Self-assessed vs. statistical evidence of racial discrimination: The case of indigenous Australians*

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ABSTRACT:
This paper provides new insights on the labour market discrimination faced by indigenous Australians - one of the most disadvantaged indigenous populations in developed countries. Combining two large, nationally-representative datasets, we decompose the employment gap between indigenous and non-indigenous populations as of 2014-2015, and show that differences in characteristics between the two groups account for only 43% of the employment gap for females, and 23% of the gap for males. We then demonstrate that statistical measures are positively related to discrimination reports of females and negatively related to discrimination reports of males. Our findings underscore the importance of improving transparency in employment processes for addressing the issue of disadvantage of racial minorities.

JEL classification: J15, J21, J71

Keywords: Racial discrimination; Employment; Australia.

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1. Introduction

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). One way to gain some insight on this issue is to analyse an alternative measure of labour market discrimination - a task pursued in this paper. We explore whether and how people's subjective reports of discrimination are related to statistical measures of discrimination. This is a meaningful task, since self-assessed discrimination measures potentially allow for 'broader concepts' of equity to be considered (Antecol et al., 2014). Furthermore, considering 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).

Our study focuses on racial discrimination in the labour market and studies the case of indigenous Australians, one of the most disadvantaged indigenous populations in developed countries in terms of standard labour market indicators (Hunter and Daly, 2013). As of 2011, only 55.9% 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 more recent study by Kalb et al. (2014), the unexplained part (that is the part attributed to discrimination) of employment differential measured as of 2008, while smaller, is nevertheless significant: around two fifth for men and one third for women.[1]

Combining two large, nationally-representative datasets, we update the existing statistical evidence of labour market discrimination against indigenous Australians providing estimates based on an extension of Oaxaca-Blinder decomposition to non-linear models as of 2014-2015 - the latest period for which data exists. We then quantify the relationship between the statistical measures of discrimination and survey reports of discriminatory treatment of indigenous Australians in the labour market. Our focus is on the gaps in employment - 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).

The nature of the link between perceived and statistical evidence of discrimination is not immediately apparent. At first glance, one might expect the likelihood of reporting discrimination to increase with an increase in the statistical measure of discrimination. This scenario, however, assumes that individuals have some knowledge on their relative standing in the labour market and are able to make informed judgments on being discriminated against. One possibility, for example, is that individuals simply misperceive discrimination: they believe they are being discriminated against when they actually are not. This is not implausible, since most would possess highly incomplete information on their relative standing in the labour market, and other things - e.g. various ideological and psychological factors or the choice of an irrelevant reference group - may inform the reports of discrimination instead. Or relatedly, perceptions of discrimination may be based on other 'nonstatistical'

[1] Kalb et al. (2014) attribute their ability to explain a larger proportion of the gap in labour market outcomes between indigenous and non-indigenous populations to controlling for previously unobserved differences in characteristics of the two groups, such as health and household composition. However, it is not implausible that some of the differences in these characteristics could be either a direct or an indirect outcome of discriminatory practices in the labour market. Such feedback effects may mean that labour market discrimination is under-estimated in their study (Grimshaw and Rubery, 2002).

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 low. Furthermore, the naive expectation of a positive association between perceived and statistical measures of discrimination does not allow for feedback effects from employers. As Barbezat and Hughes (1990) propose, however, 'employers are more likely to discriminate when employees have less accurate information and the probability of reporting, and hence detection, is low' (p. 277). Thus, in equilibrium, a high level of statistically measured discrimination will be accompanied by relatively small number of discrimination reports.

The nature of the empirical relationship between perceived and statistical measures of discrimination will thus depend on the relative importance of these scenarios in a particular context. Hampton and Heywood (1993) provide empirical evidence of a positive relationship between perceptions-based and statistical measures of discrimination in a study of gender wage discrimination within the medical profession. Nonetheless, there is also evidence to suggest that not only perceived and statistical evidence of discrimination may not be positively related, they may be unrelated or related negatively. For example, Antecol et al. (2014) do not find evidence of a strong relationship between the two measures of discrimination among lawyers. Others show that those facing the least statistically measured discrimination report the most discrimination. Studies by Kuhn (1987) and Antecol and Kuhn (2000) arrive at this finding based on representative samples of the US and Canadian women. Barbezat and Hughes (1990) provide 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 small literature.[2] First, in contrast to previous studies 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

[2] A somewhat related literature looks at the relationship between reported beliefs and objective measures applied to contexts such as corruption (Olken, 2009) and inequality (Gimpelson and Treisman, 2018).

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 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 evidence of 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 gender discrimination. Moreover, our study provides the most recent evidence on the labour market discrimination of indigenous Australians, exploiting a recently released data.

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 findings of our decomposition exercise reveal that a large part of the employment differential between indigenous and non-indigenous populations as of 2014-2015 remains unexplained. The results from the most extensive employment model specification suggest that differences in the characteristics between the two groups can account for only 43% of the employment gap for females. For men, just 23% of the gap can be attributed to differences in characteristics between the two groups. Furthermore, we find that statistical measures

of discrimination are positively (albeit only marginally statistically significantly) linked to females' reports of discrimination. For males, however, we find a negative relationship between statistical measures and the probability of reporting discrimination. While we are not able to pinpoint at a single explanation behind these results, they do underscore the importance of considering alternative measures of discrimination, in addition to statistical evidence, in evaluating the indigenous labour market disadvantage in Australia.

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 evidence of discrimination. Our ultimate goal is to explore whether and the extent to which the perceptions of discrimination are linked to 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).[3]

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.

[3]It should be explicitly highlighted that the statistical evidence of discrimination considered here is very different to the concept of statistical discrimination whereby employers may consciously discriminate because they lack information about the productivity of individuals and 'statistically discriminate' against them on the basis of easily observable characteristics (Phelps, 1972; Aigner and Cain, 1977).

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 superscript A denotes the non-indigenous population, superscript 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:[4]

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

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:

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

Perceived vs. statistical evidence of discrimination. In the second stage of the analysis we examine whether the perceived discrimination of an indigenous Australian i is related to statistical measure of discrimination by estimating a probit model of the following form:

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

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

[4]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.

We treat this analysis as purely exploratory, and therefore estimate a parsimonious specification with no additional controls. This approach follows some of the key studies in this literature (Kuhn, 1987; Barbezat and Hughes, 1990; Hallock et al., 1998), and is motivated by two key considerations. First, including controls in equation 6 runs the risk of multicollinearity if individuals' characteristics enter into equation 6 directly as controls, as well as indirectly, through SD. This is a realistic concern, given that there is inevitably a very large degree of overlap between the list of variables that should be included in equation 6 and those that enter in X in equation 2. Second, we require a variable that explains employment but does not otherwise explain perceived discrimination in equation 6. In the absence of a persuasive exclusion restriction, identification of the relationship between SD and PD will solely rely on functional form assumption which may produce misleading results (Altonji et al., 2005). In our application, however, we do not have a persuasive exclusion restriction.

The test of whether an indigenous person with higher statistically measured discrimination is more or less likely to report being discriminated against is a test of significance of coefficients δ. As discussed in the introductory section, the expected sign of δ is a priori unclear. It should be positive if individuals have some knowledge on being discriminated against and put positive weight on statistical evidence in their reporting decisions. However, there is also scope for a negative or insignificant relationship between statistical and perceived measures of discrimination. One possibility is that individuals simply believe they are being discriminated against when they actually are not. Another possibility, put forward by Kuhn (1987), is the existence of nonstatistical evidence of discrimination which comprises other forms of bias observed by individuals but not by the econometrician. Furthermore, the fact that employees may be ignorant about labour market processes may be exploited by employers in their decisions to discriminate. A high level of statistically measured discrimination may then be accompanied in equilibrium by a small number of discrimination reports (Barbezat and Hughes, 1990). While we discuss the relevance of these scenarios in the interpretation of our results, we are not ably to directly test these hypotheses against each other.

3. Data

Sources and sample. The share of indigenous Australians in the total population is small (around 3% as of 2011 (ABS, 2011a)). 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). We do, however, use the data from the Census of Population and Housing conducted in 2011 - the latest year for which data has been released - to provide some validation for our research design underlying the construction of statistical measures of discrimination based on two different datasets.

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, 2014-2015 wave of NATSISS available through the DataLab.[5]

NATSISS 2014-2015 was conducted in the period from September 2014 to June 2015 collecting nationally-representative information from 11,178 indigenous Australians (ABS, 2016). 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 2014-2015 in conjunction with comparable data on non-indigenous Australians from the 2014 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 23,000 individuals nation-wide. The annual interviews for the main sample commence towards the end of July each year and conclude by mid-February of the following year (Wilkins, 2016).

Our analysis is restricted to 22-60 years old individuals, excluding full-time students. The choice of the age brackets applied to the sample is motivated by the consideration of maximising the comparability between the indigenous and non-indigenous samples. In particular, 15-22 years olds are excluded from the analysis since individuals in this age group are particularly likely to be incomparable in a sample restricted to full time students since the fraction of those aged under 22 and in full-time education is significantly higher among the non-indigenous than among the indigenous individuals. Given the focus of the study on

[5]The DataLab operates as a restricted remote access system where authorised users can view and analyse unit record information, while the files remain in the secure environment. All analytical outputs are checked by the Australian Bureau of Statistics before being provided to researchers.

employer discrimination, those who are self-employed are further excluded from the baseline sample; however we report robustness checks using a sample where this restriction is not applied. Lastly, the analysis is restricted to those residing in non-remote areas. The exclusion of remote areas from the analysis 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).

[Table 1 about here.]

Table 1 reports the sample sizes associated with sequentially applying these restrictions to the original sample. After imposing the restrictions, we are left with a working sample consisting of 1,647 and 1,163 observations for females and males in NATSISS, and 4,914 and 4,205 observations for females and males in HILDA.

Description of variables.

Determinants of employment. 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) at the time of the survey. 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.[6] As Table 2 illustrates, only around 46% of females and 59% of males in the indigenous sample are employed. Among the non-indigenous population, employment rates are 71% for females and 84% for males. The gender gap in employment is larger among the indigenous population.

[Table 2 about here.]

[6] In the baseline sample of indigenous Australians, those who are not in the labor force comprise almost 81% of individuals who are not employed.

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 exogenous individual characteristics such as age (and age squared to account for non-linearities) and binary disability status. As Table 2 demonstrates, the average individual across our sub-samples is 40 years old. The prevalence of disability is higher among the indigenous population. 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 (omitted); Year 10-12) and tertiary qualifications obtained (non-degree and degree). Indigenous Australians are significantly less likely to hold a university degree relative to their non-indigenous counterparts. Additional covariates include 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).[7] Compared to non-indigenous Australians, indigenous Australians are less likely to have a partner although the number of children under 14 in a household is larger for indigenous individuals. Finally, all models include dummies for the location of residence to capture the available labour market opportunities.[8]

Measuring perceived discrimination. NATSISS includes a number of nuanced questions related to the perceived treatment experienced by the respondents in the context of labour market. We exploit this information to construct a binary measure of perceived discrimination that takes 1 if the respondent has had at least one of the following perceived experiences: (i) was treated unfairly in the past 12 months when applying for work, or at work, because of indigenous identity; (ii) avoided applying for work, or going to a job in the past 12 months due to unfair treatment because of indigenous identity; (iii) had difficulties finding work due to racial discrimination. This measure is highly suited for our analysis since it elicits information on discrimination specifically in the context of various 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

[7]While these household variables are not included in the baseline models due to potential endogeneity concerns, they feature in extended robustness analysis.

[8]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.

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.

[Table 3 about here.]

As Table 3 demonstrates, the prevalence of perceived discrimination is 9.5% in the sample of females. It is significantly higher among males - 15.8%. Similar patterns by gender are observed when looking at specific ingredients of perceived discrimination. For example, only 5.8% of females report unfair treatment when applying for work or at work, while nearly 12% of males do. Similarly, 4.7% of females and 5.8% of males report difficulties finding work due to racial discrimination. Moreover, some, albeit not many, individuals in both samples admit that they avoided applying for work or going to a job due to unfair treatment related to their indigenous identity.

[Table 4 about here.]

Table 4 takes a descriptive look at the relationship between employment status, job search behaviour in the past 12 months, and the prevalence of perceived discrimination. Looking at the propensity to perceive discrimination keeping employment status constant, those who have been searching for a job in the last 12 months are more likely to report discrimination. Among employed females, for example, the rate of perceived discrimination is 16.7% among job-seekers and 9.4% among non-seekers. Similarly, employed males involved in job search have a propensity of perceiving discrimination that exceeds that of non-seekers by 8 percentage points. Among non-employed females, the rate of perceived discrimination is 15.7% for job-seekers and 4.6% for non-seekers. For males who are not employed, these rates are 21.3% and 4.4% respectively.

Keeping job search behaviour constant, perceived discrimination is on average higher among those who are employed. Among job seekers, however, these differences are small: there is only 1 percentage point difference in the propensity to perceive discrimination between employed and non-employed females. This difference is 3 percentage points among job-seeking males. Looking at the sub-samples of individuals who have not been involved in job search in the preceding 12 months reveals larger differences in the propensities to perceive discrimination by employment status. The propensity of perceiving discrimination in this sub-sample is 9.4% among employed females and 4.6% among females who are not employed. These differences are larger in the sub-sample of males who have not been

searching for job. In this group, the propensity to perceive discrimination is 16.4% among the employed and only 4.4% among non-employed.[9]

4. Results

Statistical evidence of discrimination.

Determinants of employment. Table 5 presents the results of employment models given in equation 2 estimated separately by indigenous status and gender. We report coefficients (and not the marginal effects) since our calculations of statistical measures of discrimination are based on coefficients (equation 5).

Columns (1) and (4) report the estimates from parsimonious models with just age (and its squared term) and disability status employed as regressors, in addition to state/region dummies. As expected, the employment probability initially increases then decreases with age, although this relationship is statistically significant in the non-indigenous sample only. Additionally, disability is a strong negative correlate of employment probability. This effect is particularly pronounced for males, both indigenous and non-indigenous.

Next, in columns (2) and (5) we further control for the educational attainment of individuals. There are statistically significant positive returns to education. The estimated coefficients are larger for indigenous individuals. In both indigenous and non-indigenous samples, we observe larger returns to education accruing to females. Moreover, among males, there is no statistically significant effect of Year 10-12 attainment, relative to less than Year 10 attainment, on employment probability.

Finally, columns (3) and (6) report the estimates from models which additionally feature family controls. 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. Somewhat relatedly, non-indigenous Australians living in one-family or mixed households have a lower

[9] It is possible that the perceptions of discrimination among individuals who are employed but who have not been looking for a job capture discrimination experienced at work (e.g. when applying for a promotion, or a pay rise) more so than discrimination that affects the probability of holding a job. Since these discrimination experiences can be different in nature to those that statistical measure of discrimination generated based on an employment equation might capture, in robustness checks we analyse the link between perceived and statistical measures of discrimination when this group is omitted from the sample.

probability of employment compared to those in single-occupant household. For indigenous Australians, however, the estimates on these variables are positive, albeit statistically insignificant.

[Table 5 about here.]

Decomposition results. In Table 6 we report the decomposition results that are based on using the non-indigenous coefficients as the reference. We start with the results that are based on an employment model specification that includes only a few exogenous characteristics of individuals as controls: their age (including a squared term); disability status and state/region of residence. The decomposition results based on this specification for females suggest that only 21.6% of indigenous-non-indigenous gap can be attributed to differences in basic characteristics. For males, differences in characteristics account for even smaller proportion of the gap - 18.4%. In the next specification that additionally controls for the educational attainment of individuals, the explained proportion of the gap is 30.7% for females and 20% for males. Finally, a larger share of the indigenous-non-indigenous employment gap is explained when household controls are additionally included in the underlying employment models. In this case, differences in characteristics account for 43.4% of the gap for females, and 23% of the gap for males.

[Table 6 about here.]

Next, we calculate the individual-specific predicted values of discrimination given in equation 5. The summary statistics of this variable based on the version of employment equation that excludes household controls is presented in Table 7. To allow for comparisons, summary statistics of PD are reported alongside.

There is statistical evidence of discrimination for both females and males. Moreover, statistical discrimination appears to decrease with educational attainment with a gradient that is stronger and more consistent for females. In fact, for females with a tertiary degree, the sign on the predicted statistical evidence is negative. This implies that they would have had worse employment outcomes if they were getting the same rewards to their characteristics as their non-indigenous counterparts. One potential explanation for these patterns is that more educated individuals may have a higher capacity to detect discrimination, and therefore are less targeted by employers who choose to mitigate the risks associated with discriminatory behaviour.

Perceived discrimination, on the other hand, increases with educational attainment, perhaps because these individuals have higher awareness of deserving the job. Among females, the propensity to perceive discrimination is 13.3% among tertiary degree-holders while only

7.7% among those under Year 10 of schooling. Similarly, 15.6% of males with a tertiary degree and only 10.4% of males with under Year 10 of schooling report discrimination.

[Table 7 about here.]

Evidence from an alternative data source. The analysis so far has been based on jointly analysing two different datasets, HILDA and NATSISS, that contain comparable information on variables important for our analysis. This design is ultimately employed to allow for comparisons between the statistical measures of discrimination with perceptions of discrimination available in NATSISS. However, it is not implausible that the accuracy of the statistical measures of discrimination constructed based on two different datasets may be compromised. Here we make an attempt at providing some validation for the analysis of the statistical evidence of discrimination based on a single source: the Census of Population and Housing (ABS, 2011b). The latest year for which the Census data has been released is 2011, which does not precisely match the period of our baseline analysis; this should be kept in mind when drawing comparisons across the two sets of results. To ensure the comparability, we follow the definitions of the sample and variables used in the baseline analysis. The results are presented in Table 8.

First, in panel A we present the results of estimating the employment models given in equation 2. The signs of the estimated coefficients are similar to those based on the joint analysis of HILDA and NATSISS even though the magnitudes and the statistical significance levels may not match precisely. In panel B we report the results of the decomposition based on the estimates in panel A, using the non-indigenous coefficients as the reference. Based on these results, around 19% of indigenous-non-indigenous employment gap among males can be attributed to differences in characteristics. This is similar to the 20% explained part estimated based on the joint analysis of HILDA and NATSISS. For females, however, the census-based analysis suggests that only 22.1% of the gap can be explained by differences in characteristics, while in our baseline results the explained part is 30%. The difference in the time periods of the two sets of analyses may be one explanation behind this discrepancy. Considering the statistical evidence of discrimination predicted at individual level in panel C, the means for females and males are positive, and reassuringly close in size to those from the baseline analysis.

[Table 8 about here.]

Perceived vs. statistical evidence of discrimination. What is the link between statistically measured discrimination and perceptions of discrimination among indigenous Australians?

Table 9 reports the estimated marginal effects from probit regressions of perceived discrimination on statistically measured discrimination given in equation 6.

Oaxaca-Blinder decomposition is often criticised due to the specification of the regression model that results in biased coefficients. It is possible, in particular, that some of the indigenous-non-indigenous differences in characteristics are themselves the products of discrimination since discrimination may occur not just in the selection by employers, but may also form a part of the decisions indigenous and non-indigenous Australians make around study and family, among other things. Then discrimination estimates that take the distribution across such characteristics as given are likely to result in an under-estimation of labour market discrimination (Grimshaw and Rubery, 2002). Our first measure of statistical evidence of discrimination, SD 1, therefore employs the estimates from an employment model with a minimalistic exogenous list of controls: AGE, AGE^2, DISABILITY and State/Region dummies, and in doing so is largely immune to this concern.

However, an important consideration in an Oaxaca-Blinder decomposition exercise is to ensure that at least key characteristics relevant to productivity are included in the model, since otherwise they remain in the 'unexplained' part of the gap leading to over-estimation of labour market discrimination. With this consideration in mind, we construct two additional statistical measures of discrimination. The employment regressions underlying the construction of the second measure, SD 2, include education dummies in addition to the controls underlying the construction of SD 1. In SD 3, household characteristics -PARTNERED, CHILDREN AGED$\leq$ 14, ONE-FAMILY HOUSEHOLD, MIXED HOUSEHOLD - are additionally controlled for in the underlying employment model.

First, we estimate the relationship between PD and these statistical measures of discrimination in our baseline sample. The estimated marginal effects are reported in panel A of Table 9. The results employing SD 1 suggest that females perceive the discrimination they are receiving. This is especially so in the absence of additional controls underlying the construction of the statistical measure of discrimination. The better we do in capturing SD, however, the further away we move from the naive positive association between SD and PD. The association with PD when SD 2 and SD 3 are employed in subsequent estimations are considerably weaker.

The results for males, on the other hand, appear to be consistent with a scenario of being discriminated against in ignorance or because of ignorance - the estimated marginal effect on SD 1 is negative, albeit insignificant. Furthermore, the addition of more controls in the

construction of the statistical measure of discrimination in fact sharpens the negative association observed for males. The estimated marginal effect on SD 3 is large and statistically significant. Thus, the feedback effects by employers, as proposed by Barbezat and Hughes (1990), are likely to be at play here.

Our focus in this study is discrimination by employers, and the baseline sample therefore excludes self-employed workers. However this group may also be prone to various forms of discrimination in the broader context of labour market, and we next check whether the results reported in panel A are sensitive to including the self-employed in the samples underlying both stages of our analysis. The results reported in panel B are very similar to those in panel A - we estimate a positive correlation between perceived and statistical measures of discrimination for females, and negative correlations between the two measures for males. Here too, we observe the positive association for females weaken and the negative association for males sharpen as we include more controls in the construction of SD.

We consider another test of sensitivity to the sample in panel C. This time we exclude from the sample underlying the regression of PD on SD individuals who are employed but who have not been looking for a job in the preceding 12 months. The motivation behind applying this sample restriction is to maximise the comparability of perceived and statistical measures of discrimination. Our statistical measure of discrimination primarily captures the discrimination that affects the probability of holding a job. The perceived discrimination measures, however, are constructed based on questions that in most cases elicit information with reference to applying for work/at work jointly. The discrimination experienced at work (e.g. when applying for a promotion, or a pay rise) is particularly relevant for the group who reports being employed but not looking for work. The attempt to isolate this group from the sample therefore is an attempt to exclude those whose discrimination experiences might be different in nature to those that SD is likely to capture. Looking at panel C, the results are qualitatively similar to those based on earlier two samples. We confirm a positive association between SD and PD for females, and a negative association between the two for males. When SD 3 is employed as a regressor, marginal effects for both females and males are highly significant and substantial in size.

We further explore the robustness of our results to changes in the way our statistical measures of discrimination were arrived at. Our baseline measure of labour market outcome 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.[10] The estimated marginal effects on statistical measures of discrimination are positive, but significant only when SD 1 is used as a regressor in the model of PD. Our estimates for males are consistent with earlier results, suggesting a negative association between perceived and statistical measures of discrimination. The estimated marginal effects in models with SD 2 and SD 3 are also statistically significant.

[Table 9 about here.]

5. Conclusion

Statistical residual-based approaches indicate that the differences in characteristics 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. We provide the latest evidence on labour market discrimination faced by indigenous Australians and confirm that the statistical evidence of discrimination faced by indigenous females and males remains substantial. Yet, as we show, statistical discrimination is only weakly positively related to perceptions of discrimination of indigenous females. Moreover, it is negatively related to perceptions of discrimination by males.

Overall, the results point out at the lack of awareness among indigenous Australians of discrimination they may be exposed to and call 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 racial discrimination in the labour market. While there is an established literature to evaluate statistical evidence of discrimination, our results confirm that their power in understanding labour market discrimination faced by racial minorities such as indigenous Australians may be

[10] 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.

limited. Such discrimination is likely to be multi-faceted, and asking people directly about their experiences of discrimination is likely to provide a valuable source of information on difference forms of bias experienced in the labour market, involving other forms of offensive treatment such as sexual harassment, verbal abuse from co-workers or clients, etc. If these forms of bias are important in labour market experiences of indigenous Australians, policies targeting statistical evidence of discrimination may not significantly affect indigenous Australians' labour market outcomes.

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). Studying individuals' perceptions of treatment received in the labour market appears to be an area with high potential returns.

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List of Tables

Table 1: Samples in NATSISS and HILDA

	Indigenous			Non-Indigenous		
Sample restrictions	Females	Males	Total	Females	Males	Total
All surveyed individuals	6,049	5,129	11,178	11,856	11,254	23,110
Indigenous excluded (HILDA)	6,049	5,129	11,178	11,560	11,025	22,585
Restricted by age (22-60 years old)	2,961	2,124	5,085	5,989	5,662	11,651
Full-time students excluded	2,798	2,056	4,854	5,689	5,466	11,155
Self-employed excluded	1,733	1,955	3,688	5,022	4,313	9,335
Remote areas excluded	1,647	1,163	2,810	4,952	4,253	9,205
Missing values removed	1,647	1,163	2,810	4,914	4,205	9,119
Study sample	1,647	1,163	2,810	4,914	4,205	9,119

Note. Number of observations corresponding to each sample are reported.

Table 2: Descriptive statistics: Employment and its correlates

	Females		Males	
	Indigenous	Non-Indigenous	Indigenous	Non-Indigenous
	(1)	(2)	(3)	(4)
EMPLOYED	0.456	0.713	0.589	0.839
	(0.498)	(0.452)	(0.492)	(0.367)
AGE	39.680	40.813	40.280	40.051
	(11.160)	(11.302)	(11.130)	(11.358)
DISABILITY	0.350	0.179	0.328	0.173
	(0.477)	(0.384)	(0.470)	(0.378)
$<$ YEAR 10	0.150	0.193	0.173	0.179
	(0.356)	(0.395)	(0.380)	(0.383)
YEAR 10-12	0.298	0.143	0.277	0.145
	(0.457)	(0.350)	(0.448)	(0.352)
TERTIARY NON-DEGREE	0.457	0.314	0.482	0.396
	(0.498)	(0.464)	(0.500)	(0.489)
TERTIARY DEGREE	0.096	0.349	0.067	0.279
	(0.295)	(0.477)	(0.250)	(0.449)
PARTNERED	0.455	0.669	0.561	0.670
	(0.499)	(0.471)	(0.496)	(0.470)
CHILDREN AGED $\leq$ 14	1.115	0.738	0.898	0.655
	(1.346)	(1.047)	(1.223)	(1.003)
SINGLE OCCUPANT HOUSEHOLD	0.131	0.107	0.170	0.161
	(0.338)	(0.309)	(0.437)	(0.368)
ONE-FAMILY HOUSEHOLD	0.779	0.795	0.742	0.736
	(0.414)	(0.404)	(0.437)	(0.441)
MIXED HOUSEHOLD	0.088	0.098	0.086	0.102
	(0.284)	(0.297)	(0.281)	(0.303)
N	1,647	4,914	1,163	4,205

Note. Means representative of the population; standard deviations in parentheses.

Table 3: Descriptive statistics: Perceived discrimination and its ingredients

	Females	Males
Treated unfairly in last 12 months when applying for work, or at work, because Aboriginal / Torres Strait Islander	0.058 (0.233)	0.115 (0.319)
Avoided applying for work, or going to a job in last 12 months due to unfair treatment because Aboriginal / Torres Strait Islander	0.005 (0.695)	0.006 (0.077)
Had difficulties finding work due to racial discrimination	0.047 (0.047)	0.058 (0.058)
PD	0.095 (0.293)	0.158 (0.365)
N	1,647	1,163

Note. Means representative of the population; standard deviations in parentheses.

Table 4: Descriptive statistics: Perceived discrimination by employment status

Employment status	Job search		PD	
			Females	Males
Employed	Yes	Mean	0.167	0.244
		SD	(0.374)	(0.431)
		N	233	209
	No	Mean	0.094	0.164
		SD	(0.293)	(0.370)
		N	519	477
Not employed	Yes	Mean	0.157	0.213
		SD	(0.365)	(0.410)
		N	242	202
	No	Mean	0.046	0.044
		SD	(0.210)	(0.205)
		N	653	275

Note. Means representative of the population; standard deviations in parentheses.

Table 5: Determinants of employment: Probit coefficients

	Females					
	Indigenous			Non-Indigenous		
	(1)	(2)	(3)	(4)	(5)	(6)
AGE	0.065*	0.042	0.085**	0.056***	0.039*	0.154***
	(0.035)	(0.037)	(0.039)	(0.021)	(0.021)	(0.023)
AGE^2	-0.064	-0.035	-0.102**	-0.070***	-0.046*	-0.194***
	(0.043)	(0.046)	(0.048)	(0.025)	(0.024)	(0.027)
DISABILITY	-0.830***	-0.759***	-0.779***	-0.626***	-0.571***	-0.672***
	(0.102)	(0.106)	(0.114)	(0.059)	(0.058)	(0.062)
YEAR 10-12		0.551***	0.504***		0.245**	0.289***
		(0.177)	(0.180)		(0.101)	(0.110)
TERTIARY NON-DEGREE		0.776***	0.680***		0.480***	0.471***
		(0.167)	(0.172)		(0.085)	(0.088)
TERTIARY DEGREE		1.682***	1.636***		0.767***	0.780***
		(0.262)	(0.275)		(0.088)	(0.093)
PARTNERED			0.388***			-0.116
			(0.108)			(0.075)
CHILDREN AGED$\leq$ 14			-0.289***			-0.349***
			(0.045)			(0.033)
ONE-FAMILY HOUSEHOLD			0.283*			-0.291***
			(0.164)			(0.098)
MIXED HOUSEHOLD			0.303			-0.386***
			(0.221)			(0.119)
CONSTANT	-1.143*	-1.376*	-2.031***	-0.481	-0.717	-2.122***
	(0.680)	(0.775)	(0.785)	(0.443)	(0.461)	(0.490)
STATE/REGION	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,647	1,647	1,647	4,915	4,914	4,911
	Males					
	Indigenous			Non-Indigenous		
	(1)	(2)	(3)	(4)	(5)	(6)
AGE	0.058	0.046	0.052	0.152***	0.139***	0.108***
	(0.043)	(0.044)	(0.047)	(0.026)	(0.026)	(0.027)
AGE^2	-0.080	-0.064	-0.081	-0.191***	-0.177***	-0.148***
	(0.053)	(0.055)	(0.058)	(0.030)	(0.031)	(0.032)
DISABILITY	-1.170***	-1.159***	-1.109***	-1.239***	-1.152***	-1.096***
	(0.130)	(0.133)	(0.140)	(0.078)	(0.077)	(0.076)
YEAR 10-12		0.223	0.217		0.203	0.205
		(0.180)	(0.178)		(0.128)	(0.127)
TERTIARY NON-DEGREE		0.685***	0.621***		0.442***	0.380***
		(0.167)	(0.163)		(0.079)	(0.081)
TERTIARY DEGREE		1.298***	1.166***		0.639***	0.542***
		(0.317)	(0.338)		(0.115)	(0.116)
PARTNERED			1.008***			0.566***
			(0.167)			(0.091)
CHILDREN AGED$\leq$ 14			-0.193***			-0.037
			(0.060)			(0.035)
ONE-FAMILY HOUSEHOLD			0.032			-0.412***
			(0.191)			(0.117)
MIXED HOUSEHOLD			0.274			-0.483***
			(0.259)			(0.116)
CONSTANT	0.078	-0.211	-0.499	-1.529***	-1.654***	-0.805
	(0.840)	(0.863)	(0.945)	(0.512)	(0.508)	(0.519)
STATE/REGION	Yes	Yes	Yes	Yes	Yes	Yes
OBSERVATIONS	1,163	1,163	1,163	4,205	4,205	4,205

Note. Dependent variable is EMPLOYED. Standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 6: Decomposition of indigenous-non-indigenous gaps in employment

	Females		Males	
	Explained	Unexplained	Explained	Unexplained
(1) Exogenous controls	21.6	78.4	18.4	81.6
(2) Exogenous controls + Education controls	30.7	69.3	20.0	80.0
(3) Exogenous controls + Education controls + Household controls	43.4	56.6	23.0	77.0

Note. Percentages of the total gap that are explained and unexplained by the characteristics are reported. Non-indigenous coefficients are employed as the reference. Exogenous controls refer to AGE, AGE^2, DISABILITY and State/Region dummies included in the estimation of equation 2; education controls include: YEAR 10-12, TERTIARY NON-DEGREE and TERTIARY DEGREE; household controls include: PARTNERED; CHILDREN AGED$\leq$ 14 ; ONE-FAMILY HOUSEHOLD and MIXED HOUSEHOLD.

Table 7: Descriptive statistics: Statistical and perceived evidence of discrimination by education

	$\hat{SD}$		PD	
	Females	Males	Females	Males
ALL	0.180	0.174	0.095	0.158
	(0.127)	(0.125)	(0.293)	(0.365)
EDUCATION LEVEL				
YEAR>10	0.262	0.249	0.077	0.104
	(0.097)	(0.118)	(0.268)	(0.306)
YEAR 10-12	0.201	0.238	0.076	0.158
	(0.112)	(0.117)	(0.264)	(0.366)
TERTIARY NON-DEGREE	0.183	0.131	0.105	0.178
	(0.109)	(0.1)	(0.307)	(0.383)
TERTIARY DEGREE	-0.025	0.026	0.133	0.156
	(0.071)	(0.063)	(0.341)	(0.363)

Note. Means representative of the population; standard deviations in parenthesis. The controls included in the employment equation underlying the construction of the statistical measure of discrimination include: AGE, AGE^2, DISABILITY, YEAR 10-12, TERTIARY NON-DEGREE, TERTIARY DEGREE and State/Region dummies.

Table 8: Statistical evidence of discrimination: Evidence from Census 2011

	A. Determinants of employment: Probit coefficients†			
	Females		Males	
	Indigenous	Non-Indigenous	Indigenous	Non-Indigenous
	(1)	(2)	(3)	(4)
AGE	0.066***	0.031***	0.016	0.085***
	(0.015)	(0.002)	(0.016)	(0.003)
AGE^2	-0.001***	-0.000***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
DISABILITY	-0.265***	-0.265***	-0.386***	-0.278***
	(0.052)	(0.008)	(0.069)	(0.011)
YEAR 10-12	0.578***	0.303***	0.519***	0.379***
	(0.052)	(0.009)	(0.058)	(0.011)
TERTIARY NON-DEGREE	0.939***	0.568***	0.852***	0.669***
	(0.050)	(0.008)	(0.054)	(0.010)
TERTIARY DEGREE	1.406***	0.829***	1.413***	0.867***
	(0.081)	(0.009)	(0.130)	(0.011)
CONSTANT	-1.634***	-0.124**	-0.007	-0.541***
	(0.321)	(0.048)	(0.360)	(0.060)
STATE/REGION	Yes	Yes	Yes	Yes
N	4,440	224,082	3,650	193,801
	B. Decomposition of gaps in employment‡			
	Females		Males	
	Explained	Unexplained	Explained	Unexplained
	22.1	77.9	18.6	81.4
	C. Individual-level statistical evidence of discrimination‡‡			
	Females		Males	
	0.171		0.197	
	(0.112)		(0.101)	

Note. † Dependent variable is EMPLOYED. Standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

‡ Percentages of the total gap that are explained and unexplained by the characteristics are reported. Non-indigenous coefficients are employed as the reference.

‡‡ Summary statistics of individual-specific measures of discrimination given in equation 5. Means representative of the population; standard deviations in parenthesis.

Table 9: Perceived vs. statistical evidence of discrimination: Probit marginal effects

	A. Baseline sample					
	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{SD1}$	0.159***			-0.055		
	(0.060)			(0.100)		
$\widehat{SD2}$		0.064			-0.064	
		(0.066)			(0.086)	
$\widehat{SD3}$			0.066*			-0.136*
			(0.038)			(0.066)
N	1,647	1,647	1,647	1,163	1,163	1,163
	B. Self-employed included in sample					
	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{SD1}$	0.149***			-0.030		
	(0.057)			(0.087)		
$\widehat{SD2}$		0.089*			-0.033	
		(0.050)			(0.076)	
$\widehat{SD3}$			0.061			-0.123*
			(0.040)			(0.065)
N	1,712	1,712	1,712	1,264	1,264	1,264
	C. Employed non-job seekers excluded from sample					
	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{SD1}$	0.197***			-0.146		
	(0.073)			(0.131)		
$\widehat{SD2}$		0.088			-0.153	
		(0.084)			(0.110)	
$\widehat{SD3}$			0.094**			-0.229***
			(0.045)			(0.082)
N	1,128	1,128	1,128	686	686	686
	D. SD based on four labour force status categories					
	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{SD1}$	0.045**			-0.024		
	(0.023)			(0.024)		
$\widehat{SD2}$		0.018			-0.034*	
		(0.024)			(0.021)	
$\widehat{SD3}$			0.028			-0.052***
			(0.017)			(0.019)
N	1,712	1,712	1,712	1,264	1,264	1,264

Note. Dependent variable is PD. The controls included in the employment equation underlying the construction of the statistical measure of discrimination include: (1) AGE, AGE^2, DISABILITY and State/Region dummies for $\widehat{SD1}$; (2) controls in (1) and YEAR 10-12, TERTIARY NON-DEGREE and TERTIARY DEGREE for $\widehat{SD2}$; (3) controls in (2) and PARTNERED, CHILDREN AGED$\leq$ 14, ONE-FAMILY HOUSEHOLD, MIXED HOUSEHOLD for $\widehat{SD3}$. Marginal effects calculated at sample means; bootstrapped standard errors presented in parenthesis. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.