weak players are more optimistic on the Strong players' willingness to choose "down" in the Sequential treatment, they should be less willing to Exit. On the other hand, if Weak players are pessimistic about an equal division, they may be more likely to exit. Fehr and Schmidt's theory does not provide any intuition on how beliefs may be affected by the treatment.

While Fehr and Schmidt (1999)'s model of inequality aversion can predict the adoption of the exit option, it does not make clear-cut predictions on whether exit should be more prevalent in the *Simultaneous* or *Sequential* version of the Inequality Game, so it does not support our initial intuition that there should be more anger, hence more socially disruptive behavior, when responsibility can be clearly attributed to the Strong players and expectations are more likely to be disappointed. To better capture this intuition, we rely on the insights of a recent model proposed by Battigalli et al. (2017). The main idea of this theoretical framework is that anger is anchored in frustration, that is the result of unfulfilled expectations. Angry players can be eager to sacrifice their own material payoffs to harm another (possibly innocent) player.

Consider again our experimental setting where a Weak player enters the game in round 1 having some expectations about the stream of future monetary payoff. In line with the model by Battigalli et al. (2017), at the beginning of the game, player i has a contingent plan and expectations about player j, and frustration is defined as the difference between the payoff player i expected ex-ante and the maximal attainable payoff ex-post. It is important to stress that the reduction in expected payoff must be both unexpected and beyond the control of player i. Suppose the Weak players in the *Simultaneous* treatment recognize the strategic uncertainty faced by the Strong player and realize that the payoff will always be very unequal. The Weak players in the *Sequential* treatment might instead have good reasons to ex-ante believe that a sizable fraction of the Strong players will behave nicely and split the money equally. As the game progresses, the Weak player might observe extremely unequal outcomes over and over again in both treatments. This experience would generate a higher frustration in the *Sequential* treatment, where he has more optimistic expectations, and this feeling can turn into anger which translates into socially disruptive behavior. In line with the idea that frustration triggers anger, the disruptive and punitive behavior can be targeted towards someone that is not necessarily responsible for generating the initial disappointment. That is exactly what happens when a subject exits the game, as the decision is taken before the counterpart has made a move and without having any information about the past behavior of this person.[9]

3.3 Inequality game and exit: results

This section is organized around two main parts. In the first, we present the aggregate results and treatment effects. In the second part, we dig deeper into individual-level behavior and focus on the use of the exit option conditional on the personal experience in the game.

3.3.1 Aggregate behavior and treatment effect

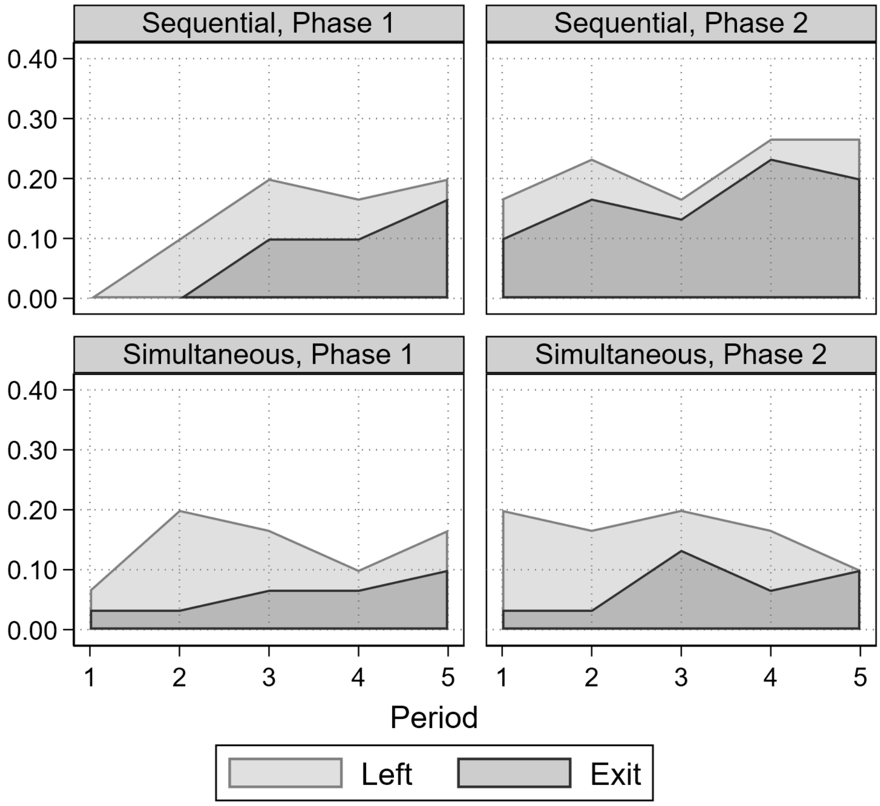
We start by studying whether and how frequently the exit option is adopted and if there is a difference between *Simultaneous* and *Sequential* treatments. We then move to the behavior of Weak and Strong players in *Exit* treatments. Finally, we assess the aggregate effect of the introduction of the exit option on behavior and outcomes, by comparing results from the *Exit* and *Control* treatments.

Adoption of the exit option. In line with the theoretical predictions, we hardly observe any exit behavior by the Strong players. The exit option was used only once out of 600 times. Instead, a non-negligible fraction of Week players used the exit option in both treatments (Figure 3.4). In the first phase the share of exit is similar in the two treatments (6% and 7% in *Simultaneous* and *Sequential*, respectively), yet the gap widens in the second phase when Weak players exit more than twice as often in *Sequential* than in *Simultaneous* (17% vs 7%). Overall, the share of Weak players choosing the exit option is almost twice as high in *Sequential* (12%) compared to *Simultaneous* (7%). In both treatments, about 30% of the Weak players used the exit option at least once.[10] To formally test if there is a gap in exit between the two treatments, we run a

[9] One may argue that in our experiment, subjects do not know what their current opponent has done in the past, but may form beliefs on it based on their previous experiences. So exit could be also seen as a form of targeted punishment, based on a sort of statistical discrimination. To our knowledge, there is no formal model that would capture this specific type of behavior.

[10] The maximum observed number of exists for a single player over the 10 periods is 4 in *Simultaneous* and 6 in *Sequential*. Weak players that exit more than once are 17% in *Simultaneous* and 30% in *Sequential*.

Figure 3.4: Actions of Weak players in the *Exit* treatments



panel linear regression where the dependent variable is the average exit per period and session (Model 1 in Table 3.1). We find evidence that the share of exit increases over periods. Importantly, this increase is significantly more prominent in the *Sequential* treatment (*Period x Sequential* in the regression), hence leading to a positive treatment effect over time.

Result 1. *Weak players' adoption of the exit option increases with experience, and more so in the Sequential compared to the Simultaneous treatment.*

Weak players behavior. As suggested by the theoretical framework, a reason why the exit option is chosen more frequently in the Sequential than in the Simultaneous treatment may be that, in the latter, aversion to disadvantageous inequality may induce Weak players to choose Left rather then Exit, if they expect Strong to play Down sufficiently often. In the Sequential treatment, instead, Left should never be played, so Exit is the only alternative for Weak players who want to avoid a highly unequal outcome. The same reasoning does not apply to the Sequential game where a Weak player does not have any way to try to exploit the generosity of the Strong player. To test if this can explain the difference across treatments, we run a panel lin-

Table 3.1: Behavior in the *Exit* treatments.

	Weak player			Strong player
	Exit	Left	Right (NE)	Up (NE)
	Model 1	Model 2	Model 3	Model 4
Sequential tr. (d)	-0.038	-0.042	0.080	-0.071
	(0.051)	(0.056)	(0.072)	(0.054)
Period	0.006	-0.003	-0.003	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
Period × Seq.	0.017**	0.002	-0.019**	0.003
	(0.007)	(0.007)	(0.008)	(0.008)
Constant	0.033	0.104***	0.862***	0.847***
	(0.036)	(0.039)	(0.051)	(0.038)
N.obs.	60	60	60	60
R-squared (overall)	0.332	0.035	0.176	0.101

Notes: Models 1 to 4 report results from panel linear regressions with session-level random effects. In Model 1, the dependent variable is the average share of exits by session and period. In Model 2, the dependent variable is the average share of Weak choosing Left by session and period. In Model 3, the dependent variable is the average share of Weak choosing Right (Nash) by session and period. In Model 4, the dependent variable is the share of Strong playing Up (Nash). For the sequential game we consider only the Right contingency (irrespectively of the actual choice of Weak – Left or Right). Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

ear regression where the dependent variable is the average Left per period and session (Model 2 in Table 3.1). We fail to provide support to the idea that Weak players choose to play Left significantly more often in *Simultaneous* than in *Sequential*.

While the treatment effect on exit is not unequivocally predicted by the theory (as there can be some substitution between Exit and Left), the theory is clear on the fact that Right in *Sequential* must be more frequent than, or at least as frequent as, in *Simultaneous*.[11] Model 3 in Table 3.1 tests if this prediction is verified in the data. The dependent variable is the average of Right (Nash) choices per period and session. We do not find support for the idea that Weak players play Nash more often in *Sequential* than *Simultaneous*. If anything, the share of Weak players who play Right decreases over time with the decline more marked for the *Sequential* treatment, and the difference is statistically significant (see *Period x Sequential*). In other words, the reason why Exit is more prevalent in the *Sequential* treatment does not lie in a form of "substitution" between Exit and Left. The exit option seems to be adopted by players who – in the *Simultaneous* treatment – would have played Right.

So far, we have established that Weak players use exit more often in the *Sequential* treatment compared to the *Simultaneous* one, and that this difference is not just driven by a substitution effect. The remainder of this section investigates the possible causes of this treatment difference

[11] This result is derived under the assumption that the beliefs about the Strong players behavior are the same across treatments. We will discuss the implications of a departure from this assumption in section 3.4.

in the use of exit.

Strong players' behavior. We now focus on the Strong players to see whether their behavior is different across treatments. It may in fact be possible to explain the treatment difference in the use of exit by the Strong players' behavior, if Strong players were more prone to behave altruistically (i.e., out-of-equilibrium) in the *Simultaneous* rather than in the *Sequential* treatment. If this is true, the difference in exit could simply be the result of different levels of inequality endogenously generated in the game. However, our data do not support this hypothesis: Strong players chose Up 86% of the times in the *Simultaneous* and 81% in the *Sequential* treatment.[12] Model 4 in Table 3.1 reports a panel regression where the dependent variable is the average number of Right plays per session and period. While we fail to find any treatment difference, it is interesting to notice that, if anything, Strong players are slightly more likely to act altruistically in *Sequential* than *Simultaneous*. This is quite in line with the idea that Strong players should be more likely to deviate from Nash when there is no risk of being exploited by the counterpart, which could in principle work to decrease the exit propensity of the Weak players.

Consequences of the introduction of the exit option. To understand the impact of the exit option on Strong and Weak players' behavior, we compare the *Exit* treatments with the *Control* treatments where the exit option is not available. As described in the previous section, the availability of the exit option should not affect the behavior of the Strong players.

Considering both the *Simultaneous* and the *Sequential* treatments, together, we observe that 82% of Strong players in *Control* compared to 84% in *Exit* play Up. In the first period, 77% in the *Control* treatment compared to 78% in the *Exit* treatments play Up. Models 3 and 6 in Table 3.2 provide further evidence that the introduction of an exit option does not change the behavior of the Strong players in both the *Simultaneous* and the *Sequential* treatments. This finding suggests that Strong players do understand that they should not react to the introduction of the exit option, as a kind action cannot dissuade the counterpart from exiting the game – recall that the decision to exit is taken before even seeing the decision of the Strong player.

Result 2. *Strong players' behavior is not statistically different across treatments and it is not affected by the introduction of the exit option.*

[12] In the *Simultaneous* treatment, Strong players can choose between Up (Nash) and Down and make only one decision in each period. In the *Sequential* treatment instead, we use the contingent response method and the Strong players have to decide for each possible node of the game. Since the Right node is selected in the vast majority of the instances (92%), we only report data for the Right node, irrespectively of which node was actually reached.

The percentage of Weak players choosing Right is 87 in the *Control* treatments compared to 84 in the *Exit* treatments. Table 3.2 also reports results for OLS estimations for Weak player behavior, and the dependent variables are Left (Model 1 and 4) and Right (Model 2 and 5), separately for *Simultaneous* and *Sequential*. In line with the predictions, we observe less Left in *Simultaneous* when exit is possible as compared to the situation in which such an opportunity is not available. Quite surprisingly, we observe more Right in Exit treatment; however, the difference manifests itself only in the first periods of the game.

Table 3.2: Comparison between the *Exit* and *Control* treatments.

	Simultaneous treatments			Sequential treatments		
	Left	Right (NE)	Up (NE)	Left	Right (NE)	Up (NE)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Exit tr. (d)	-0.173***	0.140**	0.020	-0.024	0.029	0.042
	(0.064)	(0.064)	(0.048)	(0.048)	(0.066)	(0.081)
Period	-0.017***	0.017***	0.005	-0.002	0.002	0.010*
	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
Exit tr. x Period	0.013	-0.019**	-0.002	0.001	-0.023***	-0.003
	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
N.obs.	60	60	60	60	60	60
R-squared (overall)	0.269	0.134	0.028	0.024	0.361	0.061

Notes: Models 1 to 6 report results from panel linear regressions with session-level random effects. In Models 1 and 4, the dependent variable is the average share of Weak players choosing Left by session and period. In Models 2 and 5, the dependent variable is the average share of Weak players playing Right (Nash). In Models 3 and 6, the dependent variable is the average share of Strong players playing Up (Nash). For the sequential game we consider only the Right contingency (irrespectively of the actual choice of Weak – Left or Right). Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

3.3.2 Individual history and exit

One possible explanation for the difference in exit behavior across treatments could be the individual history observed by each player. Even though there is no difference across treatments in Strong player behavior at the aggregate level, it is still important to check for individual experience. To test for individual-level history, we focus on the subsample of players who were never matched with a Strong player who played out-of-equilibrium (Down) at any time t (Figure 3.5). In the initial period of the game, we include all players as none of them has yet observed any deviation form equilibrium. In any subsequent period t, we only include Weak players who never saw a kind action of their matched partner from period 1 throughout period $t-1$.[13] Figure 3.5 presents the use of exit over time for this subset of Weak players that share a common history. Conditionally on having observed the same (unfair) history, exit

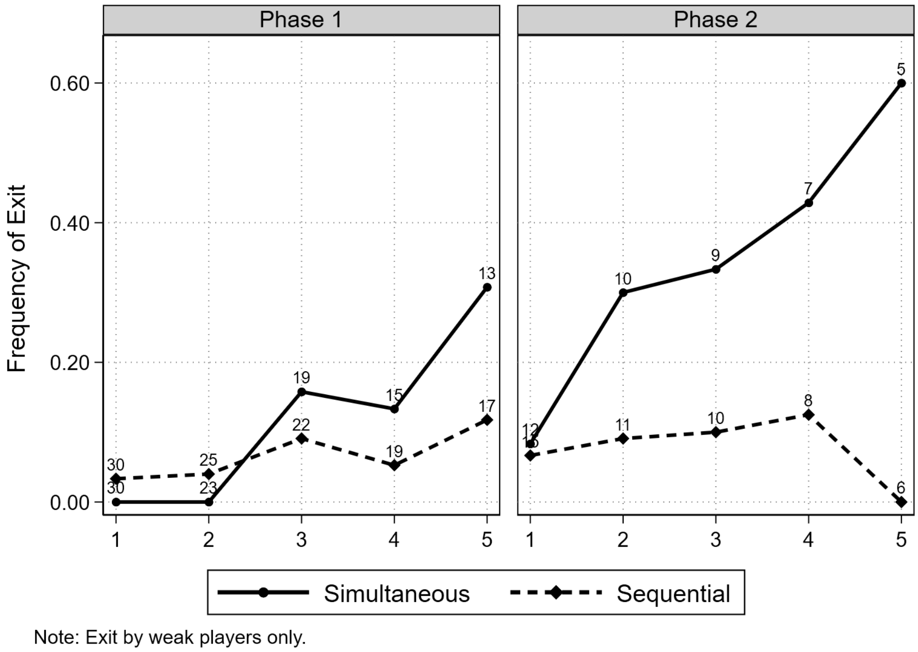
[13]That is the case if the Strong players in previous interactions always chose Nash. However, it can also be the case that a Weak player has chosen to exit in one of the previous $t-1$ periods. In fact, in such a case the Weak player is not given any information about the behavior of the counterpart. This feature of our design does prevent a Weak player to update his beliefs about Strong players behavior in case of exit.

is much more prominent in *Sequential* than in *Simultaneous*. If anything, after controlling for individual-level histories, the gap between the two treatments is even more pronounced and it manifests itself already in phase 1. On the other hand, the frequency of exit for the remaining Weak players, as shown in Figure 3.7 in Appendix 3.A, does not provide any evidence of a treatment difference.

We corroborate these findings through regressions. Table 3.4 in Appendix 3.A reports the marginal effects from probit regressions on exit choices of Weak players, with random effects at the subject level. Models 1, 2, and 3 clearly show an incremental treatment effect such that Weak players who always observed Up in all previous periods until $t-1$ are increasingly more likely to exit in period t. On the other hand, no such effect is visible for the remaining Weak players, as seen in Models 4, 5, and 6.

Table 3.3 shows the marginal effects from panel probit regressions on the exit choices of Weak players, with one observation per subject and period, and random effects at the individual level. We include the number of times the Weak player was matched with a Strong player who chose Down in the earlier periods (*Observed Down*). Recall that choosing Down signals the Strong player's intention to share equally. Models 1 and 2 in Table 3.3 shows that Weak players who have observed Down in the previous periods are in fact significantly less likely to exit, and this effect is more pronounced in the *Sequential* treatment, especially in Phase 2.

Figure 3.5: Frequency of exit for Weak players who never observed Down (out-of-equilibrium)



Notes: The horizontal axis reports the period within each phase, and the vertical axis reports the frequency of exit. Panel on the left provides the frequencies for phase 1, and the panel on the right for phase 2. The solid line is for the *Simultaneous* treatment, whereas the dashed line is for the *Sequential*. Labels on the lines provide the number of observations corresponding to that frequency. The number of observations decreases across periods since Weak players who observe a Down at time t are excluded from the analysis starting from time $t+1$.

At the end of Phase 1, players were informed about the average earnings for the Weak members of their own group and the average earnings for the 5 Strong players of the matched set. In Models 3 and 5, we include the ratio between these two averages (*Payoff ratio (ph1)*). A ratio of one implies equal earnings across the two groups. A ratio smaller than 1 indicates that Strong players were ahead and the smaller the ratio, the larger the inequality between the two groups. The idea behind this regressor is that Weak players who see a larger ratio (i.e., less inequality) in the first phase might be less likely to use the exit option in the second phase. Both Models 3 and 5 show that Weak players are less likely to exit in the *Sequential* as the payoff ratio of Weak players in Phase 1 increases.

Before the beginning of Phase 2, players also receive information on the number of times the exit option was adopted by the members of their own and their matched set in Phase 1. In Models 4 and 5 we study whether observing a higher number of exits by fellow Weak players in Phase 1 induces Weak players to exit more often in Phase 2. Results suggest that this sort of bandwagon effect is not present in our data.

Result 3. *Similar individual-level experiences induce more exit in Sequential than Simultaneous.*

Table 3.3: Individual-level history and the exit option (marginal effects)

	Exit (Yes=1 and No=0)				
	Only Weak players				
	Phase 1 only	Phase 2 only			
	Model 1	Model 2	Model 3	Model 4	Model 5
Sequential tr. (d)	-0.064	0.117*	0.363***	0.047	0.442***
	(0.083)	(0.069)	(0.119)	(0.121)	(0.135)
Period	0.026**	0.021**	0.018*	0.019*	0.021**
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Period × Seq.	0.029	0.012	0.005	0.003	0.008
	(0.018)	(0.016)	(0.015)	(0.015)	(0.016)
Observed Down	-0.051*	-0.027*			-0.040***
	(0.031)	(0.015)			(0.012)
Obs. Down × Seq.	-0.071	-0.086**			-0.045
	(0.078)	(0.034)			(0.038)
Payoff ratio (ph.1)			0.187		0.263
			(0.404)		(0.530)
Payoff ratio (ph.1) × Seq.			-1.590***		-1.249**
			(0.495)		(0.610)
Exit by other Weak in Ph.1				-0.054	-0.042
				(0.035)	(0.030)
Exit by other Weak in Ph.1 × Seq.				0.022	-0.029
				(0.045)	(0.033)
Individual characteristics	Yes	Yes	Yes	Yes	Yes
N.obs.	240	300	300	300	300

Notes: Models 1 to 5 report the marginal effects from panel probit regressions on exit choices of Weak players, with random effects at the subject level. The dependent variable takes value 1 if Weak chooses Exit and 0 otherwise. Model 1 includes only Phase 1, Models 2 to 5 include Phase 2 only. Controls for individual characteristics include age and the number of mistakes made in the control questions, and a set of dummies for: male, political orientation (indicating self-reported right-wing political views), non-German subjects, field of study (social sciences, hard sciences, and humanities). Standard errors robust for clustering at the session level (in parentheses). Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

3.4 The drivers of exit: expectations

We have documented a treatment difference in exit behavior. Disruptive behavior in the form of exit grows over time and this is true only for the *Sequential* treatment, where in Phase 2, exit is more than double than in the *Simultaneous* treatment. The gap in exit between treatments is alive and well even when juxtaposing participants with comparable individual-level experiences of inequality. This suggests that there must be something more than the mere outcomes.

This pattern cannot be explained by inequality aversion (Fehr and Schmidt, 1999) unless Weak players' expectations on others' behavior also change in a direction that is opposite to what one would expect. To rationalize the across treatment difference, Weak players should expect Strong players to be nicer – i.e., choosing Down – in *Simultaneous* than *Sequential*. If that was the case, the higher levels of exit in the *Sequential* treatment could be explained by inequality aversion. An alternative explanation, which builds on the intuition developed by Battigalli et al. (2017), is that the exit divide can be explained by a mismatch between expectations and realized outcomes in the game where Strong players could easily opt for the equal outcome. This explanation hinges on the hypothesis that Weak players are more *optimistic* about Strong players' behavior in *Sequential* than in *Simultaneous*.

Experimental design. To test these two alternative mechanisms, we run a follow-up experiment with a new sample of participants who did not take part in Experiment 1. We invited 122 subjects not familiar with Experiment 1 and we asked them to read the instructions of the original experiment. Each subject was exposed to either the simultaneous or the sequential version of the *Inequality Game*. They all read the instructions for the relevant treatment with an exit option. After reading the instructions, participants were asked to make two guesses: the number of Strong players who selected Up in the first round, and the number of Weak players who selected Right in the first round out of 10 players who did not exit. Both estimates had to be an integer between 0 and 10. The belief elicitation task was incentivized according to a quadratic scoring rule (see Instructions in Appendix 3.C). Estimates were compared with data from previous sessions of Experiment 1. In particular, we had a random draw of 10 Strong and 10 Weak players that was performed at the individual level to avoid informational spill-overs across sessions.

Participants were recruited via ORSEE (Greiner, 2015) from the same pool as the one of Experiment 1. We run 2 sessions for each between-subjects treatment at CLER in April 2018. After reading the instructions, participants had to answer the same set of 10 control questions used in Experiment 1. To ensure that participants carefully read and understood the instructions, we paid them €0.20 for each control question correctly answered at the first try. Only one of the two guesses selected at random at the end of the experiment was relevant for payments. Earnings ranged from €5.50 to €19, with an average of €15.50, including a €4 show-up fee. A session lasted 45 minutes on average.

Results for Experiment 2. Figure 3.6 reports the distribution of expectations divided by player type and treatment. Results show that, between the *Simultaneous* and *Sequential* treatments, subjects have different prior beliefs for both Strong and Weak player actions in the first period. Panel (a) of Figure 3.6 shows the distribution of guesses for the number of Strong players who chose Up for the two treatments, and Panel (b) shows the distribution of guesses for the number of Weak players who chose Right for the two treatments.[14] Mean guess for the number of

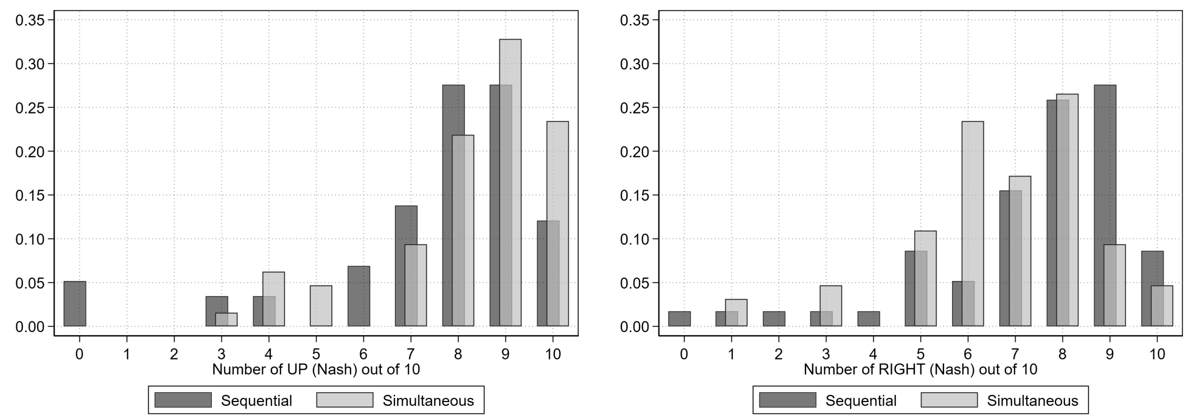
[14]For the *Sequential* treatment, subjects make their guess on Strong player actions conditional on the Weak player selecting Right.

Strong players who select Up in the first period is 8.2 for the *Simultaneous* treatment, whereas it decreases to 7.5 for the *Sequential* treatment ($p = 0.045$, Wilcoxon rank-sum test). In other words, ex ante, subjects expect Strong players to choose Down and hence be more inclined to reduce inequality more often in the *Sequential* compared to the *Simultaneous* treatments. Mean guess for the number of Weak players who select Right in the first period is 6.8 for the *Simultaneous* treatment and it is 7.4 for the *Sequential* treatment ($p = 0.011$, Wilcoxon rank-sum test). In other words, our participants in Experiment 2 can clearly recognize the fact that in the *Simultaneous* game Weak players can try to exploit Strong players with the hope of securing a higher payoff for themselves.

Figure 3.6: Expectations about Strong and Weak player actions

(a) Strong players expected to choose Up

(b) Weak players expected to choose Right



Altogether, these results suggest that subjects perceive an equitable outcome as much more likely in the *Sequential* than in the *Simultaneous* treatment. In other words, Weak players are more hopeful to be treated fairly when Strong players can unilaterally choose the equal split without any fear of being exploited. Our results are compatible with the idea that frustrated expectations can lead to more disruptive behavior, and this behavior can even be directed towards someone that is not necessarily the cause of such frustration. In this sense, explanations based on models of frustrations and anger (Battigalli et al., 2017) can better account for the gap in exit behavior compared to models of inequality aversion (Fehr and Schmidt, 1999).

Result 4. *Subjects expect the Strong players to deviate more from the Nash equilibrium and play more generously in the Sequential than in the Simultaneous treatment.*

3.5 Conclusion

Understanding the mechanisms that lead to social unrest under high inequality is important to provide effective solutions to its social consequences. In this study, we contribute to this attempt by creating an environment with endogenous high inequality, and investigating the response to the change in ex ante expectations about an equitable outcome.

Our findings suggest that the mismatch between expectations and realized outcomes is a major contributor for the decision to engage in costly punishment against an individual with unknown history. In other words, if the difference between expectations and reality is wider, then we might expect much stronger reactions to inequality than what the absolute inequality level itself might suggest. This result is in line with the theoretical framework by Battigalli et al. (2017), where frustration occurs as a result of the difference between expectations and realized outcomes, and leads to anger. Testing for the differences in ex ante expectations through belief elicitation sessions, we find evidence that when there is no strategic risk of sharing, Weak players do expect Strong players to share payoffs equally more often. Given that outcomes are not different in the two games, Weak players experience a stronger disappointment in the *Sequential* treatment, resulting in a higher degree of frustration and thus exit. Our framework is closer to the form of "simple anger" described in Battigalli et al. (2017), where an individual's tendency to hurt others depends on the degree of frustration of his expectations, but not necessarily on whether the frustration was generated by the target of the aggressive behavior or someone else.

The positive treatment effect is quite a remarkable result if one bears in mind that there is no chance of meeting the same Strong player again and, most importantly, Weak players know nothing about the history of the Strong player.[15] It could well be the case that a Weak player exits when being paired with a fair-minded player with a history of equal shares. The possibility of committing a false negative – i.e., punish someone who does not deserve it – should lower the punishment levels.[16] On the other hand, this result may in fact speak to a broader phenomenon than the stylized environment we create in the laboratory. For example, investigating the reasons behind the prevalence of engineers among the suicide bombers coming from the Middle East, Gambetta and Hertog (2009, 2016) find the main driving force as the difference between young engineering graduates' high expectations at the beginning of their study and the realities of unemployment or underemployment they face after graduation.

While the study provides insight on what drives socially disruptive behavior under high

[15] Yang et al. (2016) find evidence that inequality aversion model has less predictive power on behavior when reciprocity is possible, but the study depicts a case of direct reciprocity.

[16] Cappelen et al. (2017) and Markussen et al. (2016) report evidence that people tend to be false negative averse.

inequality, it leaves some further questions open for investigation. The first of these questions might be on the discrepancy between the Strong and Weak player attribution of responsibility. While Weak players seem to regard the same inequality levels differently under our two treatments, Strong players do not respond to the institutional environment providing them safety when they decide to be fair. Furthermore, effort in disentangling statistical discrimination from simple anger as conceptualized in Battigalli et al. (2017) is needed. Finally, our framework does not allow us to identify how much the transparency of intentions play a role in Weak player decisions. In the *Simultaneous* treatment, selfish Strong players may hide behind the institutional structure when they do not share, but this is not possible in the *Sequential* treatment. Weak players may also respond to this transparency of intentions when they exit more often in the *Sequential* treatment.

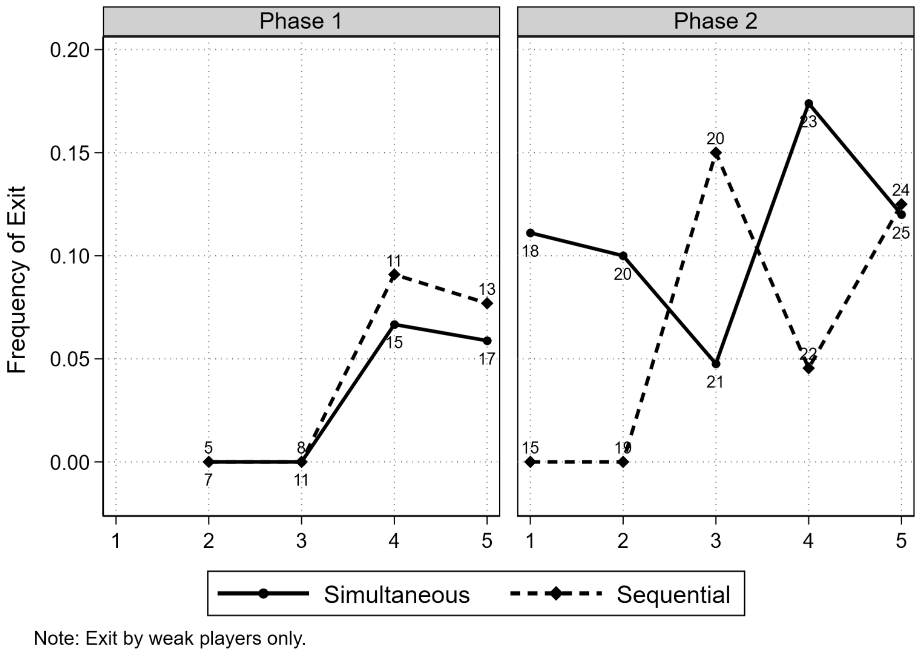
3.A Tables and figures

Table 3.4: Individual histories and exit behavior

	Exit option (Only Weak players, Yes=1 and No=0)					
	Never observed Down			Observed Down at least once		
	Phase 1 only	Phase 2 only	All phases	Phase 1 only	Phase 2 only	All phases
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Period	0.022***	0.005	0.016**	0.044	0.045***	0.041**
	(0.008)	(0.012)	(0.006)	(0.042)	(0.016)	(0.016)
Sequential	-0.099	-0.093	-0.086	-0.121	0.187	0.098
	(0.077)	(0.100)	(0.070)	(0.240)	(0.141)	(0.081)
Period $\times$ Seq.	0.038*	0.060***	0.036**	0.015	-0.035	-0.026
	(0.021)	(0.018)	(0.017)	(0.044)	(0.026)	(0.026)
Phase 2 (d)			0.017			0.060***
			(0.026)			(0.018)
Phase 2 $\times$ Seq.			0.104**			0.053
			(0.043)			(0.089)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
N.obs.	213	93	306	64	177	248

Notes: Models 1 to 6 report the marginal effects from probit regressions on exit choices of Weak players, with random effects at the subject level. The dependent variable takes value 1 if Weak chooses Exit and 0 otherwise. Models 1 and 4 include Phase 1 only, Models 2 and 5 include Phase 2 only, Models 3 and 6 include both phases. In all models except Model 4, controls for individual characteristics include age and the number of mistakes made in the control questions, and a set of dummies for: male, political orientation (indicating self-reported right-wing political views), non-German subjects, field of study (social sciences, hard sciences, and humanities). In Model 4, controls for individual characteristics include age and the number of mistakes made in the control questions, and a set of dummies for: political orientation (indicating self-reported right-wing political views), non-German subjects, field of study (social sciences, hard sciences, and humanities). The difference in Model 4 is because only male subjects exited in Phase 1. Standard errors robust for clustering at the session level (in parentheses). Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Figure 3.7: Frequency of exit for Weak players who saw at least one Down



Notes: The horizontal axis reports the period within each phase, and the vertical axis reports the frequency of exit. Panel on the left provides the frequencies for Phase 1, and the panel on the right for Phase 2. The solid line is for the *Simultaneous* treatment, whereas the dashed line is for the *Sequential*. Labels on the lines provide the number of observations corresponding to that frequency. Number of observations increase across periods since the number of Weak players with a constant history of having observed Up (NE) from period 1 throughout period $t-1$ decreases whenever they are matched with a Strong player who plays Down.

3.B Theoretical predictions

Standard game-theoretical predictions trivially suggest a unique Nash equilibrium in which the Weak player chooses Right and the Strong player chooses Up, irrespective of whether the game is played simultaneously or sequentially. The exit option is never used.

Under the assumption of inequality aversion, we consider a utility function of the Fehr and Schmidt (1999) type, where utility for player i is given by

$$U_i(x) = \begin{cases} x_i - \beta(x_i - x_j) & if \;\; x_i \geq x_j \\ x_i - \alpha(x_j - x_i) & if \;\; x_i < x_j \end{cases}$$

where $x = x_i, x_j$ denotes a vector of monetary payoffs for players i and j and α and β represents the sensitivity toward disadvantageous and advantageous inequality. We assume that $\alpha \geq \beta$ and $0 \leq \beta < 1$.

We denote with p_{right} be the expected probability attached to the event that Weak plays Right and p_{up} the expected probability that Strong plays Up. We derive equilibrium predictions based on α, β, p_{right}, p_{up}.

One threshold, γ, is relevant for deriving the theoretical predictions for the Strong players:

$$\gamma_1 = \frac{9 + 8\alpha - 10\beta}{5 + 8\alpha - 2\beta} \tag{3.1}$$

Three thresholds, θ, are relevant for deriving the theoretical predictions for the Weak players:

$$\theta_1 = \frac{4 - 8\beta}{5 + 2\alpha - 8\beta} \tag{3.2}$$

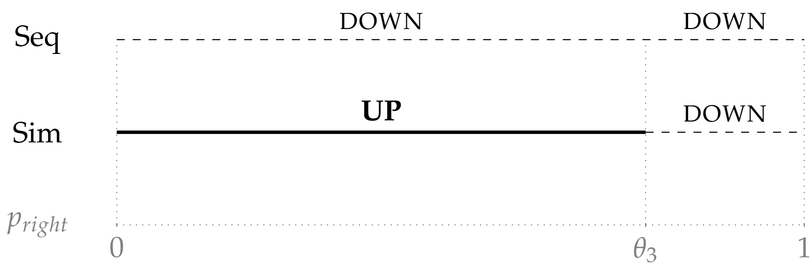
$$\theta_2 = \frac{9 - 8\beta}{9 + 10\alpha - 8\beta} \tag{3.3}$$

$$\theta_3 = \frac{5}{4 + 8\alpha} \tag{3.4}$$

Predictions for the Strong players under inequality aversion

Let us first consider the treatments without the exit option (*Control* treatments). It is immediate to see that Strong players with $\beta < 1/2$ always play Up in both treatments. Figure B1 summarizes the predictions for inequality-averse Strong players ($\alpha \geq \beta > 1/2$) for both versions of the game. In the *Sequential* treatment, an inequality-averse Strong player ($\alpha \geq \beta > 1/2$) always plays Down. In this case, the choice of the Strong players only depends on their inequality aversion and not on the beliefs about the Weak players. In the *Simultaneous* treatment instead, the share of Strong players choosing Down depends on both inequality aversion and beliefs about the Weak player behavior. In particular, a Strong player chooses Down if $\alpha \geq \beta > 1/2$ & $p_{right} > \gamma_1$. One can see from Figure B1 that inequality averse players that would play Down in *Sequential* may play Up in *Simultaneous* because they expect a large enough fraction of the Weak players to play Left.

Figure B1: Predictions for inequality-averse Strong players ($\alpha \geq \beta > 1/2$)



Considering the treatments with the exit option, the predictions for the Strong players are the same as for the *Control* treatments without the exit option. In *Sequential*, Strong players will never choose to exit, since – for any value of β, with $0 \leq \beta \leq 1$ – the utility of Exit is 0, while they can get a utility strictly higher than 0 by choosing Up.[17] The same reasoning applies for the *Simultaneous* treatment.

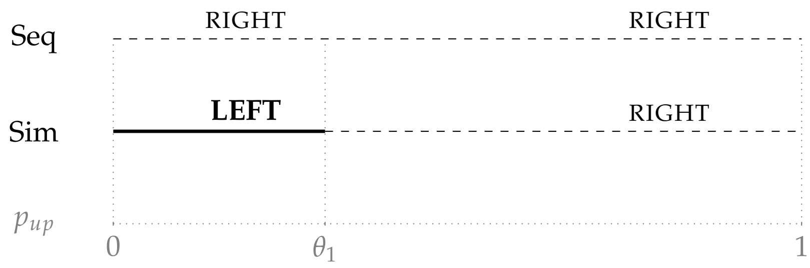
Predictions for the Weak players under inequality aversion

Figure B2 summarizes the predictions for inequality-averse Weak players in the *Control* treatments. In the *Sequential* treatment, there is no value of α and β such that Weak plays Left. In the *Simultaneous* treatment instead, a Weak player will play Left if $\beta < 1/2$ & $p_{up} < \theta_1$.

Moving to the treatments where the exit option was available, Weak players' behavior depends on their sensitivity to inequality and their expectations about p_{up}. In particular, we

[17] Conditional on Weak player choosing Right. If the Weak player chooses left, and $\beta = 1$, the utility of Up would be exactly 0.

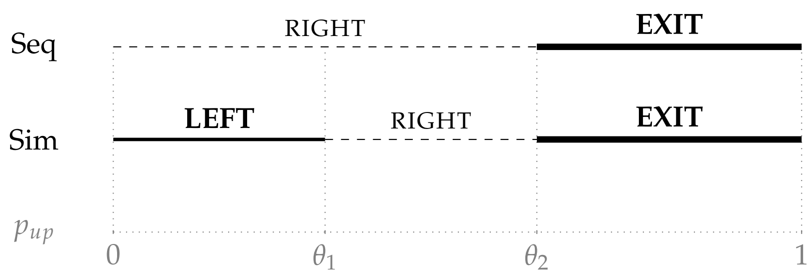
Figure B2: Predictions for inequality-averse Weak players ($\alpha \geq \beta > 1/2$) in *Control* treatments



distinguish two cases based on the parameters of the utility function.

Case 1. For $\alpha < \dfrac{9}{22} \vee \beta > \dfrac{22\alpha - 9}{64\alpha - 8}$, the predictions are shown in Figure B3. In the *Sequential* treatments, Weak players play Right unless they expect Strong players to play Up with $p_{up} > \theta_3$, in which case they prefer to Exit. In the *Simultaneous* treatments, Weak players Exit if they expect Strong players to play Up with $p_{up} > \theta_3$, as in *Sequential*. However, players with $p_{up} \leq \theta_3$ might play either Right or Left. If a Weak player expects Up with a low enough probability, she would play Left. The intuition is as follows: the Weak player has a fairly good chance to be matched with a Strong player that will choose Down and can hence exploit him by playing Left, since it would yield 9 for the Weak player.

Figure B3: Predictions for the Weak players in *Exit* treatments (case 1)

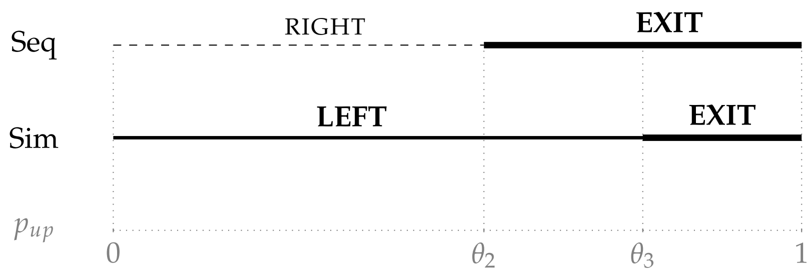


Case 2. For $\alpha > \dfrac{9}{22}$ and $\beta < \dfrac{22\alpha - 9}{64\alpha - 8}$, the predictions are shown in Figure B4. The predictions for the *Sequential* treatment are the same as in Case 1: the Weak players will play Right if $p_{up} \leq \theta_3$ and Exit otherwise. For the *Simultaneous* treatment, Weak players choose Left if $p_{up} \leq \theta_2$, and Exit otherwise. One might notice that for large enough α and small enough β, some players that were willing to Exit in *Sequential* are now willing to play Left. They will never play Right as they are very sensitive to disadvantageous inequality and hence prefer to either Exit or try to exploit the Strong players.

To sum up:

(i) The exit option does not affect the behavior of the Strong player;

Figure B4: Predictions for the Weak players in *Exit* treatments (case 2)



(ii) The fraction of Strong players playing Down in the *Simultaneous* treatment is smaller than or equal to that in the *Sequential* treatment;

(iii) Holding expectations and preferences constant across treatments, the fraction of Weak players playing Right in the *Simultaneous* treatment is smaller than in the *Sequential* treatment. The fraction of Weak players playing Left or Exit should be larger in in the *Simultaneous* treatment compared to the *Sequential* treatment;

(iv) Prediction (iii) is reinforced if Weak players expect Strong players to play Up more frequently in the *Simultaneous* treatment than in the *Sequential* treatment.

3.C Instructions

Instructions[18]

Welcome to this study on economic decision-making. These instructions are a detailed description of the procedures we will follow. You earned €4.00 to show up on time. You can earn additional money during the study depending on the choices you and the other participants will make.

During the study you are not allowed to communicate with the other participants. We also ask you to switch off your mobile phone now. If you have a question at any time, please raise your hand and remain seated: someone will come to your desk to answer it.

As we proceed with the instructions, you will be asked to answer ten questions designed to verify your understanding of the instructions.

The study is divided into **two parts.** Your final earnings depend on the results of Part 1, and the results of Part 2. You will be paid privately and in cash at the end of the study.

Your color and your team

Together with these instructions, you received a **code.** Codes have been randomly distributed, and determine your color, which will be either **red**, or **blue.**

Your color defines which **team** you belong to: the RED or the BLUE team. Each team contains ten participants.

Your color and your team will remain the same throughout the whole study.

- In **Part 1**, you will interact exclusively with participants of **your own team:** if you are red, you will only interact with other red participants, if you are blue you will only interact with other blue participants.
- In **Part 2**, you will interact exclusively with participants of **the other team:** if you are red, you will interact only with other blue participants, if you are blue you will only interact with other red participants.

We will now read instructions for Part1. Instructions for Part 2 will be distributed at the end of Part 1.

[18]Instructions for *Sequential Exit* treatment. The instructions for the other treatments are available upon request from the authors.

INSTRUCTIONS FOR PART 1

At the beginning of this Part, you will be asked to enter your code and you will learn your color and your team.

Once teams are formed, you will perform a team task. The task is to solve some math problems to reveal what is behind the big box you will see on your screen. You will be asked to add up three two-digit numbers. Every time a member of your team submits a correct answer, one more piece of what is behind the box will be revealed.

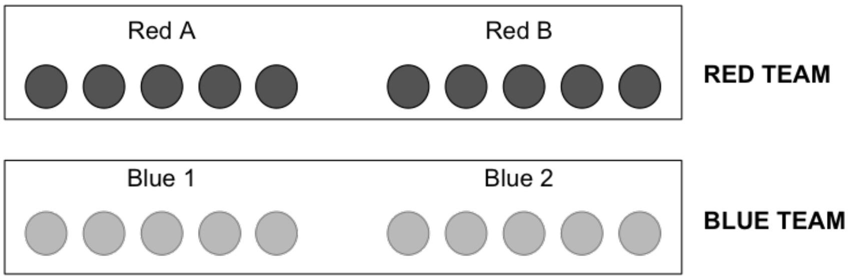
If you and your team members can uncover what is behind the box in **less than 150 seconds,** you will win **2 Euros each.** If you fail as a team, none of your team members will earn anything.

Before we start, we would like you to answer a few questions, to verify the full understanding of instructions.

INSTRUCTIONS FOR PART 2

Your set

In this Part, you will always interact only with participants of the other team. Each team is divided into two **sets** of 5 participants each, as illustrated in the following figure.



All participants in one set have the same color:

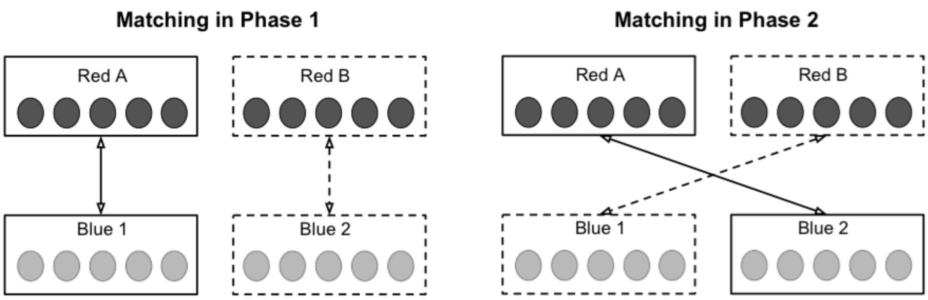
- if you are blue, all members in your set are blue;
- if you are red, all members in your set are red.

Your color and your set will remain the same, until the end of the study.

The Part is divided into two **Phases.** At the beginning of each Phase, your set will be matched with another set of the opposite color. If you are in a **blue** set, you will be matched with a **red** set, and vice versa:

- set Red A will play with set Blue 1 in Phase 1, and with set Blue 2 in Phase 2;
- set Red B will play with set Blue 2 in Phase 1, then with set Blue 1 in Phase 2.

In other words, **in each phase, your set will be matched with a different set.**



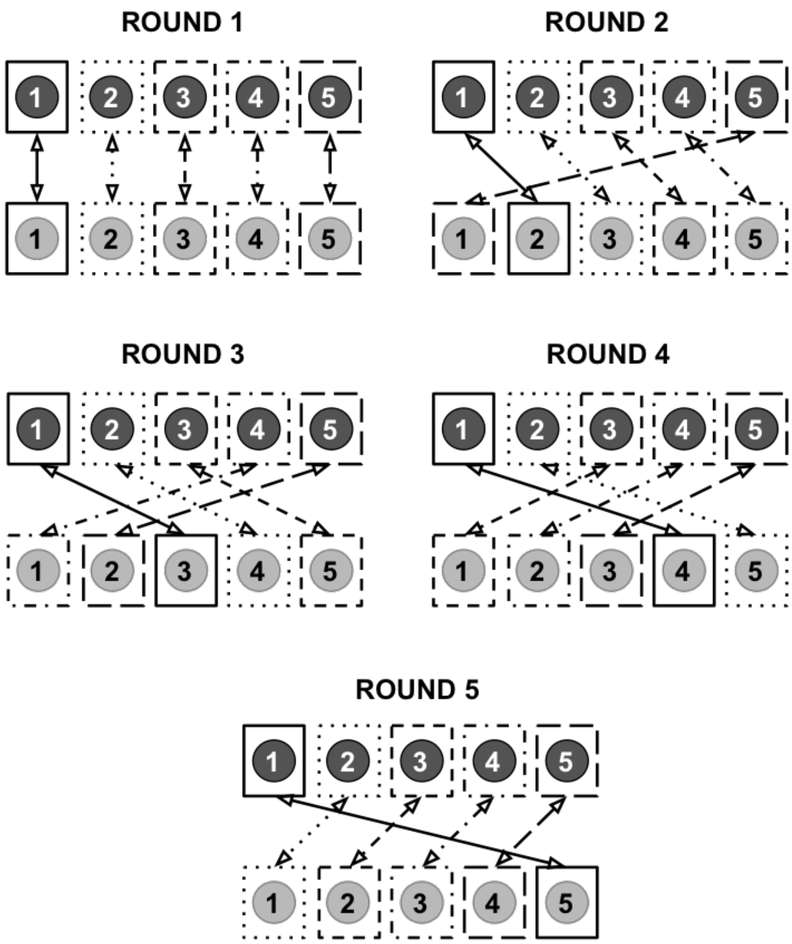
Each Phase includes 5 rounds. Hence, Part 2 lasts **10 rounds** in total.

Matching

In each round, you will be paired with a participant of the opposite color. We will call this person your **counterpart.**

- If you are **blue**, you will be paired with a **red** participant of your matched set.
- If you are **red**, you will be paired with a **blue** participant of your matched set.

You will be paired with each and every participant in your matched set once and only once. **You can never be paired with the same participant twice, throughout the whole study.** The figures below illustrate an example of the pairing structure for the five rounds of each Phase.



In other words, in Part 2 you will be paired with each and every participant of the other team once and only once.

To see how your payoffs are determined in each round, please follow the next instructions.

The “Main Game”

In each round, you and your counterpart will play the “Main Game.” Your payoff in each round depends on your choices and the choices of your counterpart.

If you are **red**, you must choose between **UP** and **DOWN**. If you are **blue**, you must choose between **LEFT** and **RIGHT**.

These choices determine your **payoff** and the payoff of your counterpart, as displayed in the following table:

		Blue Player	
		Left	*Right*
Red Player	*Up*	(10,0)	(9,1)
	Down	(1,9)	(5,5)

In the table, the numbers in the bottom-left corner of each cell represent the payoff of the **red** person, and the numbers in the top-right corner represent the payoff of the **blue** person. All payoffs are expressed in €.

This payoff table is the same for all participants.

To read the payoff corresponding to a specific pair of choices, you should

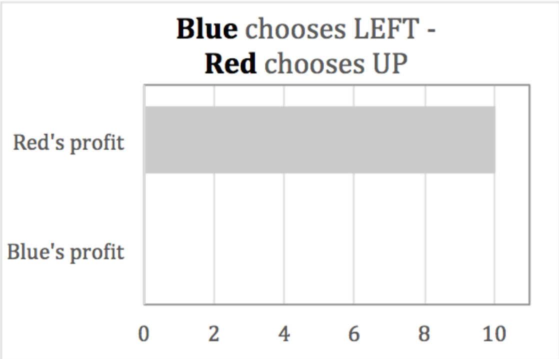
- find the row in the table that corresponds to the choice of the **red** person;
- move to the right to find the cell where this row crosses the column corresponding to the choice of the **blue** person.

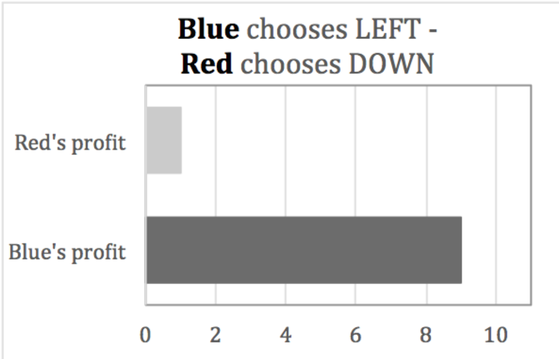
Blue moves first, and cannot condition his choice on the choice made by the **red** counterpart. **Red** moves after **blue**, and can condition his choice on the choice made by his **blue** counterpart.

Consider the case in which blue chooses LEFT.

Red can choose between UP and DOWN.

- **red** chooses UP
  - **red** earns 10;
  - **blue** earns 0.
- If **red** chooses DOWN
  - **red** earns 1;
  - **blue** earns 9.





Consider now the case in which blue chooses RIGHT.

Red can choose between UP and DOWN.

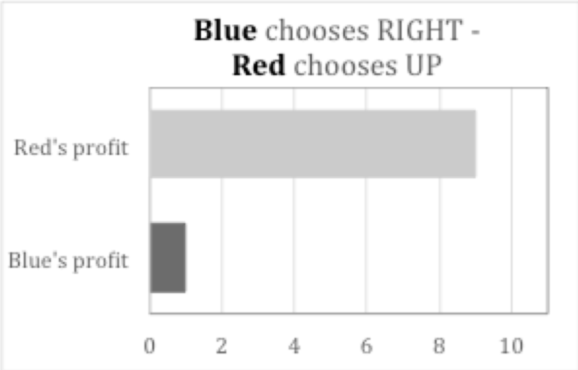
- If **red** chooses UP
  - **red** earns 9;
  - **blue** earns 1.
- **red** chooses DOWN
  - **red** earns 5;
  - **blue** earns 5.

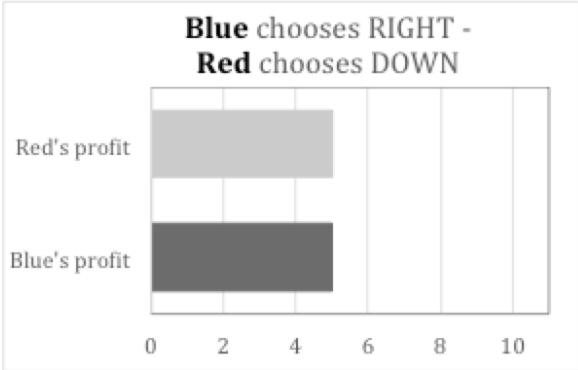
In practice, **blue** will have to answer **one question:**

- Which option do you choose: LEFT or RIGHT?

Red, instead, will have to answer **two questions:**

1. Which option do you choose if your blue counterpart selects RIGHT: UP or DOWN?
2. Which option do you choose if your blue counterpart selects LEFT: UP or DOWN?





Only one of the two choices made by red will be implemented. If **blue** selects RIGHT, the payoffs will be determined by **red**s answer to the first question. If **blue** selects LEFT, the payoffs will be determined by **red**s answer to the second question. **Red** will be informed about the relevant decision only after making both choices. It is therefore important for **red** to pay attention to both choices, as he does not know in advance which one will be relevant.

The "Exit" option

In each round, you will need to take another decision, before making your choice in the "Main Game." You will decide whether you want to EXIT this game, or STAY.

If you select EXIT, the Main Game will not be played. Regardless of the choices made by your counterpart, both of you will earn 0 in this round: If you choose EXIT, you do not have to make any choice in the Main Game

If you select STAY, the payoffs in this round will depend on the decision made by your counterpart.

- If your counterpart selects EXIT, the game will not be played. Regardless of the choices you made, both of you will earn 0 in this round.
- If your counterpart selects STAY, the payoffs will be determined by the choices you and your counterpart made in the Main Game.

You will be informed about the choice – to EXIT or STAY – of your counterpart only after taking your decision in the Main Game. If your counterpart chooses EXIT, your decision will not be relevant. **Remember that you will make this choice for each round separately.** In each round, both participants in the pair will have the chance to decide whether they would like to EXIT or STAY, before playing the Main Game, and hence **before knowing the choice made by their counterpart.**

Feedback information

After each round, you will receive information on whether your counterpart selected EXIT or STAY. In case both you and your counterpart chose STAY, you will be informed on the choice made by your counterpart in the Main Game. If you or your counterpart (or both) chose EXIT, you will not receive any information about the chosen option. You will also see your payoff and the payoff of your counterpart.

After each Phase, that is after round 5 and after round 10, you will also receive information on

- the average payoff of the members of your set over all rounds of the Phase;
- the average payoff of the members of your matched set over all rounds of the Phase;
- how frequently the participants in your set selected EXIT in all rounds of the Phase;

- how frequently the participants in your matched set selected EXIT in all rounds of the Phase.

Remember that in Phase 2 you can never be paired with any member of the set you were matched with in Phase 1.

Your earnings in Part 2

At the end of Part 2, one round from each Phase will be selected, and your payoff in those two rounds will be paid to you.

Hence, your earnings in Part 2 depend on your choices and the choices of your counterpart in one randomly selected round of Phase 1 (rounds 1-5), and in one randomly selected round of Phase 2 (rounds 6-10).

——————— *new set of instructions* ————————

Instructions for belief elicitation sessions[19]

Welcome to this study on economic decision-making. These instructions are a detailed description of the procedures we will follow. You earned 4.00 to show up on time. You can earn additional money during the study depending on the choices you make.

During the study you are not allowed to communicate with the other participants. We also ask you to switch off your mobile phone now. If you have a question at any time, please raise your hand and remain seated: I will come to your desk to answer it.

As we proceed with the instructions, you will be asked to answer ten questions designed to verify your understanding of the instructions. You will receive 20 cents for each question you answer correctly at the first trial.

You will be paid privately and in cash at the end of the study.

In this experiment, you are asked to provide an estimate about decisions made by other people who took part in a previous study. This study was conducted in Cologne, at this laboratory.

Below we report the instructions we used in this previous study. We ask you to read them on your own.

It is important that you carefully follow these instructions and fully understand the original instructions. To verify your full understanding, we ask you to answer the same quiz we administered to the participants who took part in the previous study. You will receive 20 cents for each question you answer correctly at the first trial.

When everyone has completed this quiz, we will proceed and explain your task in today's study, and how your earnings are computed.

——————— *instructions for the original experiment here* ———————

[19] Instructions for belief elicitation for the *Sequential Exit* treatment. Instructions for the *Simultaneous Exit* treatment are available upon request from the authors.

Your task.

You will be asked to guess the choices made by the participants in the first round of the previous study.

At the beginning of todays study, the computer will randomly draw the choices made in the first round by 20 of the subjects who took part in the previous study. Of these 20 participants, 10 were assigned the role of blue players, while the other 10 were assigned the role of red players. None of them chose to exit.

You need to answer two questions:

1. How many of the 10 blue players chose RIGHT in the first round?
2. How many of the 10 red players chose UP in the first round if their counterpart selected RIGHT?

For both questions, your answer should be an integer number between 0 and 10.

Your earnings.

Your earnings can vary between 0 and 13 euro per question. The closer you get to the correct answer, the higher your earnings. Please see Table 1. You earn 13 euros if your guess coincides with the right answer, or if it departs from it by at most one unit (from above or below). If instead your guess departs from the correct answer by 2 units, you earn 11; if it departs from the correct answer by 3 units, you earn 8.5, and so forth and so on. If your guess departs from the correct answer by 6 or more units you earn nothing.

Table 1: Earnings table

Distance from the correct answer	**Earnings**
0 or 1	13
2	11
3	8.5
4	5
5	0.5
6 or more	0

You will be paid for one of the two guesses selected at random by the computer. You will know which guess will be relevant for your payment only at the end of the experiment. It is hence in your interest to pay attention to both decisions.

Please raise your hand if you have any questions and I will come to your desk to answer them.

Bibliography

Abbink, K. (2012). Laboratory Experiments on Conflict. In M. Garfinkel and S. Skaperdas (Eds.), *The Oxford Handbook of the Economics of Peace and Conflict*. New York: Oxford University Press.

Abbink, K., D. Masclet, and D. Mirza (2011). Inequality and Riots - Experimental Evidence. CIRANO Scientific Series No. 2011s-10.

Aina, C., P. Battigalli, and A. Gamba (2018). Frustration and Anger in the Ultimatum Game: An Experiment. IGIER Working Paper No. 621.

Alesina, A. and G.-M. Angeletos (2005). Fairness and Redistribution. *American Economic Review 95*(4), 960–980.

Antecol, H. and D. A. Cobb-Clark (2010). Do Non-Cognitive Skills Help Explain the Occupational Segregation of Young People? IZA Discussion Paper No. 5093.

Ashton, M. C. and K. Lee (2009). The HEXACO60: A Short Measure of the Major Dimensions of Personality. *Journal of Personality Assessment 91*(4), 340–345.

Babcock, L. and S. Laschever (2009). *Women Don't Ask: Negotiation and the Gender Divide*. Princeton, New Jersey: Princeton University Press.

Baert, S. and S. Vujić (2018). Does It Pay to Care? Volunteering and Employment Opportunities. *Journal of Population Economics 31*(3), 819–836.

Balafoutas, L., N. Nikiforakis, and B. Rockenbach (2014). Direct and Indirect Punishment among Strangers in the Field. *Proceedings of the National Academy of Sciences 111*(45), 15924–15927.

Balkan, B. and S. M. Cilasun (2018). Does Gender Discrimination Contribute to Low Labor Force Participaton of Women in Turkey? Evidence from Survey and Field Data. ERF Working Paper Series No. 1205.

Barber, B. M. and T. Odean (2001). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics 116*(1), 261–292.

Barry, H. (2000). Beauty, Stature and the Labour Market: A British Cohort Study. *Oxford Bulletin of Economics and Statistics 62*(s1), 771–800.

Bartling, B. and U. Fischbacher (2012). Shifting the Blame: On Delegation and Responsibility. *The Review of Economic Studies 79*(1), 67–87.

Bartling, B., U. Fischbacher, and S. Schudy (2015). Pivotality and responsibility attribution in sequential voting. *Journal of Public Economics 128*, 133–139.

Battigalli, P., M. Dufwenberg, and A. Smith (2017). Frustration and Anger in Games. IGIER Working Paper No. 539.

Bertrand, M. and E. Duflo (2017). Field Experiments on Discrimination. In A. V. Banerjee and E. Duflo (Eds.), *Handbook of Field Experiments*, Volume 1 of *Handbook of Economic Field Experiments*, pp. 309 – 393. Oxford, UK: North-Holland.

Bertrand, M. and S. Mullainathan (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review 94*(3), 991–1013.

Bolle, F., J. H. W. Tan, and D. J. Zizzo (2014). Vendettas. *American Economic Journal: Microeconomics 6*(2), 93–130.

Borghans, L., H. Meijers, and B. Ter Weel (2008). The Role of Noncognitive Skills in Explaining Cognitive Test Scores. *Economic Inquiry 46*(1), 2–12.

Boudreau, J. W., W. R. Boswell, and T. A. Judge (2001). Effects of Personality on Executive Career Success in the United States and Europe. *Journal of Vocational Behavior 58*, 53–81.

Bowles, S., H. Gintis, and M. Osborne (2001a). Incentive-Enhancing Preferences: Personality, Behavior, and Earnings. *American Economic Review 91*(2), 155–158.

Bowles, S., H. Gintis, and M. Osborne (2001b). The Determinants of Earnings: A Behavioral Approach. *Journal of Economic Literature 39*(4), 1137–1176.

Brunello, G. and M. Schlotter (2011). Non-Cognitive Skills and Personality Traits: Labour Market Relevance and Their Development in Education & Training Systems. IZA Discussion Paper No. 5743.

Cameron, S. V. and J. J. Heckman (1993). The Nonequivalence of High School Equivalents. *Journal of Labor Economics 11*(1), 1.

Campbell, J. P., R. A. McCloy, S. H. Oppler, and C. E. Sager (1993). A Theory of Performance. In N. Schmitt and W. Borman (Eds.), *Personnel Selection in Organizations*, pp. 35–70. San Francisco: Jossey-Bass.

Cappelen, A. W., C. Cappelen, and B. Tungodden (2017). False Positives and False Negatives in Distributive Choices. Working paper.

Cappelen, A. W., T. Halvorsen, E. O. Sørensen, and B. Tungodden (2017). Face-saving or fair-minded: What motivates moral behavior? *Journal of the European Economic Association 15*(3), 540–557.

Cappelen, A. W., E. O. Sørensen, and B. Tungodden (2010). Responsibility for what? Fairness and individual responsibility. *European Economic Review 54*(3), 429–441.

Card, D. and G. B. Dahl (2011). Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior. *Quarterly Journal of Economics 126*(1), 103–143.

Carneiro, P. and J. Heckman (2003). Human Capital Policy. IZA Discussion Paper No. 821.

Cobb-Clark, D. A. and M. Tan (2011). Noncognitive Skills, Occupational Attainment, and Relative Wages. *Labour Economics 18*(1), 1–13.

Conn, S. R. and M. L. Rieke (1994). *16PF Fifth Edition Technical Manual*. Champaign, IL: Institute for Personality & Ability Testing.

Croson, R. and U. Gneezy (2009). Gender Differences in Preferences. *Journal of Economic Literature 47*(2), 448–474.

Cunha, F. and J. Heckman (2007). The Technology of Skill Formation. *American Economic Review 97*(c), 31–47.

Cunha, F. and J. J. Heckman (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Journal of Human Resources 43*(4), 738–782.

Cunha, F., J. J. Heckman, L. Lochner, and D. V. Masterov (2006). Interpreting the Evidence on Life Cycle Skill Formation. Volume 1 of *Handbook of the Economics of Education*, pp. 697 – 812. Oxford, UK: Elsevier.

Deryugina, T. and O. Shurchkov (2015). Now You See It, Now You Don't: The Vanishing Beauty Premium. *Journal of Economic Behavior & Organization 116*, 331–345.

Dohmen, T. and A. Falk (2011). Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender. *American Economic Review 101*(2), 556–90.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2009). Homo Reciprocans: Survey Evidence on Behavioural Outcomes. *The Economic Journal 119*(536), 592–612.

Doorley, K. and E. Sierminska (2015). Myth or Fact? The Beauty Premium Across the Wage Distribution in Germany. *Economics Letters 129*(6674), 29–34.

Eckel, C. C., E. Fatas, and M. J. Kass (2016). Sacrifice: An Experiment on the Political Economy of Extreme Intergroup Punishment. Working paper.

Fehr, D. (2015). Is Increasing Inequality Harmful? Experimental Evidence. WZB Discussion Paper.

Fehr, E. and U. Fischbacher (2004). Third-party punishment and social norms. *Evolution and Human Behavior 25*(2), 63–87.

Fehr, E. and S. Gächter (2000). Cooperation and Punishment ind Public Goods Experiments. *American Economic Review 90*(4), 980–994.

Fehr, E. and K. M. Schmidt (1999). A Theory of Fairness, Competition, and Cooperation. *Quarterly Journal of Economics 114*(3), 817–868.

Fischbacher, U. (2007). z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics 10*(2), 171–178.

Gambetta, D. and S. Hertog (2009). Why are there so many engineers among Islamic radicals? *European Journal of Sociology 50*(2009), 201–230.

Gambetta, D. and S. Hertog (2016). *Engineers of Jihad: The Curious Connection between Violent Extremism and Education*. Princeton: Princeton University Press.

Gelissen, J. and P. M. de Graaf (2006). Personality, Social Background, and Occupational Career Success. *Social Science Research 35*, 702–726.

Greiner, B. (2015). Subject Pool Recruitment Procedures: Organizing Experiments with ORSEE. *Journal of the Economic Science Association 1*(1), 114–125.

Groves, M. O. (2005). How Important is Your Personality? Labor Market Returns to Personality for Women in the US and UK. *Journal of Economic Psychology 26*, 827–841.

Güth, W. and M. G. Kocher (2014). More than Thirty Years of Ultimatum Bargaining Experiments: Motives, Variations, and a Survey of the Recent Literature. *Journal of Economic Behavior & Organization 108*, 396–409.

Güth, W., R. Schmittberger, and B. Schwarze (1982). An Experimental Analysis of Ultimatum Bargaining. *Journal of Economic Behavior & Organization 3*(4), 367–388.

Hamermesh, D. S. and J. E. Biddle (1994). Beauty and the Labor Market. *American Economic Review 84*(5), 1174–1194.

Heckman, J. J. (2008). Schools, Skills, and Synapses. *IZA Discussion Papers* (3515).

Heckman, J. J. and T. Kautz (2012). Hard Evidence on Soft Skills. *Labour Economics 19*(4), 451–464.

Heckman, J. J. and Rubinstein (2001). The importance of Noncognitive Skills: Lessons from GED Testing Program. *American Economic Review 91*(2), 145–149.

Heckman, J. J., J. Stixrud, and S. Urzua (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics 24*(3), 411–482.

Heineck, G. and S. Anger (2010). The Returns to Cognitive Abilities and Personality Traits in Germany. *Labour Economics 17*(3), 535–546.

Kroft, K., M. J. Notowidigdo, and F. Lange (2013). Duration Dependence and Labor Market Conditions: Evidence From a Field Experiment. *Quarterly Journal of Economics 128*(3), 1123–1167.

Kuhn, P. and C. Weinberger (2005). Leadership Skills and Wages. *Journal of Labor Economics 23*(3), 395–436.

Lacomba, J. A., F. Lagos, E. Reuben, and F. van Winden (2014). On the Escalation and De-escalation of Conflict. *Games and Economic Behavior 86*, 40–57.

Lindqvist, E. and R. Vestman (2011). The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment. *American Economic Journal: Applied Economics 3*(1), 101–128.

López Bóo, F., M. A. Rossi, and S. S. Urzúa (2013). The Labor Market Return to an Attractive Face: Evidence from a Field Experiment. *Economics Letters 118*(1), 170–172.

Ludwig, S., G. Fellner-Röhling, and C. Thoma (2017). Do Women Have More Shame than Men? An Experiment on Self-Assessment and the Shame of Overestimating Oneself. *European Economic Review 92*, 31–46.

Lundeberg, M. A., P. W. Fox, and J. Punćcohaŕ (1994). Highly Confident but Wrong: Gender ifferences and Similarities in Confidence Judgments. *Journal of Educational Psychology 86*(1), 114.

Markussen, T., L. Putterman, and J. R. Tyran (2016). Judicial Error and Cooperation. *European Economic Review 89*, 372–388.

Mobius, M. M. and T. S. Rosenblat (2006). Why Beauty Matters. *American Economic Review 96*(1), 222–235.

Mollerstrom, J., B.-A. Reme, and E. O. Sørensen (2015). Luck, Choice and Responsibility – An Experimental Study of Fairness Views. *Journal of Public Economics 131*, 33–40.

Mueller, G. and E. Plug (2006). Estimating the Effect of Personality on Male and Female Earnings. *Industrial & Labor Relations Review 60*(1), 3–22.

Munyo, I. and M. A. Rossi (2013). Frustration, euphoria, and violent crime. *Journal of Economic Behavior & Organization 89*, 136–142.

Niederle, M. and L. Vesterlund (2007). Do Women Shy Away From Competition? Do Men Compete Too Much? *Quarterly Journal of Economics 122*(3), 1067–1101.

Nikiforakis, N. (2008). Punishment and Counter-Punishment in Public Good Games: Can we Really Govern Ourselves? *Journal of Public Economics 92*(1-2), 91–112.

Nyhus, E. K. and E. Pons (2005). The Effects of Personality on Earnings. *Journal of Economic Psychology 26*, 363–384.

Palomino, F. and E. A. Peyrache (2010). Psychological Bias and Gender Wage Gap. *Journal of Economic Behavior and Organization 76*, 563–573.

Persson, E. (2018). Testing the impact of frustration and anger when responsibility is low. *Journal of Economic Behavior & Organization 145*, 435–448.

Piopiunik, M., L. Woessmann, L. Simon, and G. Schwerdt (2018). Skills, Signals, and Employability: An Experimental Investigation. IZA Discussion Paper 11283, IZA.

Potegal, M., G. Stemmler, and C. Spielberger (2010). *International Handbook of Anger: Constituent and Concomitant Biological, Psychological, and Social Processes*. New York, NY, US: Springer.

Protsch, P. and H. Solga (2015). How Employers Use Signals of Cognitive and Noncognitive Skills at Labour Market Entry: Insights from Field Experiments. *European Sociological Review 31*(5), 521–532.

Scholz, J. K. and K. Sicinski (2015). Facial Attractiveness and Lifetime Earnings: Evidence from a Cohort Study. *Review of Economics and Statistics 97*(1), 14–28.

Segal, C. (2012). Working When No One Is Watching: Motivation, Test Scores, and Economic Success. *Management Science 58*(8), 1438–1457.

Segal, C. (2013). Misbehavior, Education, and Labor Market Outcomes. *Journal of the European Economic Association 11*(4), 743–779.

Seibert, Scott E. and Kraimer, Maria L. (2001). The Five-Factor Model of Personality and Career Success. *Journal of Vocational Behavior 58*(1), 1–21.

Sobel, J. (2012). Signaling Games. In R. A. Meyers (Ed.), *Computational Complexity: Theory, Techniques, and Applications*, pp. 2830–2844. Springer-Verlag.

Spence, M. (1973). Job Market Signaling. *Quarterly Journal of Economics 87*(3), 355.

Stiglitz, J. (2012). *The Price of Inequality: How Today's Divided Society Endangers Our Future*. New York: W. W. Norton.

Ule, A., A. Schram, A. Riedl, and T. N. Cason (2009). Indirect Punishment and Generosity Toward Strangers. *Science 326*(5960), 1701–1704.

Yang, Y., S. Onderstal, and A. Schram (2016). Inequity Aversion Revisited. *Journal of Economic Psychology 54*, 1–16.

Zizzo, D. J. (2003). Money Burning and Rank Egalitarianism with Random Dictators. *Economics Letters 81*(2), 117–120.

Zizzo, D. J. and A. J. Oswald (2001). Are People Willing to Pay to Reduce Others' Incomes? *Annales d'Economie et de Statistique* (63), 1–41.