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1. Introduction

Indigenous Australians are among the most disadvantaged indigenous populations in developed countries in terms of standard labour market indicators (Hunter and Daly, 2013). As of 2011, only 55.8% of the indigenous working-age population were in the labour force compared to 76.4% among non-indigenous population (ABS, 2013). Moreover, the rate of unemployment among indigenous Australians is higher than among non-indigenous Australians (17.2% compared with 5.5%). Various policy initiatives have been undertaken over the years to address the labour market disadvantage of indigenous Australians, e.g. the Aboriginal Employment Development Policy of the Hawke Labor Government in the 1980s, the Practical Reconciliation of the Liberal Howard Government, the emphasis on 'Closing the Gap' of the Rudd Labor Government, all aimed at integrating a greater proportion of indigenous Australians into the labour market (Biddle et al., 2009). Despite these efforts, however, reducing labour market disadvantage of indigenous Australians has proved difficult. Indeed, the indicators of indigenous labour market outcomes have remained remarkably stable over the past few decades (Altman et al., 2009).

While the gaps in labour market outcomes do not necessarily imply discrimination, it is widely recognised that there is substantial scope for persistent discrimination against the indigenous population in Australia (e.g., Hunter, 2003). Discrimination against indigenous Australians has been an offence under the Commonwealth law since 1975; directly observing a discriminatory treatment therefore should be hard. A number of studies have attempted to empirically infer on the extent of indigenous labour market discrimination applying decomposition approaches introduced by Blinder (1973) and Oaxaca (1973) (or versions thereof). Discrimination in these studies is measured as part of the gap in labour market outcomes of indigenous and non-indigenous individuals that remains once all their observable productivity-related characteristics are statistically accounted for. Decompositions carried out in earlier studies (e.g., Miller, 1989; Daly, 1993) explain between just one fifth to a quarter of the gap in employment between the two populations. In a recent study by Kalb et al. (2014), the unexplained part (that is the part attributed to discrimination) of employment differential, while smaller, is nevertheless significant: around two fifth for men and one third for women.

Statistical residual-based measures of discrimination play an influential role in informing the academic and public debates on labour market discrimination. Nonetheless, whether such 'crude' measures completely capture the labour market discrimination has been questioned in the literature (Kuhn, 1990). This is a particularly relevant concern in the context of indigenous labour market discrimination since the importance of appropriately nuanced approaches in assessing indigenous well-being has been highlighted in previous studies (e.g., Thomas et al., 2010). One way to gain some insight on this issue is to analyse an alternative measure of discrimination - a task pursued in this paper. The question that we ask is 'To what extent are the statistical measures of discrimination consistent with indigenous people's reports of discrimination?' Self-assessed discrimination measures allow for 'broader concepts' of equity to be considered (Antecol et al., 2014). To the extent that survey reports are honest estimates of 'true' discrimination (Kuhn, 1987), the exercise we undertake represents a check of validity of statistical measures of discrimination. Furthermore, understanding who is more likely to feel that they are discriminated against is important from the perspective of gaining insights on the 'feedback' hypothesis of discrimination since perceptions of discrimination can influence people's labour supply decisions (e.g., Neumark and McLennan, 1995; Antecol and Kuhn, 2000).

Using two large, nationally-representative datasets, we quantify the relationship between Oaxaca-Blinder decomposition-based measures of employment discrimination and survey reports of discriminatory treatment of indigenous Australians in the labour market. Our focus is on gaps in employment (although we consider the gaps in earnings in additional estimations) - a problem of central concern in the context of discrimination and the exclusion of indigenous Australians from the labour market. According to Hunter (2003), for example, the discrimination against indigenous Australians 'appears to manifest itself in an inability to find jobs, rather than depressing the wages received' (p. 2). At first glance, one might expect the likelihood of reporting discrimination to increase with an increase in the statistical measure of discrimination. Our findings, however, suggest that statistical measures of discrimination are in fact not linked to males' reports of discrimination. Moreover, for females we find a negative relationship between statistical measures and the probability of reporting discrimination.

These results are broadly consistent with two main conjectures proposed in the literature. First, they point out at the potential importance of other 'nonstatistical' evidence of discrimination (Kuhn, 1987). This, according to Kuhn (1990), is simply a 'residual category' that comprises all evidence of discrimination not embodied in the standard statistical measure which leads individuals to recognize and report discrimination. If the quantity of such nonstatistical evidence is high, discrimination may be reported even if the statistically measured discrimination is small. Second, the results are consistent with the hypothesis on the 'quality of statistical evidence of discrimination' proposed by Barbezat and Hughes (1990). This hypothesis suggests that 'employers are more likely to indulge in discrimination when there is a low probability that such action will be detected' (p. 284-285). Unobserved differences in the quality of statistical evidence (and thereby in the ability to detect such discrimination) will then yield the negative correlation between statistical and reported measures of discrimination. Thus, our results suggest that unobserved variables such as nonstatistical evidence of discrimination or quality of statistical evidence of discrimination are potentially significant determinants of indigenous Australians' perceptions of discriminatory treatment. This underscores the importance of considering alternative measures of discrimination, in addition to statistical evidence, in evaluating the indigenous labour market disadvantage.

The relationship between survey-based perceptions of discrimination and standard Oaxaca-Blinder measures of discrimination has been considered by a small literature, which has not arrived at conclusive evidence as yet.[1] While some studies have documented a positive link between perception-based and statistical measures of discrimination (Hampton and Heywood, 1993), others have not found evidence of a strong relationship between the two (Antecol et al., 2014). Moreover, like us, some have shown that those reporting the most discrimination face the least statistical discrimination. Studies by Kuhn (1987) and Antecol and Kuhn (2000) have arrived at this finding based on representative samples of US and Canadian women. Barbezat and Hughes (1990) have provided an additional evidence of a negative relationship between statistical and self-reported measures of discrimination in the case of female college professors in the US.

Our paper makes several contributions to this literature. First, in contrast to previous studies in this strand of literature that have focused on discrimination in pay, we are the first to study discrimination in getting a job. The narrow focus on wage differentials in previous studies has been acknowledged as a shortcoming (Hampton and Heywood, 1993; Hallock et al., 1998). Hallock et al. (1998), for example, note that there are 'other ways discrimination can occur, such as discrimination in promotion or discrimination in getting a job' (p. 260), and that those distinctions could be potential explanation for the mixed evidence on the relationship between statistical and perceived measures of discrimination. Second, our study is the first to consider the relationship between statistical and perceived measures of discrimination faced by Australia's indigenous population. Previous studies in other country contexts have predominantly focused on comparisons of statistical and perceived measures of gender discrimination (exceptions include Hallock et al. (1998) who consider disability

[1] The relationship between reported beliefs and reality has also been explored in other contexts. Examples include Olken (2009) on corruption, Gimpelson and Treisman (2015) on inequality.

and Antecol et al. (2014) who consider race (within the legal profession) as additional dimensions of discrimination in the context of the US). The literature on indigenous labour market discrimination in Australia has considered survey reports of discrimination. A study by Biddle et al. (2013) has looked at the self-perceived discrimination by indigenous population and presented correlations between perceived discrimination experienced in different settings and its potential drivers. The correlates of perceived discrimination on the basis of a wider range of characteristics in the context of Australian labour market have also been examined by Hahn and Wilkins (2013). However, these studies have not considered statistical discrimination as a determinant of discrimination reports. The only Australian study that has done that is the descriptive analysis by Cobb-Clark (2012) for the case of gender discrimination; this study has shown that there is little relationship between statistical and self-reported measures of discrimination.

Methodologically, we follow the approaches taken in previous studies with two noteworthy nuances. First, our statistical measure of discrimination is derived based on a version of Oaxaca-Blinder decomposition adapted to non-linear models, since our labour market outcome of interest is a binary employment status rather than a continuous measure of wages. Second, our perception-based measure of discrimination is rather precise in that it captures perceptions of incidences of racial discrimination experienced when looking for work or when at work. Some of the previous studies in the literature (e.g., Kuhn, 1987; Barbezat and Hughes, 1990) have drawn inferences about perceptions of discrimination based on very broad questions - a fact that may have contributed to the ambiguity in the results (Hampton and Heywood, 1993). Our approach overcomes this shortcoming.

The rest of the paper proceeds as follows. The next section presents the empirical approach while section 3 describes the data. Section 4 reports the estimation results. Section 5 concludes.

2. Empirical approach

Statistical measures of discrimination. Our goal is to explore whether and the extent to which the perceptions of discrimination are determined by statistical measures of discrimination. As such, we employ statistical residual-based measures of discrimination based on decomposition approaches introduced by Blinder (1973) and Oaxaca (1973).

To arrive at estimates of employment discrimination we consider a standard model in which employment propensity Y_i^{G*} for an individual i belonging to group G (indigenous, non-indigenous) is assumed to depend on demand and supply side factors denoted as X_i^G.

Unobserved factors ε_i^G further contribute to employment propensity, leading to an equation of the form

$$Y_i^{G*} = X_i^G * \beta^G + \varepsilon_i^G \tag{1}$$

Observed employment status Y_i^G is assumed to relate to latent propensity through the criterion $Y_i^G = 1(Y_i^{G*} \geq 0)$, so that the probability of employment under an assumption of normality for ε_i becomes:

$$Pr(Y_i^G = 1 | X_i^G) = \Phi(X_i^G \beta^G), \tag{2}$$

where Φ is a normal CDF.

Standard estimates of labour market discrimination developed by Blinder (1973) and Oaxaca (1973) are based on the estimated parameters of linear models of labour market outcomes (wages, in most applications) and can be expressed in the following general form:

$$\widehat{\overline{SD_{,L}}} = \overline{X^B}\hat{\beta}^A - \overline{X^B}\hat{\beta}^B \tag{3}$$

where subscript A denotes the non-indigenous population, subscript B denotes the indigenous population, $\overline{X}$ is a row of mean values of the control variables and $\hat{\beta}$ is a vector of coefficient estimates. Following Kuhn (1987), individual-specific measure of discrimination are defined as follows:[2]

$$\widehat{SD}_{i,L} = X_i^B\hat{\beta}^A - X_i^B\hat{\beta}^B \tag{4}$$

This statistical measure of discrimination captures the difference between what an indigenous person's labour market outcome would be if he/she was getting the same returns to his/her observed characteristics as a non-indigenous person rather than as a member of the indigenous group. It cannot be used directly, however, if the outcome is binary and the coefficients are from a probit model, like in our case (equation 2), since conditional expectation $E[Y_i \mid X_i]$ may differ from the linear prediction $X_i\hat{\beta}$ (Bauer and Sinning, 2008). Therefore, we calculate the measures of discrimination in employment using conditional expectations evaluated at different coefficient estimates:

$$\widehat{SD}_{i,NL} = E_{\hat{\beta}^A}[Y_i^B \mid X_i^B] - E_{\hat{\beta}^B}[Y_i^B \mid X_i^B] \tag{5}$$

[2]This measure focuses on the difference in the returns $\beta^A - \beta^B$ to individuals' observed characteristics X_i ignoring the returns to individuals' unobserved characteristics.

Determinants of discrimination perceptions. In the second stage of the analysis we examine whether the perceived discrimination of an indigenous Australian i contains information about statistical measures of discrimination by estimating a probit model of the following form:

$$Pr(PD_i = 1|K_i, \widehat{SD}_{i,NL}) = \Phi(\gamma K_i + \delta \widehat{SD}_{i,NL}) \tag{6}$$

where PD is the individual's reported perception of labour market discrimination, $\widehat{SD}_{i,NL}$ is the statistical measure of discrimination generated based on equation 5, and K is a set of other control variables. To account for the fact that the measures of statistical discrimination are generated regressors we calculate the standard errors from bootstrapping with 1000 replications.

The test of whether an indigenous person with higher measured discrimination is more or less likely to report being discriminated against is a test of significance of coefficients δ. The expected sign of δ is a priori unclear. It should be positive if individuals put some positive weight on statistical evidence in their reporting decisions. However, it may also be negative if there are important determinants of reporting decisions (negatively) correlated with statistical discrimination omitted from equation 6. Two conjectures with respect to the nature of this omitted information have been raised by previous studies. Kuhn (1987) refers to it as nonstatistical evidence of discrimination which comprises other forms of bias observed by individuals but not by the econometrician. Alternatively, Barbezat and Hughes (1990) assume that individuals rather observe less, and that this is exploited by employers in their decisions to discriminate - a reason why a high level of statistical discrimination will be accompanied in equilibrium by a small number of reports. Thus within this approach, it is the quality of statistical evidence of discrimination that is omitted from equation 6.

Learning about the nature of omitted information determining reports of discrimination would require finding a way to measure and control for it in the regressions. For example, Barbezat and Hughes (1990) use institutional type as a proxy for the quality of statistical evidence (they assume that at public institutions salary information is more widely circulated than in private institutions). As they show, the negative correlation between statistical and reported measures of discrimination is weaker for public institutions - a finding that suggests that the omitted quality of information is potentially part of the explanation in their case. While the study by Kuhn (1987) does not employ a direct proxy for omitted nonstatistical evidence, it assumes that either the availability of such evidence or the ability to interpret it is a function of individuals' characteristics. Accordingly, characteristics such as age and education level are effectively used as proxies to infer on the unobserved level of nonstatistical evidence. In the robustness checks section we employ similar approaches to provide some insights on the nature of relationship between statistical and perceived measures of discrimination. However we are not able to directly test the hypotheses against each other to fully resolve this question.

3. Data

Sources and sample. The share of indigenous Australians in the total population is small (around 3% as of 2011 (ABS, 2011)). As a result, the number of indigenous respondents in most surveys is insufficient for detailed statistical analysis. The Census of Population and Housing does not face this constraint and has been used in previous studies on indigenous labour market outcomes (e.g., Miller, 1989; Daly, 1993); however it is not suited for our analysis since it does not have information on perceptions of discrimination. We overcome these challenges by jointly analysing two different datasets that contain comparable information on a range of variables important for our analysis - a design that was used in a recent study by Kalb et al. (2014).

Data on the indigenous population are drawn from the National Aboriginal and Torres Strait Islander Social Survey (NATSISS), a cross-sectional nationally representative study of Aboriginal and Torres Strait Islander people introduced in 2002 designed to run every six years. We utilise the most recent, 2008 wave of NATSISS available through Remote Access Data Laboratory (RADL).[3] NATSISS 2008 collected nationally-representative information from approximately 13,300 indigenous Australians (ABS, 2010). It is particularly suited for our study as it provides information on self-reported discrimination due to indigenous status along with information on standard demographic characteristics, educational background and employment outcomes. We analyse NATSISS 2008 in conjunction with comparable data on non-indigenous Australians from the 2008 wave of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a household-based panel study which has been running annually since its introduction in 2001, covering around 13,000 individuals nation-wide.

Our analysis is restricted to working-age (15-64 years old) populations[4], excluding full-time students, residing in non-remote areas. The exclusion of remote areas from the analysis

[3] The RADL operates as an online query system. The data are held on a server at the Australian Bureau of Statistics in Canberra. The registered users submit codes in SAS, SPSS or STATA to analyse the data (with a number of restrictions imposed).

[4] The results are robust to restricting the population to ages 22-60 instead (available on request).

is primarily driven by the fact that HILDA survey excludes remote areas (unless a respondent has moved to a remote area in the course of the survey). However, as noted in Kalb et al. (2014), there are other reasons to apply this exclusion. First, there is a higher prevalence of customary sector (hunting, fishing and gathering, arts and crafts, etc.) in remote areas that complicates the comparisons with mainstream employment activity. Second, comparisons of indigenous/non-indigenous outcomes may be further complicated by the fact that some indigenous individuals residing in remote areas participate in government intervention programs and there is scope for misreporting program participation as being equivalent to other employment (Hunter and Gray, 2013). However, it should also be noted that there is a higher prevalence of individuals reporting labour market discrimination in remote areas (8.9%) relative to non-remote areas (6.8%), and understanding the drivers of this discrimination reports remains an important direction of future research.

After applying these restrictions (and excluding observations with missing values for key variables), we are left with a working sample consisting of 2,229 and 2,793 observations for males and females in NATSISS, and 3,676 and 4,123 observations for males and females in HILDA.

Determinants of employment status. Our study focuses on discrimination in employment with our baseline models employing a binary employment status distinguishing between those employed and not employed (including those not in the labor force). This measure, according to Daly (1993), is particularly suited for the study of indigenous Australians since in many contexts applicable to study of this group of the population 'the distinction between unemployment and not being in the labour force has little validity' (p. 136). In many cases, both groups may be willing to take up employment if the opportunity arose but individuals may be discouraged from actively searching for work or have little incentives to register as unemployed. As Table 1 illustrates, only 64% of males and 48% of females in the indigenous sample are employed. Among the non-indigenous population, employment rates are 86% for males and 74% for females. The gender gap in employment is larger among the indigenous population.

Our statistical measure of discrimination is based on statistically accounting for a range of observable characteristics of individuals. Three groups of covariates are included in employment models. The first comprises individual characteristics such as age (and age squared to account for non-linearities) and household composition (presence of a partner, number of children under the age of 14, type of household distinguishing between single occupant (omitted); one-family and mixed households). Additional covariates include two single categorical variables for disability and daily smoker status, as well multiple categorical variables to distinguish between different states of alcohol consumption.[5] The second group are 'intervening factors' (Miller, 1989). Information of primary importance is educational attainment. We include dummies for years of schooling completed (up to Year 10; Year 10 or 11; and Year 12) and tertiary qualifications obtained (none (omitted); non-degree post-school qualification; and degree). The final set of variables are dummies for the location of residence to capture the available labour market opportunities.[6]

Indigenous Australians are on average around 4 years younger compared to non-indigenous Australians (Table 1). They are less likely to have a partner but more likely to live in households with more children. The prevalence of disability and daily smoking is higher among the indigenous population. Indigenous Australians are also significantly less likely to have completed year 12 or a university degree.

Table 1 additionally presents the results of employment models given in equation 2 estimated separately by indigenous status and gender (see odd-numbered columns). We report coefficients (and not the marginal effects) since our calculations of statistical measures of discrimination are based on coefficients (equation 5). As expected, the employment probability initially increases then decreases with age. Having a partner increases the employment probability of males, especially in the indigenous population. For indigenous females, the coefficient on PARTNERED is statistically significant and positive, although smaller compared to males, while for non-indigenous females it is negative and statistically insignificant. As expected, the number of children reduces the probability of employment, especially for females. Disability, especially among males, is a strong negative correlate of employment probability, as is the daily smoker status (with the exception of non-indigenous females, where the coefficient is statistically insignificant). Interestingly, we find that moderate drinkers (with the exception of indigenous females) are significantly more likely to be employed relative to abstainers. This is consistent with findings of 'alcohol-income puzzle' literature (e.g., Macdonald and Shields, 2001; Auld, 2005). Positive health effects as well as

[5]These include: Abstainer - up to 6 standard drinks consumed once monthly or less frequently (omitted); Moderate - up to 6 standard drinks consumed 2-3 days a month to 3-4 days a week, or up to 4 standard drinks consumed 5-6 days a week or every day: Infrequent high-risk -7 or more drinks consumed 1-2 days a week or less frequently; and Frequent high-risk - 7 or more drinks consumed 3-4 days a week to every day, or 5 or more drinks consumed 5-6 days a week or every day.

[6]These include: NSW major cities (omitted), NSW inner regional, NSW outer regional, VIC major cities, VIC inner/outer regional, QLD major cities, QLD inner regional, QLD outer regional, SA non-remote, WA major cities, WA inner/outer regional, TAS non-remote.

networking mechanisms associated with alcohol consumption are potential explanations behind this relationship. The evidence on returns to high-risk drinking is mixed with some of the estimated coefficients positive while others negative. We also observe statistically significant positive returns to years of school education. The estimated coefficients are larger for indigenous individuals. Similarly, we document positive returns to tertiary education with larger returns accruing to females in both samples. Moreover, among indigenous males the estimated coefficient on having a degree, while positive, is not statistically significant.

Perceived and statistical measures of discrimination. We employ the estimated parameters from the four employment models to calculate the statistical measures of discrimination given in equation 5. The summary statistics of this variable is presented in Table 2 (odd-numbered columns). The mean of statistical discrimination in the pooled sample is 0.308, ranging from -0.012 to 0.745. Statistical discrimination is on average larger among females (0.372) than males (0.245).

Our measure of perceived discrimination is a binary variable taking 1 if the respondents felt racially discriminated against when looking for work or when at work in the preceding 12 months. This measure is highly suited for our analysis since it elicits information on discrimination specifically in the context of labour market experiences of individuals and with reference to their indigenous status. As Hampton and Heywood (1993) note, the way questions about discrimination are phrased is likely to matter. The accuracy of perception of discriminatory treatment may be compromised, for example, if the variables are derived from broad questions either about discrimination in general (e.g. as in Kuhn, 1987) or about affirmative action not limited to the group (i.e. gender) studied (e.g. as in Barbezat and Hughes, 1990). Our measure is immune to such problems.

As Table 2 demonstrates, the prevalence of perceived discrimination in our sample is 6.8%. While the statistical discrimination is larger among females, females are less likely to report discrimination compared to males. 8.1% of males and only 5.3% of females report having experienced discrimination on the basis of their indigenous identity.

Are then those subjected to more statistical discrimination more likely to perceive being discriminated? Table 2 reports the results of probit regressions of perceived discrimination on estimated statistical discrimination in the pooled sample of males and females as well as separately by gender (even-numbered columns). We observe negative statistically significant marginal effect on statistical discrimination in the pooled sample. The results by gender groups (while statistically insignificant) suggest that this is driven by the relationship observed among females; the estimated marginal effect in the sub-sample of males is positive. In what comes next, we provide an extended analysis of the relationship between the two measures of discrimination, keeping a range of observable characteristics of individuals constant.

4. Results

Main results. Table 3 reports the results of probit estimations of the effect of statistical discrimination on the probability of reporting perceived discrimination given in equation 6. Our models include standard variables commonly found in human capital models of labour force status along with additional variables thought to be associated with an increased risk of exposure to discrimination (e.g., Biddle et al., 2013). We control for individuals' demographic characteristics (age (and age squared to account for non-linearities), presence of a partner, number of children, type of household), educational attainment, state/region dummies. Additionally, we include variables that are specific to NATSISS 2008 and capture the indigenous cultural identity and networks. CULTURAL BELONGING is based on the information on whether the respondent self-identifies 'with clan, tribal or language group'. To capture the indigenous social capital we include dummies for the proportions of indigenous friends (no or few indigenous friends (omitted), half of friends indigenous, most or all of friends indigenous).

As can be seen from the Table (columns 1-4), for indigenous males, statistical discrimination is not significantly related to the probability of reporting discrimination, although the sign of the estimated coefficient is positive. However, we estimate negative statistically significant parameter for statistical discrimination in the sample of females with a marginal effect of 12.7 percentage points. This result is consistent with findings of some of the earlier studies in the context of gender discrimination in North America (Kuhn, 1987; Barbezat and Hughes, 1990; Antecol and Kuhn, 2000) and suggests the presence of potentially omitted variables negatively correlated with statistical discrimination measure and positively correlated with the probability to report discrimination. As discussed earlier, nonstatistical evidence (Kuhn, 1987) and quality of statistical evidence (Barbezat and Hughes, 1990) are two important candidates for such omitted information. We provide some insights on the relevance of those possibilities for our context in the next sub-section where we check the robustness of our results.

What are the other factors driving the reports of discrimination? Our results indicate that age is one such factor, with the probability of reporting discrimination increasing (then decreasing) with age. This result, however, is not significant in the sample of females. Interestingly, having a partner is negatively associated with females' probability of reporting discrimination. A similar finding has been reported in a study by Antecol and Kuhn (2000). The number of young children is another negative correlate of discrimination reports. In a paper on the drivers of discrimination perceptions in Australia (not limited to indigenous population), Hahn and Wilkins (2013) also find that mothers of young children are less likely to perceive discrimination in applying for jobs than women without young children - a finding they suggest is likely to reflect the types of jobs these women tend to apply for, in particular part-time jobs. Our results also suggest that females from mixed households have a higher probability of reporting discrimination. A potential correlation of this variable with unobserved measures of exposure to risk of discrimination (e.g. socio-economic status as perceived by employers) may be one explanation behind this finding.

Our results additionally suggest that indigenous cultural identity is a strong correlate of perceived discrimination of both males and females. Those self-identifying with a clan, tribal or language group are more likely to report discriminatory treatment. The prevalence of self-perceived discrimination is also higher among those with larger proportion of indigenous friends. Both measures signal the strength of indigenous identity, and with increased strength the risk of exposure to discrimination appears to increase as well. The result on the strength of cultural identity is consistent with the previous findings in the literature. For example, in a paper based on data from the Darwin Region Urban Indigenous Diabetes study, Paradies and Cunningham (2009) find that those who identify more strongly with their culture (as indicated by recognition of homelands/traditional country, identification with a clan, tribal or language group or identifying as a member of the Stolen Generation) are more likely to report experiences of racism.

Overall, the results point out at the lack of importance of conventionally measured statistical evidence of discrimination in informing indigenous people's assessments of their experiences of discrimination. The need to adapt standard measures to evaluate indigenous populations' well-being has been highlighted in the literature (e.g., Thomas et al., 2010). A study by Ranzijn et al. (2009), for example, calls for 'cultural competence' in working in indigenous contexts, referring to skills and understandings which allow moving outside one's own cultural frameworks and the cultural limitations of one's profession or discipline (p. XV). Should one expect (the lack of) relevance of standard measures in capturing the experiences of indigenous populations vary with the strength of indigenous cultural identity? That indigenous cultural identity may introduce heterogeneity in relationships observed in different settings has been suggested in previous studies (e.g., Dockery, 2012). Here we explore whether the discrepancy between standard and self-assessed measures of discrimination is influenced by cultural identity of indigenous people. To that end, we exploit the information on the extent of indigenous cultural identity captured by CULTURAL BELONGING (whether the respondent self-identifies 'with clan, tribal or language group'). The results of estimations of models augmented to include interactions of SD and CULTURAL BELONGING are reported in columns 5-8 of Table 3. The interaction terms are significant and negative. We confirm the positive coefficients on SD for males, however this effect is reduced for those with stronger indigenous cultural identity. Similarly, for females, the negative effect of statistical evidence on the probability of reporting discrimination is larger for those with stronger indigenous identity. These findings confirm that the concerns over the 'crudeness' of standard statistical measures of discrimination are particularly valid for culturally more distinct populations.

Robustness checks. We start by examining whether our baseline results are driven by the omission of arguably important correlates of discrimination reports specific to the context of indigenous population. The results after including relevant additional variables in estimations are summarised in Table 4.

One potential issue is that there may be a conflation between perceived discrimination and exposure to opportunities to experience that discrimination. For example, indigenous people who are in employment (and potentially less likely, on average, to have experienced statistical discrimination in the process of seeking employment) may have more instances in which there is the opportunity to experience discrimination (e.g. in promotion, from work colleagues or customers/clients). To assess this possibility, we augment the baseline model with measures of employment status of individuals. We distinguish across individuals in two types of employment arrangements: those who are and those who are not employed under Community Development Employment Projects (CDEP) scheme, an indigenous-specific government intervention program (with those not employed omitted from the regressions). The estimated marginal effects on employment dummies are insignificant, with the exception of negative significant marginal effect on EMPLOYED CDEP in the sample of males. Our estimates on SD after including employment dummies remain remarkably similar to those from the baseline model.

The high rate of arrest among indigenous population has been recognised as an important driver of the low levels of indigenous employment (e.g., Borland and Hunter, 2000). The experience of arrest is likely to be associated with an increased risk of exposure to labour market discrimination; indeed it has been shown to affect individuals reports of discriminatory treatment (Biddle et al., 2013). We augment our baseline model with a new binary variable, HAD CONTACT WITH POLICE, that equals 1 if the respondent had experiences of being charged, arrested or incarcerated. Surprisingly, the estimated marginal effects on this variable, while negative, are statistically insignificant. Moreover, their inclusion leaves the estimates on SD unaffected.

To capture the effect of individuals' cultural identity and networks on discrimination reports, our baseline models included measures of individuals' identification with clan, tribal or language group, and prevalence of indigenous individuals among their friends. We showed that these variables are among the most important drivers of indigenous individuals' perceived discrimination. Here we include additional measures of culture that are likely to affect individuals' risk of exposure to labour market discrimination. These are: SPEAKS INDIGENOUS LANGUAGE, a dummy that equals 1 if the respondent speaks an indigenous language well, and ALL-INDIGENOUS HOUSEHOLD, a dummy that equals 1 if all persons in respondent's household are identified as indigenous. The estimated marginal effects on these two variables are positive, however they are insignificant. Importantly, the estimated marginal effects on SD are robust to including these additional controls in the estimations. They remain so also after controlling for all the additional variables jointly (columns 6 and 12 of Table 4).

We further explore the robustness of our results to changes in the way our statistical measures of discrimination were arrived at. The results of this exercise are summarised in panel A of Table 5. First, we consider changes in our baseline measure of labour market outcome, which is defined as a binary employment status. While this approach has the benefit of minimizing the probability of misclassification of employment status - an issue that is apparently of particular relevance to indigenous population (Daly, 1993) - it conceals information on different states of employment. To allow for more heterogeneity among labour force participants, we instead consider four different labour force states in the model underlying the decomposition: not in the labour force, unemployed, part-time employed and full-time employed. Following Kalb et al. (2014), we treat them as capturing the extent of an individual's labour market involvement and estimate ordered logit (instead of probit) models of labour force status.[7] The estimated marginal effects on SD are negative in both male and female models (A.1. in Table 5); they are also statistically insignificant.[8]

Second, we consider discrimination in earnings. NATSISS 2008 collects information on personal weekly incomes but not earnings of respondents. To overcome this limitation and arrive at a measure of earnings that could be jointly analysed with the precise measure of earnings available in HILDA, we restrict the sample to those employed full-time (working at least 35 hours a week) and who report that their principal source of weekly personal income is from their employer as well as report that they do not receive Government pensions or allowances.[9] We obtain results that are consistent with our baseline estimates: positive marginal effects for males and negative marginal effects for females. These results, too, are statistically insignificant (it should be noted that the sample sizes in this case are considerably smaller).

Oaxaca-Blinder decomposition is often criticised due to the specification of the regression model that results in biased coefficients. We conduct a robustness check for the specification of the regression model underlying the decomposition. The results are reported in panel B of Table 5. One potential issue with our measure of statistical discrimination may be the choice of controls in the employment equation. It is possible, in particular, that indigenous people perceive some of the indigenous-non-indigenous differences in characteristics to be themselves the products of discrimination. Education may be one such characteristic. Then discrimination estimates that take the distribution across education levels as given may not indicate the true correlation between the two measures of discrimination. We therefore check the sensitivity of the results to the use of estimates from employment equations that omit the tertiary education controls. Our results are very similar to the baseline (model B.1.). They don't change much when both school and tertiary education controls are excluded from employment equations underlying the decomposition (model B.2.).

As discussed earlier, our finding of lack of positive association between statistical and self-assessed measures of discrimination is likely a result of at least two possibilities. First, the hypothesis on the quantity of nonstatistical evidence of discrimination proposed by Kuhn (1987) suggests that there are other forms of bias, unobserved by the econometrician but

[7] Using Schwarz's Bayesian Information Criterion (Schwarz, 1978), Kalb et al. (2014) test the performance of ordered logit against less restrictive multinomial logit, showing that the use of the former in this case is justified.

[8] All models reported in Table 5 include the full list of other controls from the baseline model (see columns 1-4 of Table 3). A.2. additionally control for job tenure and work experience. While the results are not reported here for the purpose of saving space, they are available on request.

[9] A similar approach is adopted in a study by Birch (2014).

observed by individuals, that influence their decisions to report discrimination. Second, the quality of statistical evidence hypothesis raised by Barbezat and Hughes (1990) suggests that an inverse relationship between statistical measures of discrimination and discrimination reports may be observed if individuals have access to statistical evidence of varying quality (unobserved), which affects the employers ability to discriminate and their chances of detection. What can we learn about the nature of omitted variables in the context of our study? One approach to shed light on this question, according to Kuhn (1990), is to explore which individuals are more likely to report discrimination (presumably they are the ones to encounter more nonstatistical evidence of discrimination). In the case of Kuhn's 1987 study, it is the young, well-educated women who report more discrimination. As Kuhn (1990) suggests, younger, more educated women may be more willing to label as discrimination and less willing to tolerate behaviour considered acceptable, for example, by their mothers. Indeed he proposes 'changing general attitudes with age and education as a most likely explanation' (p. 291).

Following these findings, we perform a partial test of the two hypotheses on the nature of omitted information in our models by splitting the sample according to age and education of individuals. First, we consider whether the observed relationship between the statistical and perceived measures of discrimination varies across different age cohorts by re-estimating the models in the samples of younger (15-30) and older (31-64) individuals (panel C of Table 5). Second, we consider whether the relationship between the two measures of discrimination varies across individuals with different levels of education. We re-estimate the baseline models separately for individuals with and without tertiary level of education (panel D of Table 5). The results suggest that the finding on negative statistically significant relationship between SD and PD in the sample of females is largely driven by older and more educated females. One possibility is that it is these females that are more perceptive to nonstatistical discrimination. In the sample of males, on the other hand, we find that statistical evidence of discrimination is more likely to feed into the reports on discriminatory treatment among younger more educated males (we estimate positive statistically significant marginal effects in the samples of 15-30 years olds and those with tertiary education). A complete test of these hypotheses would require availability of rich set of variables to proxy for omitted information - something we are not able to pursue within the scope of the current study.

As a final step, we conduct an exploratory exercise where we look at the relationship between discrimination and subsequent outcomes by estimating models controlling for perceived and statistical measures of discrimination. The literature on discrimination has been concerned with its employment-related consequences (e.g., Neumark and McLennan, 1995; Antecol and Kuhn, 2000). Our data allows us to consider one potentially important outcome of discrimination: job search behaviour. In Table 6 we report the results of probit regressions of SD and PD on a binary variable taking 1 if the respondent had looked for work in the preceding 12 months (these regressions do not include other controls). We find that an increase in discrimination is associated with an increase in the probability of searching for a job. Our results indicate that both SD and PD are significant positive correlates of job search behaviour among males. For females we estimate a statistically significant parameter on PD but not on SD. The results reported in panels B and C of the Table reveal that the results on the positive significant effect of SD are largely driven by the sub-sample of employed. In fact we find that it is positively and statistically correlated with the probability of job search among both males as well as females. Perceived discrimination, too, has a positive statistically significant effect on job search for both genders. Employed males and females are more likely to engage in job search if they have increased evidence of either statistical or nonstatistical discrimination. The results reported in panel C of the table are those from the sample of unemployed. While the estimated parameters on SD are statistically insignificant, we find that PD is associated with an increase in the probability of job search in this case too. We prefer not to interpret too much into these findings at this stage, however they point at a promising avenue for future research.

5. Conclusion

Statistical residual-based approaches indicate that the differences in productive skills between indigenous and non-indigenous Australians do not completely explain the existing disparities in employment. This is likely, at least to some extent, due to discrimination. Yet, as this paper documents, statistical measures of discrimination are largely unrelated to perceptions of discrimination reported by indigenous males. Moreover, lower levels of statistical discrimination are associated with higher probability of reported discrimination among females.

We believe that two possibilities are likely to explain these results. First, indigenous individuals' assessment of discrimination may be based on nonstatistical evidence of discrimination (Kuhn, 1987). This may involve other forms of offensive treatment such as sexual harassment, verbal abuse from co-workers or clients, etc. If our results are indeed suggestive of the importance of nonstatistical evidence of discrimination, policies targeting statistical discrimination may not significantly affect indigenous Australian's perceptions of discrimination. Instead, there needs to be more focus on addressing indigenous bias more broadly to cover various other forms it may take. A second possibility is that indigenous individuals may be poorly informed on statistical evidence of discrimination (Barbezat and Hughes, 1990). This scenario calls for efforts to target transparency in employment relations. Accurate information about employer policies and practices can help 'to identify lawbreakers and encourage compliance with employment laws, to distinguish "good" and "bad" employers, and to understand contemporary workplace practices' (Estlund, 2014, p.781). However, employment-related information is often not readily available to outsiders or even insiders of an organization (e.g., Estlund, 2011, 2014).

The findings of this study are important in advancing the understanding of indigenous labour market disadvantage in Australia. While there is an established literature to evaluate statistical discrimination, our results confirm that their power in understanding labour market discrimination faced by indigenous Australians may be limited. Such discrimination is likely to be multi-faceted; our findings allude to the importance of other nonstatistical evidence of discrimination. Studying individuals' perceptions of treatment received in the labour market appears to be an area with high potential returns to further analysis.

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List of Tables

Table 1: Determinants of employment status

	Indigenous				Non-Indigenous			
	Males		Females		Males		Females	
	Mean	Coeff	Mean	Coeff	Mean	Coeff	Mean	Coeff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employed	0.638		0.476		0.857		0.736	
Age	37.570	0.060*	37.468	0.124***	41.339	0.149***	41.403	0.142***
		(0.027)		(0.021)		(0.021)		(0.017)
Age^2		-0.089**		-0.159***		-0.209***		-0.195***
		(0.033)		(0.028)		(0.024)		(0.021)
Partnered	0.499	0.649***	0.475	0.179*	0.659	0.378***	0.649	-0.080
		(0.136)		(0.097)		(0.111)		(0.075)
Children aged $\leq$ 14	0.835	-0.073	1.176	-0.302***	0.590	-0.095**	0.645	-0.358***
		(0.045)		(0.038)		(0.043)		(0.032)
Type of household								
Single occupant	0.153		0.098		0.145		0.116	
One-family	0.736	-0.225	0.798	0.122	0.776	-0.184	0.801	-0.069
		(0.184)		(0.160)		(0.124)		(0.104)
Mixed household	0.110	-0.148	0.102	0.001	0.077	-0.280*	0.082	-0.150
		(0.255)		(0.190)		(0.156)		(0.132)
Disability	0.560	-0.553***	0.574	-0.384***	0.185	-0.999***	0.186	-0.594***
		(0.119)		(0.087)		(0.082)		(0.074)
Daily smoker	0.506	-0.401***	0.501	-0.400***	0.228	-0.295***	0.176	-0.074
		(0.111)		(0.088)		(0.090)		(0.073)
Alcohol consumption								
Abstainer	0.353		0.552		0.235		0.427	
Moderate	0.509	0.381**	0.415	0.036	0.584	0.433***	0.518	0.463***
		(0.122)		(0.088)		(0.087)		(0.056)

Table 1: Determinants of employment status (continued)

	Indigenous				Non-Indigenous			
	Males		Females		Male		Female	
	Mean	Coeff	Mean	Coeff	Mean	Coeff	Mean	Coeff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ALCOHOL CONSUMPTION								
INFREQUENT HIGH-RISK	0.017	-0.638*	0.002	-0.995	0.080	0.207	0.033	0.642***
		(0.336)		(0.190)		(0.142)		(0.152)
FREQUENT HIGH-RISK	0.120	0.462*	0.029	-0.180	0.099	0.074	0.019	0.290
		(0.215)		(0.190)		(0.207)		(0.194)
SCHOOLING								
<YEAR 10	0.326		0.284		0.092		0.088	
YEAR 10 OR 11	0.460	0.474***	0.484	0.434***	0.400	0.115	0.371	0.304**
		(0.134)		(0.158)		(0.109)		(0.096)
YEAR 12	0.213	0.560***	0.230	0.893***	0.507	0.282**	0.539	0.471***
		(0.162)		(0.144)		(0.112)		(0.108)
TERTIARY QUALIFICATIONS								
NONE	0.578		0.576		0.383		0.450	
NON-DEGREE	0.352	0.290**	0.328	0.538***	0.374	0.231***	0.261	0.288***
		(0.120)		(0.094)		(0.084)		(0.071)
DEGREE	0.068	0.360	0.095	0.557***	0.242	0.268**	0.287	0.341***
		(0.314)		(0.180)		(0.113)		(0.084)
STATE/REGION		Yes		Yes		Yes		Yes
N	2229		2793		3676		4123	

Note.—Odd-numbered columns report weighted means. Even-numbered columns report coefficients from probit models defined in equation 2 along with standard errors clustered at the household level (in parenthesis). * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level. Alcohol consumption categories are defined in footnote 5. State/region dummies are listed in footnote 6.

Table 2: Perceived and statistical discrimination measures

	All		Males		Females	
	Mean	ME	Mean	ME	Mean	ME
	(1)	(2)	(3)	(4)	(5)	(6)
PD	0.068		0.081		0.053	
SD	0.308	-0.055**	0.245	0.021	0.372	-0.031
		(0.025)		(0.058)		(0.032)
Other controls		No		No		No
N	5022		2229		2793	

Note.—SD stands for statistical discrimination while PD - for perceived discrimination. Odd-numbered columns report weighted means. Even-numbered columns report marginal effects from probit regressions of PD on SD (with no other controls included) along with standard errors calculated from bootstrapping with 1000 replications (in parenthesis). * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level.

Table 3: The effect of statistical discrimination on perceived discrimination: Baseline results

	Males		Females		Males		Females	
	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SD	0.310	0.057	-1.240*	-0.127*	1.859*	0.483*	-0.137	-0.024
	(0.780)	(0.142)	(0.675)	(0.068)	(0.940)	(0.282)	(0.881)	(0.151)
SD * Cultural belonging					-2.135***		-1.608**	
					(0.777)		(0.779)	
Age	0.039*	0.007	0.004	0.000	0.040*	0.010*	0.004	0.001
	(0.021)	(0.004)	(0.020)	(0.002)	(0.021)	(0.006)	(0.021)	(0.004)
Age^2	-0.059**		-0.010		-0.059**		-0.010	
	(0.026)		(0.025)		(0.026)		(0.025)	
Partnered	0.135	0.024	-0.213**	-0.021**	0.133	0.035	-0.219**	-0.038*
	(0.120)	(0.021)	(0.098)	(0.010)	(0.125)	(0.031)	(0.103)	(0.021)
Children aged ≤ 14	-0.012	-0.002	-0.094**	-0.009**	-0.012	-0.003	-0.093**	-0.016**
	(0.033)	(0.006)	(0.040)	(0.004)	(0.034)	(0.009)	(0.043)	(0.009)
Type of household								
One-family	-0.163	-0.031	0.155	0.013	-0.174	-0.047	0.152	0.024
	(0.129)	(0.026)	(0.156)	(0.012)	(0.135)	(0.037)	(0.163)	(0.025)
Mixed household	-0.095	-0.019	0.374**	0.040*	-0.110	-0.031	0.376*	0.069*
	(0.147)	(0.029)	(0.183)	(0.020)	(0.150)	(0.042)	(0.197)	(0.037)
Disability	0.033	0.005	0.020	0.002	0.035	0.009	0.024	0.004
	(0.080)	(0.014)	(0.087)	-0.008	(0.082)	(0.021)	(0.083)	(0.015)

Table 3: The effect of statistical discrimination on perceived discrimination: Baseline results (continued)

	Males		Females		Males		Females	
	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCHOOLING								
YEAR 10 OR 11	0.125	0.022	0.034	0.003	0.131	0.034	0.040	0.008
	(0.12)	(0.021)	(0.114)	(0.012)	(0.124)	(0.03)	(0.110)	(0.021)
YEAR 12	0.072	0.012	-0.272	-0.024	0.072	0.018	-0.299	-0.046
	(0.149)	(0.02)	(0.187)	(0.016)	(0.157)	(0.04)	(0.176)	(0.028)
TERTIARY QUALIFICATIONS								
NON-DEGREE	0.083	0.015	-0.066	-0.006	0.081	0.021	-0.077	-0.013
	(0.085)	(0.015)	(0.114)	(0.01)	(0.085)	(0.022)	(0.12)	(0.02)
DEGREE	0.173	0.033	0.246	0.030	0.144	0.039	0.228	0.046
	(0.167)	(0.035)	(0.148)	(0.020)	(0.171)	(0.049)	(0.157)	(0.034)
CULTURAL IDENTITY								
CULTURAL BELONGING	0.364***	0.062***	0.324***	0.0311***	0.896***	0.205***	0.966**	0.147*
	(0.096)	(0.015)	(0.1)	(0.009)	(0.22)	(0.069)	(0.342)	(0.077)
HALF FRIENDS INDIG	0.250**	0.047**	0.182*	0.019*	0.255**	0.068**	0.178*	0.032*
	(0.100)	(0.019)	(0.097)	(0.010)	(0.101)	(0.028)	(0.098)	(0.019)
MOST/ALL FRIENDS INDIG	0.169	0.030	0.120	0.012	0.172	0.044	0.115	0.02
	(0.109)	(0.020)	(0.107)	(0.011)	(0.108)	(0.029)	(0.109)	(0.02)
STATE/REGION	Yes		Yes		Yes		Yes	
N	2140		2694		2140		2694	

Note.—SD stands for statistical discrimination. Odd-numbered columns report coefficients and even-numbered columns report marginal effects from probit models defined in equation 6. Standard errors calculated from bootstrapping with 1000 replications are in parenthesis. * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level. CULTURAL BELONGING is a dummy that equals 1 if the respondent self-identifies with clan, tribal or language group. State/region dummies are listed in footnote 6.

Table 4: The effect of statistical discrimination on perceived discrimination: Robustness to additional controls

	Males						Females					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SD	0.044	0.058	0.050	0.056	0.049	0.040	-0.123*	-0.120*	-0.128*	-0.125*	-0.127*	-0.116*
	(0.133)	(0.136)	(0.138)	(0.136)	(0.131)	(0.137)	(0.070)	(0.070)	(0.067)	(0.068)	(0.066)	(0.066)
Employed none-CDEP	-0.0170					-0.017	0.008					0.008
	(0.019)					(0.019)	(0.009)					(0.009)
Employed CDEP	-0.071**					-0.070	0.110					0.111
	(0.035)					(0.036)	(0.073)					(0.072)
Had contact with police		-0.002				-0.004		-0.008				-0.007
		(0.015)				(0.015)		(0.008)				(0.008)
Speaks indigenous language			0.011		0.011	0.010			0.008		0.008	0.009
			(0.021)		(0.021)	(0.022)			(0.013)		(0.012)	(0.013)
All-indigenous household				0.001	0.001	0.001				0.003	0.003	0.004
				(0.018)	(0.017)	(0.018)				(0.009)	(0.010)	(0.010)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2140	2140	2140	2140	2140	2140	2694	2694	2694	2694	2694	2694

Note.— SD stands for statistical discrimination. Marginal effects from probit regressions of SD on perceived discrimination, PD, along with standard errors calculated from bootstrapping with 1000 replications (in parenthesis) are reported. CDEP stands for Community Development Employment Projects, an indigenous-specific government intervention program. The models include all the control variables included in baseline models (columns 1-4 of Table 3). * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level.

Table 5: The effect of statistical discrimination on perceived discrimination: Various robustness checks

	Males		Females	
	ME	N	ME	N
	(1)	(2)	(3)	(4)
A. SD based on alternative labour market outcomes:				
A.1. Four labour force states	-0.035	2140	-0.032	2694
	(0.055)		(0.025)	
A.2. Ln weekly income	0.250	561	-0.038	340
	(0.280)		(0.039)	
B. SD controls for a subset of observed characteristics:				
B.1. Tertiary qualifications exluded	0.053	2140	-0.124*	2694
	(0.139)		(0.068)	
B.2. All education controls excluded	0.020	2140	-0.100*	2694
	(0.112)		(0.059)	
C. Estimation based on baseline SD by education groups:				
C.1. No tertiary education	-0.238	886	-0.035	1074
	(0.171)		(0.097)	
C.2. Tertiary education	0.315**	1243	-0.196***	1548
	(0.126)		(0.089)	
D. Estimation based on baseline SD by age groups:				
D.1. 15-30 years old	0.169*	749	0.090	727
	(0.103)		(0.118)	
D.2. 31-64 years old	-0.078	1391	-0.197*	1805
	(0.123)		(0.107)	

Note.— SD stands for statistical discrimination. Odd-numbered columns report marginal effects from probit regressions of SD on perceived discrimination, PD, along with standard errors calculated from bootstrapping with 1000 replications (in parenthesis). Even-numbered columns report respective sample sizes. The models include all the control variables included in baseline models (columns 1-4 of Table 3). A.2. additionally includes job tenure and work experience as controls. * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level. Panel A employs SDs that are based on regressions with two alternative labour market outcomes. SDs in A.1. come from ordered logit regressions with dependent variables that distinguish between four labour force states: not in the labour force, unemployed, part-time employed and full-time employed. SDs in A.2. come from OLS regressions with log of wage as dependent variable.

Table 6: The effect of discrimination measures on job search behaviour

	A. All					
	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
SD	0.439***		0.439***	-0.009		-0.003
	(0.140)		(0.141)	(0.091)		(0.090)
PD		0.170***	0.169***		0 .188***	0.188***
		(0.036)	(0.036)		(0.041)	(0.041)
N	2229	2229	2229	2793	2793	2793

	B. Employed					
	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
SD	0.420**		0.422**	0.238*		0.243*
	(0.192)		(0.196)	(0.138)		(0.139)
PD		0.079*	0.080*		0.114**	0.116**
		(0.046)	(0.047)		(0.052)	(0.055)
N	1424	1424	1424	1330	1330	1330

	C. Unemployed					
	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
SD	0.001		0.002	-0.178		-0.185
	(0.252)		(0.246)	(0.161)		(0.156)
PD		0.293***	0.293***		0.273***	0.274***
		(0.052)	(0.053)		(0.060)	(0.058)
N	805	805	805	1463	1463	1463

Note.— SD stands for statistical discrimination while PD - for perceived discrimination. Marginal effects from probit regressions of SD and PD on job search in preceding 12 months are reported. Standard errors calculated from bootstrapping with 1000 replications are in parenthesis. The models do not include additional controls. * denotes significance at 10 percent level; ** at 5 percent level; *** at 1 percent level.

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