Is there Less Discrimination in Occupations where Recruitment is Difficult?

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Abstract. We empirically test the cross-sectional relationship between hiring discrimination and labor market tightness at the level of the occupation. To this end, we conduct a correspondence test in the youth labor market. In line with theoretical expectations, we find that, compared to natives, candidates with a foreign sounding name are equally often invited to a job interview if they apply for occupations for which vacancies are difficult to fill, but they have to send twice as many applications for occupations for which labor market tightness is low. Our findings are robust against various sensitivity checks.

Keywords. Hiring discrimination, ethnic discrimination, labor market tightness, field experiments.

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1 Introduction

Becker (1957) argues that discrimination is difficult to sustain in a perfectly competitive product market, because it is costly, so that a firm that discriminates by not hiring a productive minority worker would be driven out of the market by a competing firm that takes advantage of this profit opportunity.[3] Similarly, Cahuc and Zylberberg (2004) argue that discrimination is necessarily linked to some imperfection in the labor market. Employers paying discriminated workers a wage lower than marginal productivity are driven out of the market by free entry of firms without a preference for discrimination, since these firms are willing to offer to these workers a wage that does equal marginal productivity.[4]

In reality product and labor markets are imperfectly competitive and therefore discrimination can prevail. In particular, recent contributions to the literature (see, e.g., Manning, 2003) have shown that employers, even if they operate in labor markets composed of many competing firms, can exercise a certain degree of monopsony power and can therefore discriminate against certain groups of workers without being driven out of the market. Monopsony power rises with search costs of employees and falls with search costs of employers. On the one hand, search costs incurred by workers and induced by mobility costs (Gordon and Morton, 1974; Barth and Dale-Olsen, 1999) or imperfect information (Black, 1995; Bowlus and Eckstein, 2002; Rosén, 2003) limit the capacity to change employer and, hence, confer some power to employers to discriminate. On the other hand search costs on the employers' side increase foregone output

[3] Bergmann (1989) criticizes this theory. She argues that it hinges on the assumptions "(1) that there are large numbers of people who are willing and able to openly violate social customs, which they themselves support and enjoy, for purposes of making money, (2) that violating customs does not entail costs that cancel out the advantage of cheap wages, and (3) that competition is intense enough to put out of business those who refrain from violating customs."

[4] Also in the case of co-worker discrimination, competitive forces eliminate wage discrimination, but lead at the same time to a completely segregated workforce. In this situation workers belonging to the majority group feel an aversion for working with members of the minority group. Employers therefore need to compensate workers belonging to the majority group. In a perfectly competitive environment this can only be financed by a lower wage for the minority workers. But under perfect competition, free entry of firms and perfect mobility of workers result in a completely segregated workforce where both groups of workers are paid their marginal product (Cahuc and Zylberberg, 2004, p. 261).

during the period that vacancies remain unfilled if a minority candidate is turned away. This means that discrimination should fall with labor market tightness. Building on the works of Black (1995) and Rosén (2003), Biddle and Hamermesh (2012) develop an equilibrium search model that theoretically underpins this intuition that employers discriminate less in a tight labor market.[5] This paper provides suggestive evidence for this second prediction.

Contrary to the relationship between competition on the product market and discrimination,[6] the relationship between labor market tightness and discrimination has received little attention in the economic literature. Biddle and Hamermesh (2012) cite Ashenfelter (1970) and Freeman (1973) arguing that "the perceived costs to employers of discriminating was higher in tight labor markets", but add that "neither found empirical evidence of cyclical movements in pure wage discrimination in the aggregate data." In their analysis Biddle and Hamermesh themselves find mixed empirical support for the US. Dustmann et al. (2010) report for Germany and the UK significantly larger unemployment responses to economic shocks for immigrants relative to natives within the same skill group, but little evidence for differential wage responses. However, these authors do not directly link these differential responses to discrimination varying with labor market tightness.[7] Last, Booth et al. (2012) suggest that the heterogeneity in discrimination rate found across Australian cities could be partly driven by differences in labor market tightness. Apart from the aforementioned authors, we could not find any discussion of this relationship in the literature.

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[5] Biddle and Hamermesh (2012) state this result only in words, but it can be formally found by differentiating their Equation (9) with respect to φ: $\frac{\partial c^*}{\partial \varphi} = \frac{(1-\beta)\lambda}{r+s+(1-\beta)\varphi\lambda}[rU_A - c^* - rU_B] < 0$, where the negative sign follows from the fact that the term between braces on the right hand-side of (9) is a weighted average of $k + x$ and rU_A and from the fact that $k + x > rU_A$, so that $c^* > rU_A - rU_B$ or, equivalently, $rU_A - c^* - rU_B < 0$. Since φ is the rate at which workers arrive at employers, this rate decreases with labor market tightness and, hence, c^* increases with tightness and, since c^* is inversely related to discrimination, discrimination falls. Note that in this differentiation we hold U_A and U_B constant. This is because in the field experiment that we consider in our empirical analysis the labor market tightness for job seekers is given. They can apply for jobs irrespectively of whether these are difficult to fill or not.

[6] See, e.g., Ashenfelter and Hannan (1986), Peoples and Saunders (1993), Black and Strahan (2001), Hellerstein et al. (2002), Black and Brainerd (2004) and, more recently, based on correspondence testing, Berson (2012).

[7] They refer to the model of Bulow and Summers (1986) mentioned in footnote 7 below, but do not mention the connection of this theory to discrimination.

In this paper we study whether ethnic discrimination in the hiring process is lower in occupations where recruitment is difficult than in occupations where it is easy. The extent of discrimination is assessed on the basis of a correspondence test in Flanders, one of the three regions in Belgium.[8] We sent out 752 fictitious job applications of school-leavers, randomly assigned to individuals with either a Flemish or a Turkish sounding name, to 376 vacancies for jobs requiring no work experience. In order to maximize the variation in occupational tightness, roughly half of the applications were sent out to vacancies that were difficult to fill according to the Public Employment Service (PES). Our analysis shows that discrimination is essentially only present in occupations without identified recruitment difficulties. This result is found to be robust to alternative measures of tightness.

This strong negative cross-sectional relationship between discrimination and recruitment difficulties does not necessarily mean that tightness *causes* less discrimination. It may be the other way around. Firms may post vacancies in occupations in which wages are so low and working conditions so bad that typically no worker, or, if any, only minority workers, not finding any other job because they are discriminated against, would want to apply. In this case the absence of hiring discrimination in occupations with recruitment difficulties is induced by discrimination in wages and working conditions by occupational segregation.[9] In order to rule this out, we check whether the found negative relationship between occupational tightness and discrimination upholds if we control for average wages and indicators of job quality. However, even if our main finding is robust for the inclusion of these control variables, we acknowledge that this is no proof that discrimination by occupational segregation plays no role. This is because these control variables are obtained from external sources and aggregated to the occupational level, so that they do not necessarily reflect the actual wages and working conditions of the jobs for which our fictitious job candidates applied.

[8] Belgium is a federal state consisting of three regions: Flanders, Wallonia and Brussels. In Flanders the official language is Dutch, in Wallonia French and in Brussels both languages are spoken.

[9] Bergmann (1989) argues that women are extensively discriminated against by this form of discrimination. Bulow and Summers (1986) rationalize this type of wage discrimination through occupational segregation in a dual labor market model where minority workers differ from the majority group in a dimension that is unrelated to productivity, such as a higher propensity to leave the job or liquidity constraints. Recently Bartolucci (2013) builds and estimates an equilibrium search model allowing for firm aside worker heterogeneity. This enables to disentangle discrimination induced by segregation from discrimination induced by between group differences in friction patterns.

Readers may take an interest in this paper for a number of additional reasons. First, we focus on ethnic discrimination of school-leavers. Discrimination of this group is particularly relevant since discrimination at the first stage of the career may cause, through scarring (Arulampalam, 2001; Gregg, 2001; Gregg and Tominey, 2005), long-term adverse labor market outcomes even if discrimination does not play a role at later stages of the career. Second, we provide evidence on hiring discrimination in the Flemish labor market. Flanders, and by extension Belgium, is an interesting case for a couple of reasons. In 2011, the youth unemployment rate in Belgium of non-EU-15 residents was as high as 32% compared to 18% for natives, resulting in a gap of fourteen percentage points, which is reported to be one of the largest in the OECD (Nonneman, 2012).[10] Furthermore, in the 1990's the International Labor Office (ILO) conducted a series of ethnic discrimination studies in the three Belgian regions on the basis of audit and correspondence tests. Discrimination was in Belgium found to be a significant and, compared with other OECD countries, more pronounced impediment to the employment of foreigners (Arrijn et al. 1998). However, OECD (2008) argues that the results of the ILO studies probably had a stronger policy impact in Belgium than elsewhere. Affirmative action in combination with a stricter anti-discrimination legislation introduced in 2007 should have diminished labor market discrimination. Together with the very recent studies of Capéau et al. (2012a) and Capéau et al. (2012b) our findings raise doubts on this conjecture. Third and last, in a sensitivity analysis we adopt the econometric framework recently proposed by Neumark (2012) to correct for the potential bias introduced by (ethnic) group differences in the variance of unobservable job-relevant characteristics.

This article is structured in the following way. In the next section we outline our experimental design. Subsequently we present a statistical analysis of the resulting dataset. A final section concludes and provides a brief discussion.

[10] In 2007, just before the Great Depression, this gap was 11.7 percentage points. This evidence for Belgium is in line with higher relative unemployment rates among ethnic minorities in economic downturns as found by Dustmann et al. (2010) and at least superficially consistent with higher discrimination rates in loose labor markets.

2 Experimental Design

2.1 Detecting Ethnic Discrimination by a Correspondence Test

Correspondence experiments testing for the presence of discrimination in the labor market have been extensively used (and refined) during the last decade. These experiments consist in sending carefully matched pairs of fictitious written job applications, randomly assigned to individuals revealing their minority status by their name or another individual characteristic, to real job openings and monitoring the subsequent callback. Concerning the identification of ethnic discrimination the extensive correspondence test conducted by Bertrand and Mullainathan (2004) is seminal. These authors show that, in the US labor market at the start of the former decade, applications with white-sounding names received 50% more positive callback on their job applications than those with African-American-sounding names. In Europe, pervasive levels of ethnic labor market discrimination are found in Greece, Ireland, Sweden and the UK (Drydakis and Vlassis, 2010; McGinnity and Lunn, 2011; Bursell, 2007; Carlsson and Rooth, 2007; Wood et al., 2009). Besides, recent correspondence studies conclude that there is evidence of varying degrees of hiring discrimination based upon, for example, (i) gender in Austria, France and Spain, (ii) beauty in Sweden and (iii) sexual orientation in Austria, Greece and Sweden (Weichselbaumer, 2004; Petit, 2007; Albert et al., 2011; Rooth, 2009; Weichselbaumer, 2003; Drydakis, 2009; Ahmed at al., 2011). Furthermore, the correspondence methodology has also been applied to identify discrimination in other markets (e.g., Carlsson and Eriksson, 2012, in the Swedish housing market).

These field experiments have been widely viewed as providing the most convincing evidence on discrimination (Riach and Rich, 2002; Pager, 2007). Researchers using non-experimental data possess far less information than employers do. Native and foreign employees who according to these data appear similar to researchers may therefore be very different from the employers' perspective. By conducting a correspondence test, selection on individual unobservable characteristics is not an issue since all the employers' decision making information is controlled for by the researcher. Thereby strict equivalence between candidates is ensured. As a consequence this approach allows disentangling employer discrimination from alternative explanations for differential hiring rates between migrants and natives, such as differential employee preferences and network effects.[11]

2.2 Construction of Applications and Matching with Vacancies

We generated template CVs and cover letters for eight profiles of school-leavers. First, three middle educated profiles with a secondary education diploma (ISCED[12] 3) in commerce, metallurgy and organization help. Second, five high educated profiles holding a professional bachelor in business administration (ISCED 5) with a different specialization (accounting and tax, finance and insurance, logistics, marketing and legal practice).[13] This bachelor was chosen because some of its specializations (accounting and tax and logistics) typically match with "bottleneck" occupations where recruitment is difficult, while the other specializations typically match with "non-bottleneck" occupations. For the middle educated all three chosen forms of specialization match with both, bottleneck and non-bottleneck occupations.

All profiles were single males with the Belgian nationality who graduated in June 2012. Depending on the region of the announced workplace in the vacancy, their residence was located in one of the suburbs of Antwerp or Ghent, the two largest cities in Flanders. Middle educated school-leavers were 18 years old and high educated school-leavers 21. So, none of the candidates experienced a grade retention in the past. In addition we added to each application the following features: Dutch as a mother tongue,[14] adequate French and English language skills, driving license, computer skills and student employment experience. Moreover, the cover letters signaled a motivated, structured and capable person. For the high educated school-leavers also sport club membership and student leadership were mentioned. Last, we included a fictitious postal address

[11] Recently, Behtoui and Neergaard (2010) showed that ethnic differences in social networks, for which most non-experimental studies are not able to control, explain a substantial fraction of wage disadvantages among immigrant workers.

[12] ISCED stands for International Standard Classification of Education.

[13] This degree is among the highest that migrants obtain in Flanders (Duquet et al., 2006).

[14] Thereby, we isolate the effect of ethnicity from potential language effects. Baert and Cockx (2013) report that in Flanders Dutch is spoken at the parental home among three quarters of the pupils whose grandmother on mother's side has a non-Western nationality.

(based on real streets in middle-class neighborhoods) and the date of birth to the resumes. The CV and cover letters are available on request.

During five months, from November 2011 until March 2012, we randomly selected vacancies from the database of the Flemish Public Employment Service (PES or "VDAB" in Dutch), the major job search channel in Flanders, for which (at least) one of our eight profiles meet the minimum educational requirement. We restricted the analysis to vacancies for which no work experience was required and which were posted less than a fortnight before the start of the experiment.[15] We also ensured that roughly half of the vacancies referred to occupations that the PES identified as "difficult to fill" (see Section 2.4).

The ethnicity of the candidate was only signaled by the name. Turkish names were used because the Turkish community forms the most significant ethnic minority in Ghent and the second most important one in Antwerp. In addition, the unemployment rate for residents of non-EU-15 countries (among which Turkey) is very high. In 2011 23% of the active non-EU-15 residents were unemployed in Belgium, compared to 6% of the active Belgians.[16] Finally, typical Flemish and Turkish names can be easily distinguished.[17]

For each of the eight aforementioned profiles of school-leavers we created two types of CVs and cover letters: "Type A" and "Type B". This allowed us to send two applications, one of each type and of each ethnic group, to the same vacancy. To maximize comparability, both application types were identical in all job-relevant characteristics, such as number of months of experience in student work,[18] language skills and quality of extra-curricular engagements (cf. supra). Type A and Type B candidates were educated in the same type of school, with comparable reputation. The

[15] This choice was made in order to maximize the callback rate, since interviews with human resources managers revealed that filled vacancies are not always immediately removed from the PES database.

[16] Source: Eurostat.

[17] Based on frequency data on first names and surnames we chose "Thomas Mertens" and "Jonas Vermeulen" as Flemish sounding names and "Emre Sahin" and "Okan Demir" as Turkish sounding names. We checked that these names were no stereotypes. Assigning different pairs of names to the middle and high educated individuals allowed letting both categories of individuals apply for vacancies of the same employer without risking detection.

[18] Note that restricting the analysis to school-leavers has an advantage from a methodological point of view. Controlling for human capital is easier for them, since we need not take labor market experience (beyond student work) into account.

applications just differed in inessential details, such as the name of the school, favorite sports and other particular engagements, and in fonts and lay-out.[19] In order to completely erase any dependence of callbacks on the application type, Flemish and a Turkish sounding name were alternately assigned to the Type A and Type B versions and, subsequently, both sent in an alternating order to a vacancy, each time with a one-day delay in between.

We matched to each assigned name an email address and a mobile phone number. These were registered with large commonly used internet and telecommunication providers. For each application sent we logged the number of announced (similar) job positions in the vacancy, the address of the workplace, the gender of the recruiter (if available), the date of the application, the application profile (one of the five high educated or one of the three middle educated) and the application type (A or B).

2.3 Measurement of Callback

All applications were sent to the employer by email. Callbacks for interviews were received by telephone voice mail or by email. The content of the responses are available on request. Since we included postal addresses with a nonexistent street number in the applications, callback via regular mail could not be measured. However, several human resource managers confirmed that employers rarely, if ever, invite job candidates by regular mail to selection interviews. To minimize inconvenience to the employers, invitations were immediately declined. All callback later than 40 days after sending the application was neglected. This, however, turned out to be an artificial restriction since no response was received after 40 days.

In our analysis we distinguish between two interpretations of *positive* callback. In a narrow sense, we classify the feedback from the employer side as positive if the candidate is invited to an interview related to the job to which he applied. This definition is mostly used in the literature and is therefore our benchmark definition. We also consider the receipt of an alternative job proposal and the request to provide more information or to contact the recruiter as positive callback in a broad sense. In what follows, we will refer to these two interpretations of callback as “invitation to a job interview” and “any positive reaction”.

[19] To be as realistic as possible, we adapted templates that the PES posts on its website as examples for job seekers.

2.4 Variation in Occupational Characteristics

We matched each vacancy one-to-one with an occupation in the classification list of the PES.[20] As mentioned in Section 2.2, roughly half of the applications were sent out to occupations identified by the PES as "bottleneck" occupations. For each occupation the research unit of the PES publishes each year (we use the 2011 version) two measures of labor market tightness. First, the so-called "bottleneck" status of the occupation. This status is obtained combining three statistical criteria and is then assessed by a number of labor market specialists. These three criteria are that (i) there must be at least ten vacancies registered in the PES database for the occupation to be retained, (ii) the vacancy filling rate must be lower than the median filling rate for all occupations together, and (iii) the median duration until a vacancy in this occupation is filled must be greater than the median for all occupations together. A second measure of labor market tightness reported by the PES is the median duration required to fill a vacancy in an occupation. This duration is right censored at vacancy withdrawal. In the benchmark empirical analysis we rely on the first measure. The second measure is used in a sensitivity analysis as a robustness check. Table B.1 in Appendix B lists the classifications of the occupations, some variables characterizing these occupations and the number of fictitious applications that were sent to each of these occupations. First, both PES measures of labor market tightness for these occupations in 2011 are reported. The occupations with the minimum and maximum median vacancy duration in our experimental dataset are consultant in recruitment and selection (13 days) and demonstrator (109 days). "Bottleneck" occupations are industrial cleaner, classic cleaner, private cleaner, customs declaration officer, executive expedition operator, planning and logistics clerk, shipping agent at the quay, bookkeeper, accountant, seller, representative, call center employee and tele-seller. Second, the table contains a measure of the extent to which the occupation is dominated by women,[21] an indicator of intensive customer contact in the occupations, the average wage in the occupation[22]

[20] This occupation classification is a classification at 5-digit level. The PES classifies occupations in bottleneck and non-bottleneck occupations at this level.

[21] This measure is reported by the PES. It reports the share of women among all registered unemployed desiring this occupation in 2011.

[22] Source: Directorate-general Statistics and Economic information of Belgium. These averages are not measured for the occupational classification of the PES but for the ISCO-08 classification at 3-digit-level which is, however, closely related to the former classification. ISCO stands for International Standard Classification of Occupations. We use the

and a measure of job quality.[23] The latter statistics will be used in the regression analyses. Last, the table reports the number of observations (twice the number of vacancies) for each of the occupations by level of education. For three occupations (administrative clerk, commercial clerk and representative) applications were sent out for both middle and high educated profiles, depending on the particular requirements in the vacancy. Table B.2 presents summary statistics on the mentioned occupation characteristics by the bottleneck status of the occupation. It also contains statistics on the additional variables included in the regression analyses reported or mentioned in Section 3.

2.5 Research Limitations

In short we assess some research limitations inherent to our experimental design. For an in-depth discussion of the strengths and weaknesses of correspondence tests in general we refer to Riach and Rich (2002) and Pager (2007) and for an elaboration on the ethical aspects of these tests to Riach and Rich (2004).

First, our experimental design can only demonstrate discrimination, if any, at the initial stage of the selection process. Since we simply measure callback rates for first interviews, we cannot make any statements about discrimination in the later stages of the selection process, let alone in wages. However, Bertrand and Mullainathan (2004) argue that a lower number of interview rates are expected to be reflected in reduced job offers and in lower earnings. Moreover, since job interviews are costly, firms invite candidates to an interview only if they have a reasonably high chance of getting the job. Cédiey et al. (2008) report that 85% of the total discrimination rate they identify within a field experiment conducted in France comprising all stages of the hiring process is realized before the employer meets the candidate in an interview.

2010 statistics since those of later years are not yet available.

[23] This measure was constructed on the basis of the 3,442 employed Belgians responding to the fifth European Working Conditions Survey conducted in 2010. Following Eurofound (2012) we combined the answers to a set of questions in this survey to three job quality measures (with values between 0 and 1) at the ISCO-08 occupational classification 3-digit-level (see the previous footnote) capturing: (i) prospects, (ii) intrinsic job quality and (iii) working time quality. These measures were then aggregated to one measure by taking their mean.

Second, we only investigate discrimination for a selection of occupations and for vacancies posted in the PES database. Possibly, discrimination is more or less pervasive in other sectors than those covered by the database and among employers who rely on other channels (e.g. social networks) for filling their vacancies. It is unclear whether these limitations, taken together, may lead to an overestimation or an underestimation of discrimination in the Flemish youth labor market. However, it is important to keep in mind that we are especially interested in the relationship between discrimination and labor market tightness. If, therefore, the limitations mentioned proportionally shift the discrimination measures for bottleneck and non-bottleneck occupations, our main research conclusions remain valid.

Last, as demonstrated by Heckman (1998), a standard correspondence test does not allow distinguishing between taste-based discrimination (Becker, 1957) and statistical discrimination (Arrow, 1971). Kaas and Manger (2012) and Carlsson and Rooth (2008) show how, to some extent, these forms of discrimination can be disentangled within the correspondence test framework. However, this is outside the scope of this article. An alternative way to discriminate between taste-based and statistical discrimination would be available if only one of the two would (theoretically) vary with labor market tightness. However, in the discussion of our results in Section 4 we explain why this is not the case.

3 Results

In Section 3.1 we report the main results of our analysis. We show that discrimination is absent in bottleneck occupations while it is important and highly significantly different from zero in non-bottleneck occupations. Subsequently, we check to what extent our main results uphold if we control for other occupational characteristics which may correlate with both, the bottleneck status of the occupation and the extent of discrimination. In Section 3.2 we test the robustness of these results by allowing for more subtle forms of discrimination as in the heteroskedastic probit model of Neumark (2012) on the one hand and by adopting alternative measures of labor market tightness at the occupational level on the other hand.

3.1 Main Results

3.1.1 Descriptive analysis

Table 1 presents the main experimental results using our narrow definition of positive callback, i.e. the invitation of our fictitious job candidates to an interview. The reader can find in Table B.3 (in Appendix B) the corresponding descriptive statistics for the alternative callback measure, i.e. receiving any positive reaction. Since two applications were sent to each vacancy there are four possible outcomes: (i) positive callback for neither candidate, (ii) positive callback for both candidates, (iii) only positive callback for the Flemish candidate and (iv) only positive callback for the Turkish candidate. Overall, in 79 (139) of the 372 vacancies at least one candidate received an invitation to a job interview (any positive reaction). 29 (45) cases resulted in a positive callback for just the Flemish candidate and 7 (15) for the Turkish candidate only. The net discrimination rate is calculated as the ratio of the difference between the number of vacancies in which the Flemish and, respectively, Turkish candidate was treated favorably, and the total number of vacancies in which at least one candidate received a positive callback. Overall the net discrimination rate is 0.28 (0.22) adopting the narrow (broad) definition of positive callback. A standard χ^2 test of the hypothesis that the candidates of both ethnicities were equally often treated unfavorably is rejected at the 1% level. Based on this statistic we conclude that there is evidence of discrimination against Turkish school-leavers in the Flemish labor market.

Table 1 and Table B.3 show the same descriptive statistics after splitting up the data in vacancies for bottleneck and non-bottleneck occupations. For the remainder of this subsection, we will focus, unless stated otherwise, on the results for this split-up and on our narrow interpretation of positive callback, i.e. the invitation to a job interview. Note that the results based on the broad interpretation, i.e. any positive reaction, are qualitatively the same across all presented statistics.

Table 1: The Probability of an Invitation to a Job Interview: Unequal Treatment of Flemish and Turkish Job Candidates.

Occupations	Jobs	Neither callback (No.)	Both callback (No.)	Only Flemish callback (No.)	Only Turks callback (No.)	ND	χ^2
All	376	297	43	29	7	0.278***	13.44
Bottleneck	181	144	24	7	6	0.026	0.077
Non-bottleneck	195	153	19	22	1	0.500***	19.17

*Note. ND: net discrimination rate. The null hypothesis is that both individuals are equally often treated unfavorably. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.*

Table 1 indicates that the net discrimination rate varies with labor market tightness at the occupational level in the expected direction. It is hardly different from zero for bottleneck occupations. In sharp contrast, this statistic is 0.50 for non-bottleneck occupations: while for 22 of the 195 vacancies only the Flemish candidate received a positive callback, just one vacancy resulted in a positive response for the Turkish candidate only.

Table 2 presents callback rates by ethnicity. These confirm the findings based on the net discrimination rate. The callback rate is defined as the number of positive callbacks relative to the total number of sent applications. The callback ratio is obtained by dividing the Flemish callback rate by the Turkish callback rate. This ratio is only significantly different from one for the individuals applying to non-bottleneck occupations. Candidates with Turkish sounding names need to send out more than twice as many job applications to be invited to as many job interviews as the Flemish candidates.

Intuitively, bottleneck occupations are expected to have a higher callback rate than non-bottleneck occupations, because the bottleneck should reflect a lack of candidates for the job, so that applicants should have higher chances of being retained for a job interview. However, even if this expectation is confirmed on average, we observe for Flemish candidates the reverse (see Table 2). We explain this as follows. A vacancy is difficult to fill if there is an insufficient number of job applicants who match the requirements of the vacancy. Even if in the field experiment we attempted to match the profiles of the job applicants as closely as possible to the requirements mentioned in the vacancy, we might not have been equally successful in this attempt across occupations.[24] Consequently, if the quality of the match in bottleneck occupations is systematically lower than in non-bottleneck occupations, we may observe a lower callback rate in bottleneck occupations. Notice, however, that this does not necessarily invalidate the analysis, since, as we control for the profile of the candidates of different ethnicity, a match is equally inadequate for candidates with a Turkish and a Flemish sounding name.

More concretely, there are reasons to believe that in our data the profile of job candidates was less well matched in bottleneck than in non-bottleneck occupations. For instance, an important share of the applications for bottleneck occupations is for classic and private cleaning services. The average callback rate for both the Flemish and Turkish candidates to these occupations is very low, namely 0.09. In view of the social context, employers may prefer females to males for these kinds of jobs. In addition, our medium skilled candidates might have been relatively overqualified for these jobs. If we exclude these 168 applicants (84 vacancies) from the analysis, the likelihood of being invited to a job interview (getting any positive reaction) of Flemish candidates for bottleneck occupations increases indeed from 0.17 (0.32) to 0.24 (0.39). This is higher than the callback rate in non-bottleneck occupations. Observe that this does not affect our conclusion of vanishing discrimination when candidates apply for bottleneck occupations, since, after exclusion of these observations, the callback rate of Turkish applicants for bottleneck occupations increases at nearly the same rate, i.e. to 0.23 (0.41). Given this observation, we will control in the regression analysis reported in next subsection for potential mismatch between the requirement of the job and the profile of the applicant by conditioning on a measure of overeducation and of female dominance in the occupation.

Table 2: The Probability of an Invitation to a Job Interview: Positive Callback Rates for Flemish and Turkish Job Candidates.

	Average callback rate	Callback rate Flemish	Callback rate Turks	Callback ratio	t
All	0.162	0.191	0.133	1.440***	3.727
Bottleneck	0.169	0.171	0.166	1.033	0.276
Non-bottleneck	0.156	0.210	0.103	2.050***	4.594

*Note. The null hypothesis is that the callback rate is equal for both ethnicities. Standard errors are corrected for clustering of the observations at the vacancy level. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.*

[24] We acknowledge that these mismatches are flaws in the design of our experiment.

Figure A.1 and Figure A.2 (Appendix A) provide alternative descriptive evidence for the main finding that discrimination in not present in bottleneck occupations. In these figures we present scatter plots of the average callback rate of Flemish applicants against the average callback rate of Turkish applicants for 12 occupation aggregates. This aggregation is required to avoid too large sampling error in cases where the number of applicants for a particular occupation is too small.[25] The figures in Appendix A show that for both measures of callback for most non-bottleneck occupation aggregates the points lie below the 45° degree line. This means that the callback for candidates with Turkish sounding names within these occupations is on average lower than the callback for the natives. By contrast, for most bottleneck occupation aggregates the points are very close to the 45° degree line.

3.1.2 Regression Analysis

In the previous subsection we provided descriptive evidence that job applicants with a Turkish sounding name are less discriminated against if they apply for bottleneck professions. There are, however, several reasons to believe that this relationship between discrimination and the type of profession is not causal. In this subsection we investigate this issue based on various regression analyses.

The results of these regressions are reported in Table 3 in case callback measures invitation to an interview and in Table B.5 in Appendix B if callback measures any positive reaction. As a benchmark, we first present in column (1) of Table 3 and column (1) of Table B.5 the probit model that reproduces the findings of the descriptive analysis in Table 2 (and Table B.4). Note that, since characteristics of applicants are by construction orthogonal to ethnicity, including these characteristics in the probit model does not affect the estimates of our main coefficients of interest, i.e. interaction effects with ethnicity. We therefore choose to exclude these characteristics from the probit regressions. In our experimental dataset, overall, a Turkish sounding name lowers the

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[25] We followed the following aggregation rule. Occupations with strictly more than 20 applicants are not grouped. The other occupations are grouped keeping bottleneck and non-bottleneck occupations segregated, and not aggregating occupations that differ in the first two digits according to the occupational classification of the PES. Occupations for which this aggregation procedure did not yield more than 20 applicants were dropped from the analysis: 154 of the 752 observations had to be dropped for this reason.

probability of receiving an invitation to a job interview by 11 percentage points after applying for a non-bottleneck occupation, while for bottleneck occupations the callback rate does not differ between the Turks and the Flemish. The hypothesis that the differential callback rate between Flemish and Turkish applicants is equal for bottleneck and non-bottleneck professions is rejected at the 1% level.

A concern is that the bottleneck status of a job may correlate with other determinants of discrimination, so that the observed correlation is not causal. Therefore, in the regressions of which the results are presented in columns (2) to (7) of Table 3 and Table B.5, we include additional interactions between Turkish origin and a number of potential determinants of discrimination that may be correlated with the bottleneck status of an occupation. These variables are, except for specifications (6) and (7), also included without interaction.

First, one could expect that recruitment difficulties at the occupational level are related to the required level of education. Moreover, both theoretical[26] and empirical[27] evidence show that discrimination decreases with the level of education, so that our findings on labor market tightness could just reflect this relationship. We therefore include in all subsequent specifications an indicator identifying the high educated applicants, i.e. those holding a professional bachelor in business administration.

Second, as discussed in the previous subsection, bottleneck status of the occupation may correlate with the extent of mismatch between our fictitious job candidates and the jobs they apply for. Therefore, we add, from column (3) onwards, two proxies of mismatch between the profile of the fictitious job candidates and the requirements in the jobs for which they apply. On the one hand, we adopt an indicator of overeducation that equals one if the educational level of the candidate strictly exceeds the minimal level required in the vacancy. This measure is very strongly negatively correlated with the indicator of education. This is why after inclusion of this variable

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[26] Taubman and Wales (1974) argue that higher education can act as a prejudices reducing screening device. In addition, if the level of education is reflected in the value of the worker's product, one can use the model of Biddle and Hamermesh (2012) to show that discrimination decreases with the level of education: It is clear from their equation (9) that c^* increases, and hence discrimination decreases with the worker's product, i.e. with x. This is because the opportunity cost of an unfilled vacancy increases with x.

[27] See Bursell (2007), Carlsson and Rooth (2007) and Wood et al. (2009).

the partial effect of higher education is no longer significantly different from zero. On the other hand, we add the measure of female dominance in an occupation defined in Section 2.4. After inclusion of these variables the coefficient capturing the effect of bottleneck status on the callback rate for Flemish applicants increases. In case of to the probability of any positive reaction, it becomes even positive, albeit not significantly so.[28] This suggests that the opposite findings in Tables 2 and B.4 indeed reflect that mismatch is higher in bottleneck occupations and is partially accounted for by our indicators.

Third, from column (4) on, we include two additional well-known determinants of discrimination: an indicator of customer contact and the fraction of foreign workers in the sector. Customer induced discrimination (Becker, 1957) is expected to be higher in occupations with intensive customer contact. In addition, according to the social distance theory (Akerlof, 1997) hiring discrimination should fall with the fraction of foreign workers in the firm (sector).[29] Even if there is only weak empirical evidence for this theoretical prediction (Bursell, 2007; Carlsson and Rooth, 2007; Wood et al., 2009), we try to capture this relationship by including a variable measuring the fraction of workers with a non-Western nationality in the sector of the firm as a proxy of the fraction of foreign workers in the firm itself.[30]

Fourth, in the Introduction we mentioned that our findings could reflect discrimination induced by occupational segregation. In this interpretation the absence of discrimination in bottleneck occupations would conceal lower wages and worse working conditions in these occupations relative to non-bottleneck occupations. That is why, we include from column (5) onwards interactions between Turkish name and both the average wage level in the occupation in 2010 and the job quality measure defined in Section 2.4.

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[28] These partial effects are not reported in the tables. They are equal to -0.017 (0.042) for invitation to an interview and 0.014 (0.050) for any positive reaction.

[29] This relationship is consistent with the literature on ethnic workplace segregation (see, e.g., Åslund and Skans, 2010).

[30] To our knowledge, these data are not available at the firm level in Belgium. This variable was constructed by first identifying the sector of the employer that posted the vacancy. We did this by linking, on the basis of the online database of the Flemish business magazine "Trends", the name of the employer to the sector. Then we merged this information to the fraction of workers with a non-Western nationality in the corresponding sector (2-digit level) in Flanders on December 31, 2009 (source: Datawarehouse of the Belgian federal public service of social security). Note that this proxy is also imperfect in the sense that all candidates in our empirical setting have the Belgian nationality.

As two last alternative specifications, and to saturate occupation controls further, in column (6) and column (7) we substitute the occupational characteristics in (5) that are not interacted with the indicator of ethnicity in the specification by occupational and vacancy specific fixed effects and estimate a linear probability model.

Table 3 and Table B.5 reveal that the inclusion of the mentioned interaction variables and fixed effects hardly affects the estimated average partial effects for the main variables of interest, i.e. the interactions between Turkish origin and the bottleneck status of the occupation. Equality of the corresponding partial effects is, for all specifications, rejected at the 1% significance level. Furthermore, in line with the literature column (2) reports evidence that higher educated are less discriminated against than lower educated. In the subsequent specification this significance disappears because of the aforementioned correlation with the indicator of overeducation. In addition, in some specifications we get (weakly) significant evidence for more discrimination in female-dominated occupations. The coefficients of the interactions between Turkish origin, and customer contact and the fraction of foreign workers in the sector are not significant. Last, in line with the interpretation of discrimination by occupational segregation, we find evidence of significantly more discrimination in better paid occupations. This contrasts with the negative correlation that is found between our indicator of job quality and discrimination. The latter is, however, only marginally significant.

We also tried out a number of alternative specifications in which Turkish origin is interacted with (i) the indicators both of moderate and of intensive customer contact; (ii) the fraction of Turkish (instead of non-Western) workers in the sector; (iii) other employer (or vacancy) characteristics (which we did not expect to be correlated with the bottleneck status of the occupation), such as the number of announced (similar) job positions by the vacancy, the province of the workplace or the gender of the recruiter. Last, we also broke up our job quality measure in its three sub-measures (see footnote 21). None of these alternative specifications, of which the results are presented in Table C.1 and Table C.2 of Appendix C, modifies our main conclusions in any way. We could not test whether recruiters belonging to an ethnic minority would discriminate differently, since hardly any recruiter had a foreign sounding name.

Table 3: The Probability of Invitation to a Job Interview: Main Regression Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name * Bottleneck occupation	**-0.006**	**-0.006**	**-0.004**	**-0.003**	**-0.004**	**-0.003**	**-0.003**
	(0.020)	**(0.020)**	**(0.020)**	**(0.020)**	**(0.020)**	**(0.022)**	**(0.020)**
Turkish name * Non-bottleneck occupation	**-0.108*** **	**-0.107*** **	**-0.109*** **	**-0.102*** **	**-0.102*** **	**-0.105*** **	**-0.105*** **
	(0.023)	**(0.100)**	**(0.023)**	**(0.023)**	**(0.023)**	**(0.025)**	**(0.024)**
Turkish name * High educated		0.091***	0.056	0.058	0.083	0.139*	0.019
		(0.029)	(0.063)	(0.065)	(0.094)	(0.083)	(0.113)
Turkish name * Overeducated			-0.027	-0.032	-0.029	0.115	-0.081
			(0.060)	(0.061)	(0.062)	(0.076)	(0.085)
Turkish name * Measure of female dominance in occupation			-0.005	-0.013	-0.050**	-0.054*	-0.051*
			(0.016)	(0.016)	(0.023)	(0.032)	(0.030)
Turkish name * Intensive customer contact				-0.013	0.009	-0.020	-0.005
				(0.040)	(0.048)	(0.050)	(0.050)
Turkish name * Fraction foreign workers in sector				0.019	0.015	0.019	0.015
				(0.014)	(0.016)	(0.036)	(0.020)
Turkish name * Log(average wage in occupation)					-0.094**	-0.088*	-0.101**
					(0.038)	(0.050)	(0.050)
Turkish name * Job quality measure					0.074*	0.099*	0.090*
					(0.044)	(0.052)	(0.053)
Dependent variable: invitation to a job interview	x	x	x	x	x	x	x
Dependent variable: any positive reaction							
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Difference between "Turkish name * Bottleneck occupation" and "Turkish name * Non-bottleneck occupation" (p-value)	0.000	0.000	0.000	0.000	0.001	0.004	0.001
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Except for "Turkish name", "Bottleneck occupation" and "Non-bottleneck occupation" all variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

3.2 Sensitivity Analyses

In what follows we further test the robustness of our results. First, in Section 3.2.1, we control for ethnic group differences in the variance of unobservable determinants of positive callback. Second, in Section 3.2.2 and Section 3.2.3, we investigate whether our finding of a negative cross-sectional relationship between the bottleneck status of an occupation and labor market discrimination upholds for other measures of labor market tightness at the occupational level.

We also attempted to exploit the time-series relationship between labor market tightness at the macro level and labor market discrimination. To this end, we interacted Turkish origin with a measure of labor market tightness defined by the ratio of the number of vacancies reported by the PES to the number of registered unemployed job seekers in Flanders in the month the job application was sent out. The results of this exercise are reported in Table C.3 and Table C.4 of Appendix C. The estimated coefficient for the interaction between Turkish origin and labor market tightness at the macro level, for most specifications, is, as expected, positive in case of invitations for a job interview, but is negative when measuring any positive reaction. However, since there is limited variation in this macro variable (the experiment only lasted five months), none of these effects is significantly different from zero.

3.2.1 Control for Ethnic Group Differences in the Variance of Unobservable Job-Relevant Characteristics

Heckman and Siegelman (1993) show that not controlling for group differences in the variance of unobservable job-relevant characteristics (and thereby of unobservable determinants of positive callback) can lead to spurious evidence of discrimination. To see this more clearly, assume that both the average observed and unobserved determinants of productivity are the same for Flemish and Turkish candidates for an unfilled vacancy, but that the variance of unobservable job-relevant characteristics is higher for Turkish than for Flemish youth. In addition, suppose that the employer considers the observed determinants of productivity, as inferred from the CV and the motivation letter, are relatively low compared to the job requirement. In that case it is rational for the employer to invite the Turkish and not the Flemish candidate, since, as the variance of unobservable job relevant characteristics is higher for the Turkish than for the Flemish candidates, it is more likely that the sum of observed and unobserved productivity is higher for the Turkish candidates. A correspondence test that detects discrimination against Turks could therefore underestimate the extent of discrimination. However, with other assumptions the bias may be in the opposite direction. Neumark (2012) explicitly addresses this critique and provides a statistical procedure in order to recover unbiased estimates of discrimination. In what follows, we succinctly describe Neumark's approach. Subsequently, we apply this method to check to what extent our conclusions are sensitive to this critique.

It is well known that in a standard probit model only the ratio of the coefficients to the standard deviation of the unobserved residual is identified. In estimations the standard deviation is usually arbitrarily set to one. In our case this means that the variance of unobservable job-relevant characteristics is implicitly assumed to be equal (to one) for both ethnic groups, which for aforementioned reasons may bias the intensity of discrimination. Neumark (2012) shows, however, that if the researcher observes job-relevant characteristics that affect the native and migrant populations' propensities of callback in the same way, one can identify the ratio of the standard deviation of the unobserved productivity components of these groups. The intuition is that if in a standard probit the estimated coefficients of these job-relevant characteristics differ by ethnicity, then this must be a consequence of a differential standard deviation, since by assumption the coefficient of these characteristics should be the same across ethnic groups (and since, as mentioned before, in a probit model only the ratio of the coefficients to the standard deviation is identified). To implement this idea, we therefore estimate a heteroskedastic probit model in which the variance of the error term is allowed to vary with ethnicity.

To identify the heteroskedastic probit model we assume that (i) the distance between the place of living of the candidate and the announced workplace and (ii) the particular application profiles, *beyond* their education level (high or middle educated), influence the callback rates in a similar way for Flemish and Turkish candidates. The hypothesis that the coefficients of these variables are equal across ethnic groups cannot rejected on the basis of a likelihood ratio test (p-value 0.88, resp. 0.87 for invitation to a job interview, resp. any positive reaction).

Table 4 reports the estimation results. In line with Neumark (2012), we obtain a (non-significantly) higher estimated variance of the error term for the foreign candidates. The overall average partial effects of the interaction variables of interest are closely comparable to the effects outlined in Table 3 and Table B.5. They, however, can be decomposed in two parts. First, in the partial effect of the variables of interest, holding the variance constant. Second, in the effect of the variables of interest via their impact on the variances of the unobservables. By disentangling these components we find that the partial effects on the probability of callback are somewhat larger in magnitude than the ones reported in Table 3 and Table B.5.[31] However, the differential discrimination rate between bottleneck and non-bottleneck occupations is hardly affected.

Table 4: The Probability of Positive Callback: Heteroskedastic Probit Estimates.

	Dependent variable			
	Invitation for a job interview		**Any positive reaction**	
Overall average partial effect				
Turkish name * Bottleneck occupation	-0.005	(0.021)	-0.012	(0.028)
Turkish name * Non-bottleneck occupation	-0.106***	(0.024)	-0.139***	(0.028)
*Difference between "Turkish name * Bottleneck occupation" and "Turkish name * Non-bottleneck occupation" (p-value)*	0.001		0.014	
Average partial effect through level				
Turkish name * Bottleneck occupation	-0.059	(0.069)	-0.037	(0.066)
Turkish name * Non-bottleneck occupation	-0.156**	(0.065)	-0.162***	(0.057)
*Difference between "Turkish name * Bottleneck occupation" and "Turkish name * Non-bottleneck occupation" (p-value)*	0.002		0.021	
Average partial effect through variance				
Turkish name * Bottleneck occupation	0.046	(0.054)	0.026	(0.051)
Turkish name * Non-bottleneck occupation	0.045	(0.050)	0.034	(0.067)
*Difference between "Turkish name * Bottleneck occupation" and "Turkish name * Non-bottleneck occupation" (p-value)*	0.975		0.984	
$ln(\sigma_T/\sigma_F)$	0.252	(0.301)	0.169	(0.342)
Observations	752		752	

*Note. Heteroskedastic probit estimates. Other controls: indicator of high educational attainment interacted with indicator of Turkish name, indicator of bottleneck occupation, indicator of high educational attainment, normalized variable capturing the distance (in minutes by car) between the announced workplace and the place of living of the candidate and six indicators for the eight application profiles except one reference profile for both high and middle level of education. Standard errors, corrected for clustering at the vacancy level and calculated using 500 bootstrap replications, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.* $ln(\sigma_T/\sigma_F)$ *stands for the natural logarithm of the ratio between the standard deviation of unobservables for the Turkish and the Flemish subpopulation.*

[31] In contrast to Neumark (2009) who approximates the effect of a discrete change in the variables of interest by a partial derivative, we explicitly take the discrete nature of these variables into account and measure these effects on the basis of discrete changes in the callback probability.

3.2.2 The Median Vacancy Duration in the Occupation as Alternative Measure of Tightness

In this subsection, we reproduce the results of Table 3 and Table B.5 with an alternative variable capturing labor market tightness, i.e. the median vacancy duration in the occupation to which the individual applies. We normalize this variable by subtracting the sample average and, for purposes of comparability with our results reported in Section 3.1, we divide the result by the difference between the average of this median duration in bottleneck occupations and the corresponding average in non-bottleneck occupations. By the latter division a unit increase in this variable corresponds to increasing the median vacancy duration of an average non-bottleneck occupation to that of an average bottleneck occupation, i.e. increasing the median duration by approximately 13 days. Table 5 and Table B.6 show that increasing the median vacancy duration in the occupation by the latter difference lowers discrimination by some value between 0.03 and 0.05 for invitations to an interview, and between 0.03 and 0.04 for any positive reaction. Although these magnitudes are smaller than the differences in discrimination between bottleneck and non-bottleneck occupations in Table 3 (ranging from 0.10 to 0.11) and Table B.5 (ranging from 0.13 to 0.15), which can be explained by the fact that some occupations with high median vacancy durations are not classified as bottleneck occupations (see Table B.1), are highly significant, confirming thereby that labor market discrimination is lower in occupations with high labor market tightness.

The reader might be worried that higher vacancy durations correlate with higher uncertainty for employers to fill their vacancy. If so, the positive relationship between vacancy duration and the callback rate of Turkish candidates may reflect that employers invite minority candidates to an interview to avoid this uncertainty rather than because the vacancy is on average difficult to fill. However, if we additionally include the standard deviation of the vacancy duration and its interaction with ethnicity in the probit model, then our reported findings are hardly affected, and the coefficients of these new variables are, for most of the alternative specifications, not significantly different from zero (see Tables C.5 and C.6).

Another concern is that the coefficients of both measures of labor market tightness, the median vacancy duration and the bottleneck status, may be affected by a simultaneity bias. We cannot exclude that vacancy durations are longer because of discrimination. However, if this were the case, the finding of less discrimination for bottleneck occupations would be strengthened, since we do not find a positive, but a *negative* relationship between vacancy duration and discrimination.

Table 5: The Probability of Invitation to a Job Interview: Median Vacancy Duration in the Occupation as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.059*****	**-0.058*****	**-0.058*****	**-0.054*****	**-0.054*****	**-0.055*****	**-0.056*****
	(0.016)	**(0.015)**	**(0.015)**	**(0.015)**	**(0.015)**	**(0.016)**	**(0.015)**
Turkish name * Median vacancy duration in the occupation	**0.027*****	**0.032*****	**0.032*****	**0.042*****	**0.049*****	**0.049*****	**0.048*****
	(0.008)	**(0.009)**	**(0.009)**	**(0.010)**	**(0.011)**	**(0.013)**	**(0.013)**
Turkish name * High educated		0.076***	0.053	0.054	0.107	0.139*	0.019
		(0.028)	(0.062)	(0.063)	(0.098)	(0.084)	(0.110)
Turkish name * Overeducated			-0.022	-0.025	-0.015	0.115	-0.079
			(0.060)	(0.060)	(0.061)	(0.077)	(0.082)
Turkish name * Measure of female dominance in occupation			0.006	0.003	-0.044*	-0.045	-0.042
			(0.016)	(0.017)	(0.023)	(0.030)	(0.029)
Turkish name * Intensive customer contact				-0.068*	-0.050	-0.082	-0.067
				(0.039)	(0.044)	(0.056)	(0.055)
Turkish name * Fraction foreign workers in sector				0.031**	0.023	0.025	0.026
				(0.014)	(0.015)	(0.034)	(0.019)
Turkish name * Log(average wage in occupation)					-0.129***	-0.119**	-0.131**
					(0.039)	(0.050)	(0.049)
Turkish name * Job quality measure					0.092**	0.117**	0.109**
					(0.044)	(0.051)	(0.052)
Dependent variable: invitation to a job interview	x	x	x	x	x	x	x
Dependent variable: any positive reaction							
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Variable "Median vacancy duration in the occupation" is normalized by subtracting the sample mean and dividing the result by the difference between the average of this median duration in bottleneck occupations and the corresponding duration in non-bottleneck occupations, i.e.by approximately 14 days Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

3.2.3 The Average Callback Rate in the Experiment as Alternative Measure of Tightness

As a third robustness check, we follow Kroft et al. (2013) by using the average callback rate in the experiment by (group of) occupation(s) as an alternative measure of tightness. To that purpose we estimate the following fixed effect linear probability model:[32]

$$(1)\ y_{i,o} = \delta^{\bar{o}} + \gamma^{\bar{o}} DT_i + X_i \Gamma_1 + Z_o \Gamma_2 + \varepsilon_{i,o},$$

where $y_{i,o}$ is the discrete indicator of callback for individual *i* in occupation o, DT_i is equal to one if the individual i has a Turkish name and is zero otherwise, X_i is the vector of individual characteristics, i.e. the indicators of education and overeducation, Z_o is the vector of occupational specific characteristics (which are the same ones as the ones reported in Table 3), and $\varepsilon_{i,o}$ is the error term. The parameter $\delta^{\bar{o}}$ is an occupational group specific fixed effect and $\gamma^{\bar{o}}$ is an occupational group specific coefficient of having a Turkish name on callbacks. The bar over the superscripts o of the fixed effect coefficients superscripts denotes that these fixed effects are grouped over some professions. It was necessary to impose this grouping, since otherwise the number of observations in particular occupations would have been too small for a reliable analysis. We follow the same rules for this aggregation as we did for the descriptive analysis in Figure A.1 and Figure A.2. We retain 12 groups of professions and 598 out of the 752 observations for this analysis. Notice that the coefficients of the occupational specific characteristics can be identified from the occupational group specific fixed effects $\gamma^{\bar{o}}$ by the within variation in the grouped professions.

The occupational group specific fixed effect $\delta^{\bar{o}}$ can be viewed as an alternative measure of tightness, since it is equal to the expected callback rate in a particular (group) of profession(s). So, in order to verify how discrimination (as measured by $\gamma^{\bar{o}}$) varies with tightness at the grouped occupational level, we estimate the correlation between $\delta^{\bar{o}}$ and $\gamma^{\bar{o}}$. Kroft et al. (2013) demonstrate that the standard estimate of this correlation is biased downwards. We therefore

[32] This corresponds to Equation (3) in Kroft et al. (2013). These authors consider the variation over metropolitan areas (MSA) in the United State instead of over occupations, and the variable of interest is not the indicator of Turkish name, but the log of unemployment duration

follow their proposal to account for this bias by including a bias correction term in this estimation. We refer to Kroft et al. (2013) for technical details.

The findings of this analysis are reported in Table 6. In the first row we report the point estimate on DT_i in a regression in which the fixed effects are only included in levels. This measures the average discrimination over occupations in the sample, assuming that this discrimination is constant over occupations. This reconfirms that applicants with Turkish sounding names are very significantly discriminated against on average. The second row shows that we can reject that this discrimination is the same across the retained groups of occupations at a 6.1% level of significance in case of invitation to a job interview and at a 0.4% level in case of any positive reaction. The third row show the bias corrected estimate of correlation between the estimates of $\delta^{\bar{o}}$ and $\gamma^{\bar{o}}$. Consistent with our previous findings, we find that this correlation is positive. It is estimated to be equal to 0.669 for the first measure and 0.348 for the second measure. The standard errors are, however, large. Only the correlation in case of the invitation to an interview is significantly positive (p = 0.058). This relative imprecision is not surprising in view of the small number of observations on which we base our analysis.

Table 6: The Probability of Positive Callback: Average Callback Rate in the Experiment as Alternative Measure of Tightness.

	Dependent variable			
	Invitation for a job interview		**Any positive Reaction**	
Point estimate on DT_i	-0.044*** [0.007]	(0.016)	-0.072*** [0.001]	(0.022)
Inequality of occupation-specific interaction terms ($\gamma^{\bar{o}}$) (p-value)	[0.061]		[0.004]	
Correlation between occupational group fixed effects and occupational groupspecific interaction terms: $corr(\delta^{\bar{o}}, \gamma^{\bar{o}})$	0.669* [0.058]	(0.426)	0.348 [0.167]	(0.359)
Observations	586		586	

*Note. All regressions include the whole set of explanatory variables reported in Table 3. Standard errors, corrected for clustering at the vacancy level are reported between parentheses, p-values are in brackets. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.*

4 Conclusion and Discussion

To the best of our knowledge, this study is the first to empirically study the relationship between labor market discrimination and labor market tightness. Theory predicts that if employers have difficulties in filling a vacancy, refusing a minority worker is extra costly in terms of forgone output, since the vacancy then risks to remain vacant for a long time. In the correspondence test that we conducted, applicants with a Turkish sounding name were no longer discriminated against if they applied for occupations with recruitment difficulties. In contrast, if they applied for occupations for which there are plenty of candidates, they had to send twice as many applications than candidates of native origin to be invited to a job interview. These results were found to be robust to a number of sensitivity analyses. They suggest that ethnic discrimination is a second order motive: Employers discriminate against foreign minorities if this does not interfere with their first motive, i.e. profit maximization.

Notice that the arguments explaining why one should expect less discrimination in occupations where recruitment is difficult are analogous to the ones Blanchard and Diamond (1994) use in their ranking model to rationalize why long-term unemployed relative to short-term unemployed are more likely to be recruited in a tight labor market. In this model the firm meets multiple workers and hires the one with the shortest unemployment duration. Since, in a tight labor market, employers have fewer candidates for each vacancy, long-term unemployed applicants face less competition from short-term unemployed and have more chances to be offered a job. Similarly, employers may rank job applicants according to their minority status, because they dislike minority workers (taste-based discrimination) or because they expect these workers to be less productive on average (statistical discrimination). In case of a tight labor market, minority workers are then, by analogy with the long-term unemployed in Blanchard and Diamond (1994), more likely to be successful in their job search.

Other theoretical frameworks with which we can compare our results are screening models (Vishwanath, 1989; Lockwood, 1991). In these models unemployment duration is used as a signal of the unobserved productivity of unemployed workers. When the labor market is tight this signal is more informative than if it is not, because the most productive workers are hired before they have a chance to become long-term unemployed. Hence, long unemployment duration signals low quality. By contrast, in a downturn unemployment duration is less informative about the average quality of workers, since then the more productive workers may also be long-term unemployed. Consequently, negative duration dependence in the job finding rate is pro-cyclical. Kroft et al. (2013) provide empirical evidence for this hypothesis. As in case of the ranking model, one could be tempted to argue that a model of statistical discrimination in which it is the minority status instead of unemployment duration that signals the average quality of applicants, is analogous to this screening model, and therefore expect worse outcomes for ethnic minorities in occupations with recruitment problems. Following this analogy, statistical discrimination would predict an opposite relationship between discrimination and labor market tightness than the one we find. However, this analogy is not valid. In case of unemployment duration the quality of the signal is, as explained, affected by tightness. By contrast, the minority status is an immutable characteristic that does not depend on the state of the economy. It is not so that when unemployment is high, productive workers are more likely to have a minority status, like they would be more likely to be long-term unemployed.

As mentioned in the Introduction, the strong negative cross-sectional relationship between discrimination in hiring and recruitment difficulties we find does not necessarily mean that tightness causes less discrimination. It could even reflect more discrimination in wage and working conditions by occupational segregation if vacancies are difficult to fill *as a consequence* of low wages and bad working conditions in these occupations. We acknowledge that this interpretation cannot be excluded, even if our findings are robust for the inclusion of indicators of wages and working conditions at the occupational level. This is because these indicators reflect averages within occupations which need not necessarily reflect the true wages and conditions in the jobs to which the fictitious candidates in our experiment applied.

These limitations call for further research. One option would be to exploit geographic variation in labor market tightness, such as Kroft et al (2013) do, to study the cyclical sensitivity of the duration dependence in the job finding rate. However, in this case the challenge is to prove that the geographical variation in tightness is not correlated with geographical variation in discriminatory attitudes of employers or that local tightness reflects concentrations of occupations with bad working conditions. Similar problems would show up if one would try to exploit the time variation in labor market tightness. Identification of a causal effect clearly requires some exogenous variation in tightness such as could be caused by variation in legal training requirements in particular professions, or by exogenous variations in labor demand, or supply, as e.g. caused by the Mariel boatlift, a declaration of Fidel Castro in 1980 allowing Cubans to temporarily freely emigrate to the U.S., on the Miami labor market (Card, 1990). Moreover, to identify the causal effect on discrimination in a difference-in-differences approach, correspondence tests targeted on the relevant populations should already be set up before the exogenous shock comes about. This is clearly difficult, because exogenous shocks can by definition not be anticipated.

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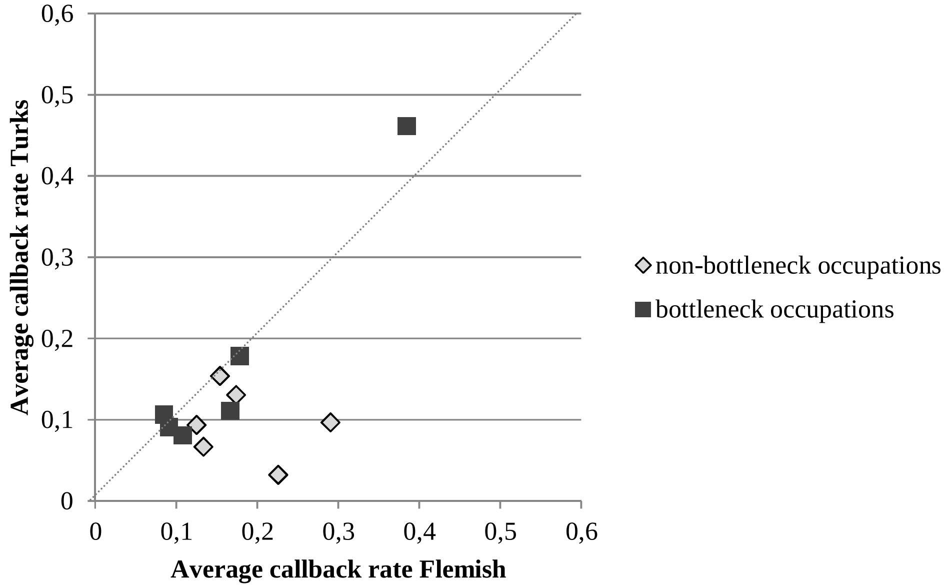
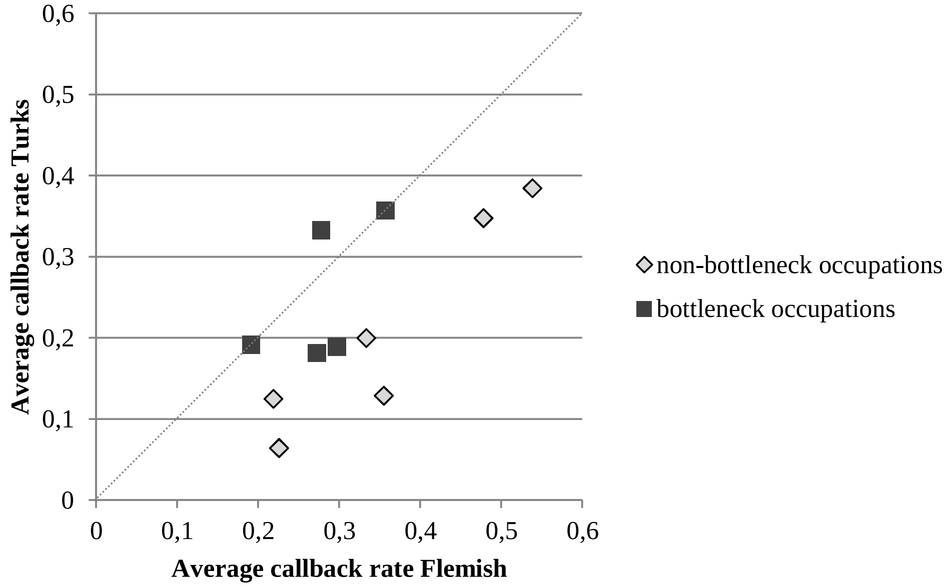
Appendix A: Descriptive Analysis of the Data: Scatter Plots

Figure A.1: Average Invitation Probability to a Job Interview in Occupation Groups.



Note. We followed the following aggregation rule. Occupations with strictly more than 20 applicants are not grouped. The other occupations are grouped keeping bottleneck and non-bottleneck occupations segregated, and not aggregating occupations that differ in the first two digits according to the occupational classification of the PES. Occupations for which this aggregation procedure did not yield more than 20 applicants were dropped from the analysis: 154 of the 752 observations had to be dropped for this reason.

Figure A.2: Average Probability of Any Positive Reaction in Occupation Groups.



Note. We followed the following aggregation rule. Occupations with strictly more than 20 applicants are not grouped. The other occupations are grouped keeping bottleneck and non-bottleneck occupations segregated, and not aggregating occupations that differ in the first two digits according to the occupational classification of the PES. Occupations for which this aggregation procedure did not yield more than 20 applicants were dropped from the analysis: 154 of the 752 observations had to be dropped for this reason.

Appendix B: Additional Tables (first part)

Table B.1: Occupations in Experimental Dataset: Descriptive Statistics.

Occupation	Median vacancy duration in days (in 2011)	Bottleneck occupation (in 2011)	Measure of female dominance in occupation	Intensive customer contact	Average wage (in 2010)	Job quality Measure	Number of middle educated applicants	Number of high educated applicants
Consultant in recruitment and selection	13	No	67.65%	No	2966	0.698	0	2
Executive clerk	28	No	73.28%	No	3073	0.709	2	0
Administrative clerk	28	No	73.51%	No	3169	0.709	36	26
Tutor	29	No	60.23%	No	4216	0.680	0	2
Window cleaner	30	No	1.88%	No	2243	0.612	2	0
Industrial cleaner	32	Yes	5.79%	No	2090	0.642	2	0
Consultant in marketing and publicity	35	No	54.46%	No	3997	0.698	0	12
Accountancy clerk	35	No	71.11%	No	3381	0.739	0	44
Executive assistant human resources	38	No	67.65%	No	3169	0.734	0	4
Warehouseworker components and parts	40	No	5.99%	No	2444	0.580	2	0
Assistant bookkeeper	41	No	63.00%	No	3381	0.720	0	20
Notary clerk	41	No	81.82%	No	2735	0.734	0	10
Teller financial institutions	41	No	80.62%	Yes	3381	0.720	0	8
Customs declaration officer	41	Yes	44.00%	No	2966	0.698	0	2
Executive assistant general directorate	42	No	70.38%	No	3073	0.723	0	4
Classic cleaner	42	Yes	69.66%	No	2090	0.642	94	0
Seller	44	Yes	73.39%	Yes	2233	0.630	6	0
Adjuster of a packaging machine	46	No	38.76%	No	2608	0.595	10	0
Legal service clerk	47	No	70.32%	No	2735	0.734	0	26
Bank clerk	47	No	57.75%	No	3381	0.720	0	8
Production worker	47	No	25.84%	No	2369	0.596	62	0
Bookkeeper	50	Yes	53.63%	No	4468	0.720	0	56
Room attendant	52	No	56.02%	No	2066	0.597	2	0
Executive expedition operator	55	Yes	47.35%	No	2966	0.698	0	10
Car cleaner	55	No	7.33%	No	2243	0.612	12	0
Executive assistant sales, marketing and publicity	56	No	54.46%	No	3169	0.723	0	8
Commercial clerk	56	No	60.01%	Yes	2392	0.723	18	28

Planning and logistics clerk	56	Yes	41.77%	No	2966	0.698	0	26
Private cleaner	65	Yes	93.23%	Yes	2090	0.642	74	0
Accountant	68	Yes	36.69%	No	4468	0.720	0	18
Shipping agent at the quay	69	Yes	6.90%	No	2966	0.698	0	6
Investigator	70	No	63.83%	No	2515	0.654	2	0
Insurance clerk	73	No	56.15%	No	3550	0.732	0	30
Representative	80	Yes	32.42%	Yes	3550	0.732	30	6
Call center employee	84	Yes	69.22%	No	2515	0.654	22	0
Consultant in finance	106	No	26.77%	No	3381	0.720	0	6
Tele-seller	106	Yes	65.27%	Yes	2392	0.656	10	0
Demonstrator	109	No	81.33%	Yes	2392	0.656	4	0

Note. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.

Table B.2: Applicant's and Occupational Characteristics in the Experimental Dataset by the Bottleneck Status of the Occupation.

	Bottleneck occupations	**Non-bottleneck occupations**
High educated	0.343 (0.475)	0.610 (0.488)
Overeducated	0.680 (0.467)	0.451 (0.498)
Measure of female dominance in occupation	0.624 (0.214)	0.565 (0.201)
No customer contact	0.387 (0.488)	0.651 (0.478)
Intensive customer contact	0.348 (0.477)	0.149 (0.356)
Moderate customer contact	0.265 (0.442)	0.200 (0.401)
Fraction foreign workers in sector	0.046 (0.036)	0.022 (0.023)
Fraction Turkish workers in sector	0.531 (0.567)	0.164 (0.266)
Log(average wage in occupation)	7.855 (0.221)	7.964 (0.136)
Job quality measure	0.675 (0.037)	0.693 (0.054)
Job quality measure: prospects	0.688 (0.062)	0.718 (0.055)
Job quality measure: intrinsic job quality	0.687 (0.047)	0.719 (0.060)
Job quality measure: working time quality	0.646 (0.024)	0.641 (0.055)
More than one similar job announced	0.215 (0.412)	0.056 (0.231)
Work place province: East-Flanders	0.387 (0.488)	0.426 (0.495)
Work place province: Antwerp	0.238 (0.426)	0.267 (0.443)
Work place province: West-Flanders	0.050 (0.218)	0.133 (0.340)
Work place province: Flemish Brabant	0.083 (0.276)	0.118 (0.323)
Work place province: Limburg	0.022 (0.147)	0.056 (0.231)
Sex of contact person: male	0.359 (0.480)	0.503 (0.500)
Sex of contact person: female	0.597 (0.491)	0.467 (0.500)
Sex of contact person: unknown	0.044 (0.206)	0.031 (0.173)

Note. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector. The reported statistics are averages and standard deviations are in parentheses.

Table B.3: The Probability of Any Positive Reaction: Unequal Treatment of Flemish and Turkish Job Candidates.

Occupations	Jobs	Neither callback (No.)	Both callback (No.)	Only Flemish callback (No.)	Only Turks callback (No.)	ND	χ^2
All	376	237	79	45	15	0.216***	15.00
Bottleneck	181	111	44	14	12	0.029	0.154
Non-bottleneck	195	126	35	31	3	0.406***	23.06

*Note. ND: net discrimination rate. The null hypothesis is that both individuals are treated unfavorably equally often. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.*

Table B.4: The Probability of Any Positive Reaction: Positive Callback Rates for Flemish and Turkish Job Candidates.

	Average callback rate	Callback rate Flemish	Callback rate Turks	Callback ratio	t
All	0.290	0.330	0.250	1.319***	3.945
Bottleneck	0.315	0.320	0.309	1.036	0.391
Non-bottleneck	0.267	0.338	0.195	1.737***	5.094

*Note. The null hypothesis is that the callback rate is equal for both ethnicities. Standard errors used for calculating t-values are corrected for clustering of the observations at the vacancy level. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level.*

Table B.5: The Probability of Any Positive Reaction: Main Regression Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name * Bottleneck occupation	**-0.011**	**-0.011**	**-0.011**	**-0.010**	**-0.004**	**0.005**	**0.005**
	(0.028)	**(0.028)**	**(0.027)**	**(0.028)**	**(0.020)**	**(0.029)**	**(0.028)**
Turkish name * Non-bottleneck occupation	**-0.144*** **	**-0.144*** **	**-0.143*** **	**-0.138*** **	**-0.138*** **	**-0.155*** **	**-0.155*** **
	(0.028)	**(0.028)**	**(0.028)**	**(0.028)**	**(0.028)**	**(0.030)**	**(0.029)**
Turkish name * High educated		0.136***	0.098	0.109	0.104	0.044	0.078
		(0.038)	(0.074)	(0.076)	(0.106)	(0.121)	(0.109)
Turkish name * Overeducated			-0.030	-0.034	-0.035	-0.056	-0.019
			(0.070)	(0.072)	(0.072)	(0.103)	(0.079)
Turkish name * Measure of female dominance in occupation			-0.024	-0.033*	-0.051	-0.048	-0.049
			(0.019)	(0.020)	(0.028)	(0.035)	(0.034)
Turkish name * Intensive customer contact				0.006	0.009	-0.028	-0.026
				(0.047)	(0.056)	(0.064)	(0.062)
Turkish name * Fraction foreign workers in sector				0.019	0.021	0.022	0.021
				(0.019)	(0.022)	(0.039)	(0.025)
Turkish name * Log(average wage in occupation)					-0.040	-0.024	-0.023
					(0.046)	(0.054)	(0.051)
Turkish name * Job quality measure					0.044	0.045	0.044
					(0.049)	(0.053)	(0.053)
Dependent variable: invitation to a job interview							
Dependent variable: any positive reaction	x	x	x	x	x	x	x
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Difference between "Turkish name * Bottleneck occupation" and "Turkish name * Non-bottleneck occupation" (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Except for "Turkish name", "Bottleneck occupation" and "Non-bottleneck occupation" all variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table B.6: The Probability of Any Positive Reaction: Median Vacancy Duration in the Occupation as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.080*****	**-0.079*****	**-0.079*****	**-0.075*****	**-0.075*****	**-0.077*****	**-0.077*****
	(0.020)	**(0.020)**	**(0.020)**	**(0.020)**	**(0.020)**	**(0.021)**	**(0.020)**
Turkish name * Median vacancy duration in the occupation	**0.030****	**0.037****	**0.035****	**0.042****	**0.046*****	**0.041****	**0.041****
	(0.014)	**(0.014)**	**(0.015)**	**(0.017)**	**(0.018)**	**(0.021)**	**(0.020)**
Turkish name * High educated		0.107***	0.084	0.096	0.109	0.036	0.066
		(0.038)	(0.070)	(0.073)	(0.107)	(0.121)	(0.105)
Turkish name * Overeducated			-0.019	-0.030	-0.029	-0.059	-0.023
			(0.067)	(0.069)	(0.070)	(0.102)	(0.075)
Turkish name * Measure of female dominance in occupation			-0.010	-0.019	-0.048	-0.044	-0.046
			(0.020)	(0.021)	(0.030)	(0.037)	(0.035)
Turkish name * Intensive customer contact				-0.048	-0.041	-0.065	-0.069
				(0.052)	(0.057)	(0.072)	(0.069)
Turkish name * Fraction foreign workers in sector				0.039**	0.037*	0.032	0.040*
				(0.019)	(0.021)	(0.036)	(0.024)
Turkish name * Log(average wage in occupation)					-0.071	-0.063	-0.060
					(0.050)	(0.057)	(0.055)
Turkish name * Job quality measure					0.061	0.068	0.069
					(0.052)	(0.055)	(0.054)
Dependent variable: invitation to a job interview							
Dependent variable: any positive reaction	x	x	x	x	x	x	x
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Variable "Median vacancy duration in the occupation" is normalized by subtracting the sample mean and dividing the result by the difference between the average of this median duration in bottleneck occupations and the corresponding duration in non-bottleneck occupations, i.e. by approximately 14 days. Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Appendix C: Additional Tables (second part)

Table C.1: The Probability of Invitation to a Job Interview: Alternative Controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Turkish name * Bottleneck occupation	**-0.004**	**-0.005**	**-0.004**	**-0.005**	**-0.004**	**-0.004**
	(0.020)	**(0.020)**	**(0.020)**	**(0.020)**	**(0.020)**	**(0.020)**
Turkish name * Non-bottleneck occupation	**-0.102*** **	**-0.101*** **	**-0.102*** **	**-0.101*** **	**-0.102*** **	**-0.102*** **
	(0.023)	**(0.023)**	**(0.023)**	**(0.023)**	**(0.023)**	**(0.023)**
Turkish name * High educated	0.082	0.089	0.085	0.062	0.082	0.105
	(0.091)	(0.092)	(0.089)	(0.090)	(0.086)	(0.097)
Turkish name * Overeducated	-0.027	-0.025	-0.033	-0.032	-0.036	-0.030
	(0.060)	(0.062)	(0.058)	(0.060)	(0.061)	(0.063)
Turkish name * Measure of female dominance in occupation	-0.052**	-0.049**	-0.052**	-0.046**	-0.055**	-0.049**
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
Turkish name * Intensive customer contact	0.017	0.013	0.003	0.017	0.010	0.010
	(0.051)	(0.049)	(0.047)	(0.048)	(0.046)	(0.047)
Turkish name * Moderate customer contact	0.022					
	(0.036)					
Turkish name * Fraction foreign workers in sector	0.014		0.011	0.012	0.016	0.018
	(0.016)		(0.015)	(0.016)	(0.016)	(0.015)
Turkish name * Fraction Turkish workers in sector		0.006				
		(0.022)				
Turkish name * Log(average wage in occupation)	-0.103**	-0.096**	-0.156**	-0.087**	-0.100***	-0.094**
	(0.046)	(0.038)	(0.066)	(0.035)	(0.038)	(0.037)
Turkish name * Job quality measure	0.078*	0.069		0.070*	0.080*	0.069
	(0.045)	(0.043)		(0.042)	(0.043)	(0.043)
Turkish name * Job quality measure: prospects			0.168**			
			(0.072)			
Turkish name * Job quality measure: intrinsic job quality			-0.071			
			(0.044)			
Turkish name * Job quality measure: working time quality			0.040*			
			(0.022)			
Turkish name * More than one similar job announced				-0.066		
				(0.054)		
Turkish name * Work place province: Antwerp					-0.030	
					(0.039)	

Turkish name * Work place province: West-Flanders					-0.032 (0.038)	
Turkish name * Work place province: Flemish Brabant					0.015 (0.043)	
Turkish name * Work place province: Limburg					-0.014 (0.142)	
Turkish name * Sex of contact person: female						-0.000 (0.029)
Turkish name * Sex of contact person: unknown						0.120 (0.081)
Dependent variable: invitation to a job interview	x	x	x	x	x	x
Dependent variable: any positive reaction						
Linear probability model						
Probit model (average partial effects are reported)	x	x	x	x	x	x
Occupational specific fixed effects						
Vacancy specific fixed effects						
Difference between “Turkish name * Bottleneck occupation” and “Turkish name * Non-bottleneck occupation” (p-value)	0.003	0.000	0.005	0.000	0.000	0.000
Observations	736	736	736	736	736	736

*Note. The variables that are interacted with “Turkish name” are also included without interaction with this variable. Except for “Turkish name”, “Bottleneck occupation” and “Non-bottleneck occupation” all variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign (or Turkish) workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table C.2: The Probability of Any Positive Reaction: Alternative Controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Turkish name * Bottleneck occupation	**-0.010** **(0.027)**	**-0.010** **(0.027)**	**-0.010** **(0.027)**	**-0.010** **(0.027)**	**-0.009** **(0.028)**	**-0.010** **(0.027)**
Turkish name * Non-bottleneck occupation	**-0.138***** **(0.028)**	**-0.137***** **(0.028)**	**-0.138***** **(0.028)**	**-0.138***** **(0.028)**	**-0.138***** **(0.028)**	**-0.138***** **(0.028)**
Turkish name * High educated	0.101 (0.103)	0.108 (0.102)	0.079 (0.098)	0.094 (0.104)	0.111 (0.098)	0.113 (0.106)
Turkish name * Overeducated	-0.036 (0.072)	-0.029 (0.071)	-0.036 (0.070)	-0.034 (0.072)	-0.047 (0.071)	-0.029 (0.072)
Turkish name * Measure of female dominance in occupation	-0.048* (0.028)	-0.050* (0.028)	-0.047* (0.028)	-0.050* (0.028)	-0.054* (0.029)	-0.051* (0.028)
Turkish name * Intensive customer contact	-0.002 (0.059)	0.013 (0.057)	-0.004 (0.055)	0.012 (0.055)	0.015 (0.056)	0.008 (0.055)
Turkish name * Moderate customer contact	0.031 (0.055)					
Turkish name * Fraction foreign workers in sector	0.021 (0.022)		0.017 (0.020)	0.020 (0.021)	0.022 (0.021)	0.017 (0.022)
Turkish name * Fraction Turkish workers in sector		0.013 (0.026)				
Turkish name * Log(average wage in occupation)	-0.026 (0.053)	-0.043 (0.046)	-0.026 (0.069)	-0.037 (0.046)	-0.038 (0.047)	-0.042 (0.045)
Turkish name * Job quality measure	0.034 (0.053)	0.040 (0.049)		0.043 (0.049)	0.041 (0.049)	0.044 (0.049)
Turkish name * Job quality measure: prospects			0.031 (0.081)			
Turkish name * Job quality measure: intrinsic job quality			-0.016 (0.059)			
Turkish name * Job quality measure: working time quality			0.034 (0.030)			
Turkish name * More than one similar job announced				-0.026 (0.065)		
Turkish name * Work place province: Antwerp					-0.017 (0.052)	
Turkish name * Work place province: West-Flanders					-0.028 (0.060)	
Turkish name * Work place province: Flemish Brabant					0.012 (0.063)	

Turkish name * Work place province: Limburg					-0.132 (0.187)	
Turkish name * Sex of contact person: female						0.032 (0.038)
Turkish name * Sex of contact person: unknown						0.086 (0.075)
Dependent variable: invitation to a job interview						
Dependent variable: any positive reaction	x	x	x	x	x	x
Linear probability model						
Probit model (average partial effects are reported)	x	x	x	x	x	x
Occupational specific fixed effects						
Vacancy specific fixed effects						
Difference between “Turkish name * Bottleneck occupation” and “Turkish name * Non-bottleneck occupation” (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Observations	736	736	736	736	736	736

*Note. The variables that are interacted with “Turkish name” are also included without interaction with this variable. Except for “Turkish name”, “Bottleneck occupation” and “Non-bottleneck occupation” all variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign (or Turkish) workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table C.3: The Probability of Invitation to a Job Interview: Labor Market Tightness at the Flemish Level as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.059******	**-0.059******	**-0.058******	**-0.054******	**-0.054******	**-0.055******	**-0.056******
	(0.016)	**(0.016)**	**(0.016)**	**(0.015)**	**(0.015)**	**(0.016)**	**(0.016)**
Turkish name * Labor Market Tightness	**-0.002**	**0.005**	**0.006**	**0.006**	**0.008**	**0.006**	**0.005**
	(0.014)	**(0.014)**	**(0.015)**	**(0.014)**	**(0.014)**	**(0.018)**	**(0.016)**
Turkish name * High educated		0.064**	0.030	0.040	0.063	0.130	0.002
		(0.029)	(0.064)	(0.064)	(0.092)	(0.084)	(0.113)
Turkish name * Overeducated			-0.037	-0.043	-0.040	0.111	-0.088
			(0.061)	(0.061)	(0.061)	(0.077)	(0.084)
Turkish name * Measure of female dominance in occupation			-0.003	-0.014	-0.057**	-0.060*	-0.057*
			(0.016)	(0.016)	(0.023)	(0.033)	(0.032)
Turkish name * Intensive customer contact				-0.005	0.016	-0.003	0.007
				(0.004)	(0.050)	(0.051)	(0.050)
Turkish name * Fraction foreign workers in sector				0.028*	0.023	0.026	0.027
				(0.014)	(0.016)	(0.034)	(0.020)
Turkish name * Log(average wage in occupation)					-0.106***	-0.106**	-0.117**
					(0.040)	(0.052)	(0.051)
Turkish name * Job quality measure					0.086**	0.110**	0.103*
					(0.044)	(0.053)	(0.054)
Dependent variable: invitation to a job interview	x	x	x	x	x	x	x
Dependent variable: any positive reaction							
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational specific fixed effects						x	
Vacancy specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table C.4: The Probability of Any Positive Reaction: Labor Market Tightness at the Flemish Level as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.080*** (0.020)**	**-0.080*** (0.020)**	**-0.079*** (0.020)**	**-0.075*** (0.020)**	**-0.075*** (0.020)**	**-0.077*** (0.021)**	**-0.077*** (0.020)**
Turkish name * Labor Market Tightness	**-0.018 (0.019)**	**-0.008 (0.018)**	**-0.008 (0.018)**	**-0.011 (0.019)**	**-0.009 (0.019)**	**0.002 (0.023)**	**-0.013 (0.021)**
Turkish name * High educated		0.088** (0.038)	0.056 (0.071)	0.083 (0.072)	0.075 (0.104)	0.028 (0.120)	0.049 (0.107)
Turkish name * Overeducated			-0.030 (0.069)	-0.038 (0.069)	-0.038 (0.069)	-0.063 (0.101)	-0.032 (0.077)
Turkish name * Measure of female dominance in occupation			-0.017 (0.020)	-0.035* (0.021)	-0.059** (0.030)	-0.057 (0.037)	-0.058 (0.036)
Turkish name * Intensive customer contact				0.028 (0.054)	0.031 (0.062)	0.003 (0.069)	0.007 (0.067)
Turkish name * Fraction foreign workers in sector				0.037* (0.020)	0.038* (0.022)	0.033 (0.036)	0.042* (0.025)
Turkish name * Log(average wage in occupation)					-0.054 (0.048)	-0.052 (0.056)	-0.046 (0.054)
Turkish name * Job quality measure					0.059 (0.050)	0.062 (0.055)	0.062 (0.054)
Dependent variable: invitation to a job interview							
Dependent variable: any positive reaction	x	x	x	x	x	x	x
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational specific fixed effects						x	
Vacancy specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table C.5: The Probability of Invitation to a Job Interview: Median Vacancy Duration in the Occupation as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.059*** (0.016)**	**-0.058*** (0.015)**	**-0.058*** (0.015)**	**-0.054*** (0.015)**	**-0.054*** (0.015)**	**-0.055*** (0.016)**	**-0.056*** (0.015)**
Turkish name * Median vacancy duration in the occupation	**0.028*** (0.009)**	**0.028*** (0.010)**	**0.027*** (0.009)**	**0.036*** (0.010)**	**0.036*** (0.010)**	**0.032** (0.013)**	**0.032*** (0.012)**
Turkish name * Standard deviation of vacancy duration in the occupation	**-0.002 (0.007)**	**0.005 (0.007)**	**0.007 (0.008)**	**0.008 (0.008)**	**0.019** (0.080)**	**0.022* (0.011)**	**0.021* (0.020)**
Turkish name * High educated		0.083*** (0.030)	0.064 (0.062)	0.066 (0.064)	0.113 (0.095)	0.140* (0.083)	0.020 (0.011)
Turkish name * Overeducated			-0.021 (0.059)	-0.024 (0.059)	-0.010 (0.059)	0.117 (0.077)	-0.077 (0.079)
Turkish name * Measure of female dominance in occupation			0.007 (0.016)	0.005 (0.016)	-0.055** (0.022)	-0.055 (0.030)	-0.053* (0.028)
Turkish name * Intensive customer contact				-0.076 (0.047)	-0.065 (0.049)	-0.097 (0.057)	-0.083 (0.055)
Turkish name * Fraction foreign workers in sector				0.030** (0.014)	0.024 (0.015)	0.025 (0.034)	0.026 (0.019)
Turkish name * Log(average wage in occupation)					-0.157*** (0.041)	-0.146*** (0.049)	-0.157*** (0.048)
Turkish name * Job quality measure					0.134*** (0.047)	0.163*** (0.053)	0.153*** (0.053)
Dependent variable: invitation to a job interview	x	x	x	x	x	x	x
Dependent variable: any positive reaction							
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Variable "Median vacancy duration in the occupation" is normalized by subtracting the sample mean and dividing the result by the difference between the average of this median duration in bottleneck occupations and the corresponding duration in non-bottleneck occupations, i.e.by approximately 14 days Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*

Table C.6: The Probability of Any Positive Reaction: Median Vacancy Duration in the Occupation as Alternative Measure of Tightness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Turkish name	**-0.080*** (0.020)**	**-0.079*** (0.020)**	**-0.079*** (0.020)**	**-0.075*** (0.020)**	**-0.075*** (0.020)**	**-0.077*** (0.021)**	**-0.077*** (0.020)**
Turkish name * Median vacancy duration in the occupation	**0.035** (0.017)**	**0.034** (0.016)**	**0.032** (0.016)**	**0.040** (0.018)**	**0.038** (0.019)**	**0.032 (0.023)**	**0.032 (0.022)**
Turkish name * Standard deviation of vacancy duration in the occupation	**-0.007 (0.010)**	**0.003 (0.011)**	**0.003 (0.011)**	**0.004 (0.012)**	**0.010 (0.013)**	**0.012 (0.016)**	**0.012 (0.015)**
Turkish name * High educated		0.110*** (0.042)	0.089 (0.070)	0.099 (0.072)	0.110 (0.103)	0.037 (0.121)	0.066 (0.104)
Turkish name * Overeducated			-0.018 (0.067)	-0.029 (0.069)	-0.026 (0.069)	-0.058 (0.102)	-0.022 (0.074)
Turkish name * Measure of female dominance in occupation			-0.010 (0.020)	-0.018 (0.022)	-0.052* (0.030)	-0.050 (0.036)	-0.052 (0.035)
Turkish name * Intensive customer contact				-0.051 (0.055)	-0.048 (0.062)	-0.073 (0.076)	-0.077 (0.074)
Turkish name * Fraction foreign workers in sector				0.038** (0.019)	0.037* (0.021)	0.032 (0.036)	0.040* (0.024)
Turkish name * Log(average wage in occupation)					-0.082 (0.053)	-0.078 (0.057)	-0.074 (0.054)
Turkish name * Job quality measure					0.080 (0.057)	0.093 (0.061)	0.095 (0.060)
Dependent variable: invitation to a job interview							
Dependent variable: any positive reaction	x	x	x	x	x	x	x
Linear probability model						x	x
Probit model (average partial effects are reported)	x	x	x	x	x		
Occupational-specific fixed effects						x	
Vacancy-specific fixed effects							x
Observations	752	752	752	736	736	736	736

*Note. The variables that are interacted with "Turkish name" are, except for specifications (6) and (7), also included without interaction with this variable. Variable "Median vacancy duration in the occupation" is normalized by subtracting the sample mean and dividing the result by the difference between the average of this median duration in bottleneck occupations and the corresponding duration in non-bottleneck occupations, i.e. by approximately 14 days. Except for "Turkish name", all other variables are normalized by subtracting the sample mean. Continuous variables are further normalized by dividing by the sample standard deviation. Standard errors, corrected for clustering at the vacancy level, are in parentheses. ***(**)((*)) indicates significance at the 1% (5%) ((10%)) level. When including the fraction of foreign workers in the sector, 16 observations are dropped since neither the name of the firm nor its sector is given in 8 vacancies posted by labor market intermediaries. See Section 2.2 for a definition of the level of education, Section 2.4 for a definition of the occupational characteristics and Section 3.1.2 for a definition of overeducation and the fraction of foreign workers in the sector.*