Minority Earnings Disparity Across the Distribution

Krishna Pendakur and Ravi Pendakur[1]

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[1] Department of Economics, Simon Fraser University, pendakur@sfu.ca; Public and International Affairs, University of Ottawa, Pendakur@uottawa.ca; Krishna Pendakur acknowledges the financial support of the Research on Immigrants and Integration in the Metropolis (RIIM) Center of Excellence. Both authors acknowledge the contributions of our colleagues on this work: Tom Crossley, Jane Friesen, Brian Krauth, Steeve Mongrain, and Simon Woodcock. Finally, we are grateful for the valuable research assistance of Keerthik Sasidharan.

Abstract

We use quantile regression methods on 2001 Census data to assess disparity at four points in the conditional distribution of earnings of native-born ethnic minorities (the 20th, 50th, 80th and 90th percentile) as well as the mean. In doing so, we examine the assess the degree to which minorities face earnings differentials at both the top and bottom of the conditional distribution as well as the mean, thereby testing the degree to which the mean difference is representative of differences across the distribution. We consider glass ceilings for Canadian-born ethnic minorities, and find evidence that some groups, such as Chinese-origin people, do indeed face more earnings disparity at the top of the distribution than in other parts. However, other groups face different structures. South Asian-origin workers face greater disparity at the bottom than at the top, and Black workers face great disparity across the distribution. We interpret these latter patterns as identifying poor access of minority workers to good jobs in various parts of the distribution, rather than as negating a glass ceiling.

1. Introduction

The idea of a glass ceiling blocking progress for women has recently gained some attention in the economics literature. Using quantile regression techniques, these studies often conclude that there are differences in the promotion opportunities for women as compared to men and that women are effectively blocked from jobs at the upper end of the spectrum. The context of labour market outcomes for ethnic minorities is another natural domain in which to consider glass ceilings. In this paper, we use the same techniques of quantile regression to assess differences in the conditional distribution of earnings between ethnic minority and majority workers in Canada. Our data are drawn from the full 20% sample of the 2001 Census of Canada. This large sample allows us to examine the effect of ethnicity rather than of immigration, by including only Canadian-born workers and since we are not focused on the relative attainment of women versus men, we treat men and women separately. This paper is the first to consider glass ceilings in the context of inequality across ethnic groups using quantile regression methods.

The general idea behind glass ceiling arguments is that ‘good’ jobs, which pay more than necessary to attract labour, are in short supply, and are therefore rationed. If the rationing process is inequitable across groups, subordinate groups will have earnings distributions which look similar to that of the dominant group over ordinary jobs, but which are comparatively thin over the high-paying good jobs. However, identifying glass ceilings is not a straightforward process because it requires examining the distribution of jobs and remuneration at different points in the earnings distribution. Several papers have used quantile regression methods to explore labour market data for evidence of a glass ceiling faced by women. In this context, a glass ceiling is understood to manifest as a large disparity in the top of the distribution, with less disparity in the middle and bottom of the distribution, conditional on the productivity-related characteristics of workers (such as education). Albrecht et al (2003) and Joo Kee (2005) find exactly this pattern in Sweden and Australia, respectively. Other papers find somewhat more complex patterns across the conditional distribution (see: Garcia et al (2001), Dolado and Llorens (2004) and de la Rica et al (2005) for Spain; Machado and Mata (2001) for Portugal; Arulampalam et al (2004) for a comparison of 11 European countries).

The literature on glass ceilings for women finds large disparities at the top of the conditional earnings distribution. For example, Albrecht finds earnings disparity on the order of 20% at the top decile cutoff of conditional earnings. However, most papers also find large differences in other parts of the conditional earnings distribution. de la Rica et al (2005) find large differences in the bottom part of the conditional distribution, which they label a ‘sticky floor’, a term which is now found in many papers in the literature. They explain this sticky floor as resulting from the interaction of the labour force participation decision, firm investments in workers and the productivity of workers. However, because none of these papers use data with a plausible instrument for labour force participation, they are not able to correct for its endogeneity, and cannot fully assess their story.

We investigate disparity within gender groups in the Canadian born groups. Thus we exclude much the plausible variation in labour force participation probabilities across groups – that between immigrants and native-born workers and that between men and women. While our data also lack an instrument for labour force participation, it is arguably less important when looking for glass ceilings facing native-born ethnic minority workers than when looking for glass ceilings facing women. This is because the participation rates of Canadian-born, non-Aboriginal ethnic minority workers are not very different from those of Canadian-born white workers.

We find that in comparison with white women, visible minority women attain almost the same earnings across the conditional distribution. In contrast, Aboriginal women earn much less at the bottom and nearly as much at the top, which brings to mind a ‘sticky floor’ pattern.

Amongst men, visible minorities and Aboriginals face the greatest earnings disparity at the bottom of the conditional distribution. However, if we focus on the older and more educated men, we find that visible minority men face the greatest disparity, compared to white men, at the top. This finding is consistent with and similar in spirit to Albrecht et al’s (2003) conception of a glass ceiling.

Looking within the visible minority category, we see some heterogeneity across groups. First, we find that in comparison with British-origin men and women, Chinese-origin men and women face more earnings disparity at the top of the conditional earnings distribution than in other parts of the conditional distribution. Thus, Chinese-origin men and women face a glass ceiling in the sense of Albrecht et al (2003). Second, some groups have little or no variation in earnings disparity across the quantiles: Caribbean and Arab and West Asian men and women do not face a glass ceiling in the sense of Albrecht et al (2003); rather they earn less at all quantiles. Thus, like de la Rica et al (2005) and Arulampalam et al (2005), depending on the minority group in question, we find disparity across the conditional distribution of earnings.

2. The Empirical Literature

The standard approach of estimating conditional mean earnings differentials has led many researchers across disciplines to assess the existence of a glass ceiling in very specific occupational or industrial niches. For example, see Orcutt-Duleep and Sanders (1992)on Asian-Americans, Greve and Salaff (2005) on Chinese immigrants, Boyd and Thomas (2001) on Canadian immigrant engineers, Menges and Exum (1983) on women in academia, Schwartz (1992) on women in industry, Rashid(2005) on immigrants in Sweden, Tang(1997) on Blacks and Asians in science and engineering fields.

The literature in economics has also explored this area especially in the context of male-female inequality. Since Kuhn (1987), there is consensus in the U.S. that women in the upper income quantiles typically have slower promotion rates (see Lazear and Rosen (1990) for an associated model). The introduction of quantile regression methods to economics (see Koenker and Bassett 1978, Buchinsky 1994, 1996, 1998b) led to a new generation of glass-ceiling studies, wherein researchers applied quantile regression to study the returns to education by gender in the United States. This growing body of literature focuses on gender wage gaps and attempts to measure earnings disparity in different parts of the conditional distribution in order to assess the glass ceiling hypothesis. Albrecht et al (2003) define a glass ceiling as the

> *phenomenon whereby women do quite well in the labour market up to a point after which there is an effective limit on their prospects. The existence of a glass ceiling would imply that women's wages fall behind men's more at the top of the wage distribution than at the middle or bottom.*

For these authors, glass ceilings only affect the top of the conditional distribution. Albrecht et al (2003) and Joo Kee (2005) find exactly this pattern in Sweden and Australia, respectively.

Garcia et al(2001), Dolado and Llorens (2004); and De la Rica et al (2005) explore Spanish data from the European Community Household Panel (ECHP) to shed light on these same issues. They find that for highly educated women, there is a glass ceiling at the upper quantiles (as was found in Sweden), but for less educated women, they find the largest differentials at the bottom of the distribution. In contrast Machado and Mata (2001) using Portuguese data from the ECHP find that the largest gaps across the largest earnings differentials are closer to the median of the conditional earnings distribution.

Arulampalam et al (2004), who also use the ECHP, studies the same question in eleven European countries. They find that women earn substantially less than men at the top of the earnings distribution in most of the countries they study. But they also find important differentials at the bottom of the distribution in about half the countries.

The papers which find differences in the lower quantiles of the conditional distributions tend to interpret the effects at the bottom of the distribution as being due to some process which is different in spirit from a glass ceiling. In particular, de la Rica et al (2005) posit that the disparity at the bottom of the conditional distribution is due to the interaction of women's participation decision, education decisions and firm investment decisions. For example, less educated women might have lower labour force attachment and attract lower investment from their employer.

The treatment of participation effects in the estimation of earnings disparities across men and women typically requires instruments for participation which are independent of conditional earnings. None of the above papers examining male-female disparity treat endogeneity formally because such instruments are not available. While one might argue that these effects are small in the Nordic countries where participation rates are very similar across men and women, this is a much harder case to make in southern Europe. Whereas participation rates differ greatly between men and women, they hardly vary at all between ethnic groups in the native-born population. Since our study is of native-born ethnic minorities only, our analysis of earnings disparity is in some sense more straightforward because the participation decision is neither a feature of theory, nor an important part of the econometrics.

3. Theories of Discrimination and Conditional Distributions

Most theories of discrimination against particular population groups are theories that explain (or deny the existence of) differences in the conditional mean of earnings, wages or other labour market outcome. For example, Becker's (1957) classic work on discriminatory preferences in competitive labour and product markets predicts that the result of such preferences is segregation of workers into sub-economies. Because returns to scale are assumed constant, each sub-economy is equally productive, so that wages are equal for all workers with identical productive characteristics. That is, discriminatory preferences result in segregation, and segregation results in equality of the mean of wages conditional on productive characteristics.

If the assumptions of competitive product and labour markets are relaxed, the 'separate-but-equal' conclusions do not follow. For example, if product markets are not competitive so that some firms make excess profits which are partially shared with (possibly unionized) workers, workers in those firms will earn more money than identical workers in other firms with less excess profits. Or, if some workers receive wage premia to induce them to provide unobservable effort, these workers will make more money than identical workers in work environments without these wage premia. The presence of rents, quasirents, or efficiency wages all may result in wage dispersion among workers with identical potential productivity.

If ethnic discrimination on the part of employers, workers or customers results in white workers ending up in the high-wage firms/jobs and non-white workers ending up in the low-wage firms/jobs, then the segregation of workers across firms/jobs by ethnicity results in differential outcomes. That is, the mean of earnings, conditional on productive characteristics of the worker, is different across groups. This model also has a prediction about the conditional variation of earnings: because majority workers have a higher probability of securing 'good' jobs, the top end of their conditional earnings distribution is pulled upwards. Thus, the upper quantiles of the conditional earnings distribution for majority workers will be higher than the corresponding quantiles of conditional earnings for minority workers. However, lower quantiles of the conditional distributions could well be identical for majority and minority workers.

Alternatively, one might relax the perfect information assumptions implicit in Becker's model to allow for 'statistical discrimination' on the part of employers, workers or customers. In these cases, difficulties faced by (majority) employers in assessing the quality of individual minority workers result in poorer mean outcomes for minority workers (see, eg, Phelps 1972, Arrow (1973), or Loury and Coate (1993)). Under this model, good firms offer both good wages and investments (such as training) in worker productivity to majority workers, but not to minority workers on the grounds that minority workers are 'inferior'. These beliefs are then corroborated by the higher productivity (due to higher investments) of majority workers. Here, firm investments result in quasi-rents which may be extracted by workers to raise their wages. If there is variation in investments, then there will be resulting variation in wages for majority workers, but no corresponding variation in wages for minority workers. The result is that the conditional mean of wages will be lower for minority workers, and the conditional variation in wages will be lower for minority workers.

Fryer (2004) notes an additional feature of such models once embedded in a dynamic framework (see also Lazear and Rosen (1990) for a similar view of male-female differentials). If some minority workers are hired into good firms, they will be the very highest-potential minority workers, because minorities are subjected to a higher entry bar. These workers will thus attract greater investment from the firm, and be promoted faster than typical majority workers within the firm. The result here is that some of the difference posited above in the conditional mean and conditional variation of wages will be undone. In particular, the highest-performing minority workers may fare very well in comparison with high-performing majority workers. Conditional on characteristics, we would expect the top of the wage distribution to be similar for minority and majority workers.

Similar results of segregation and inequality across groups arise in social interaction models (eg: Durlauf, 1999; Glaeser, Sacerdote and Schienkman 1996) and other network models (eg: Calvo-Armengol (2004), Granovetter (2005 forthcoming)). In the former models, within-group interactions are more valuable to people than are cross-group interactions. In the latter models, most jobs are filled through referrals and acquaintanceships which may be governed by group-based networks. Both processes may result in segregation across groups. Inequality across groups would follow from such segregation in the presence of rents (e.g., Moro and Norman 2004 refer to access to such rents as a "productivity enhancing technology").

We use the phrase 'glass ceiling' to describe any process by which minorities are unable to access the highest paying jobs that might be suitable, in an abstract sense, to their potential productivity. Any of the 'imperfect market' assumptions above may give rise to glass ceilings of one sort or another. The important feature of our investigation is that we condition out observable characteristics of workers when we try to assess the existence and relevance of a glass ceiling effect. We use quantile regression to directly assess how minority status affects earnings at different quantiles of the conditional earnings distribution. The approach of Albrecht et al (2003) is to assume that all productivity-related characteristics are conditioned out in the quantile regression so that glass ceilings are characterised by greater earnings disparity in the upper conditional quantiles in comparison with the lower and middle conditional quantiles.

When we come to real-world data, however, it is likely that some of the variation in potential productivity across workers is not observed, and thus will show up in the distribution of earnings conditional on observables. In an environment where some variation in potential productivity is not observed, we may expect to see differences at other parts of the distribution (conditional on observables). For example, if raw ability is not observed but does affect potential productivity, then there may exist a glass ceiling for less-able workers which would manifest as a differential between majority and minority workers at the lower quantiles of the earnings distribution conditional on observables. Thus, law-firm partner or software designer might be good jobs suitable to workers with high raw ability, and minority workers with high raw ability might have poor access to such jobs. Publicly-employed secretary or bus driver might be good jobs suitable to workers with median raw ability, because such jobs pay a lot conditional on productivity-related characteristics, and minority workers with median ability might have poor access to these jobs.

It is thus possible that glass ceilings may affect workers in all parts of the conditional distribution. However, this view has an important disadvantage in comparison with Albrecht's approach: a glass ceiling which can only bind at the top of the conditional distribution is a testable hypothesis, but a glass ceiling that can bind anywhere in the conditional distribution is not testable. However, it provides an alternative interpretation for `sticky floors' to the participation-driven stories offered by de la Rica (2005).

4. Data and Methodology

Our data come from a customized micro data file drawn from the master file of the 2001 Census of Canada which initially contained information from all the long form records collected. So, we have records for about 20 per cent of households in general, and 100 per cent of households living on those Aboriginal reserves participating in the Census. However, since some reserves, particularly those in Ontario and Quebec, chose not to participate in the Census, the representativeness of the Aboriginal sub-sample is weakened.

We define 3 broad ethnic categorizations of interest: Aboriginal, visible minority and white. These categories match those used in employment equity policy in Canada. A person is classified as Aboriginal if any of their self-reported ancestry is Aboriginal, Métis, Inuit, or North American Indian. A person is classified as visible minority if they are not Aboriginal and reported a visible minority origin in the 'population group' question of the Census. The origins correspond to non-European / non-Aboriginal origins. All others are classified as white. We also explore the 4 largest ethnic groups within the visible minority category: Arab/West Asian, Caribean, Chinese and South Asian.[2]

Since our focus is on the native-born population and our interest in ethnic minorities, the master file of the Census is the only reasonable data source for this investigation. The reason is that visible minorities born in Canada and aboriginals each make up at most 3% of the Canadian-born population, so estimation and inference requires very large samples. The population examined consists of all Canadian-born residents of Canada, 25 to 64 years of age, whose

[2] The visible minority flag is drawn from question 19 on the 2001 Census which asks about visible minority status. However, question 19 does not allow multiple responses so we use the ethnic origin variables (question 17) to identify individual and combinations of ethnic groups.

primary source of income is from wages and salaries. People without any schooling were dropped from the sample as were those who did not report any income.

The dependent variable in all regressions is the natural logarithm of earnings from wages and salaries. There are two lists of control variables used in regressions. Regressions labeled 'personal' control for age (8 categories), schooling (13 categories), marital status (5 categories), household size, official language knowledge (3 categories), 12 area-of-residence categories (10 CMAs, a small CMA identifier and a non-CMA identifier), and 3 categories for group membership: white, aboriginal and visible minority. Regressions labeled 'work' include all the preceding variables plus full time-part time status (2 categories), weeks of work (11 categories), occupation (10 categories) and industry (20 categories.

Although Statistics Canada guidelines do not allow release of the unweighted counts of population groups in our analysis, our final samples contain approximately 900,000 observations each for men and women. Table 1 reports the means of the variables used in our analysis from a subsample matching that of our analysis, but drawn from the public-use micro data of the 2001 Census. Our sample matches the means in Table 1 to at least two decimal places for all variables except the Aboriginal population. For this group, we have a much higher proportion than in the public use sample because census long forms are administered to 100% of reserve residents.

As noted above, we are unable to formally correct for the endogeneity of participation because we lack an instrument correlated with participation but uncorrelated with wages or earnings. However, we note that the participation rates of Canadian-born visible minorities (which does not include Aboriginals) are very similar to those of Canadian-born whites. Logistic regressions of the probability of sample inclusion for workers aged 25-64 on the vector of personal characteristics show that visible minority men and women have insignificantly different probabilities of participation from white men and women. In contrast, Aboriginal men and women have much lower participation rates than white men and women, which suggests that results for Aboriginals may be harder to interpret. However, if the sample is restricted to people aged 40-64 who have some university education, the participation probabilities of Aboriginal and visible minority men and women are statistically indistinguishable from those of white men and women. Thus, we may have more faith in the results for Aboriginals for this population subgroup, discussed below in Table 3. See Appendix Table A1 for details.

We use quantile regression to estimate the conditional p'th quantile of log earnings attributable to ethnic group membership conditional on observable characteristics (see Buchinsky 1998a for a review of these methods in an economics context). For any given set of right-hand side conditioning variables, *X*, and left-hand side response variable, *Y*, the quantile regression finds parameters to fit the model:

$$P[Y \leq X\mathbf{b}_p] = p .$$

When *p=0.50*, this corresponds to median regression, whose parameters can be found by minimizing the sum of absolute deviations of *Y* from the regression line $X\mathbf{b}_{0.50}$. When *p* corresponds to a different quantile, the spirit of the optimization is still to minimize functions of absolute deviations, but the computations are via linear programming. We use Stata to estimate all models presented in this paper. All estimation is via unweighted quantile regression (incorporation of sample weights in the optimization make little difference to the results presented). Standard errors are estimated by Stata via the bootstrap. Because quantile regression can be computationally expensive with large samples, we use 20% of white workers and 100% of visible minority and Aboriginal workers in all reported estimates. However, because the variance of estimated differentials between groups depends most strongly on highest variance component, sampling white workers does not much increase the variance of our coefficients of interest.

The residual in quantile regression is different from that in mean (ordinary least squares) regression. In particular, the residuals e_i, $e_i = Y_i - X_i\mathbf{b}_p$, are not mean-zero by construction. Rather, the quantile regression coefficients satisfy the restriction that the ratio of the sum of negative residuals to the sum of positive residuals is equal to *p/1-p*. Thus, if *p=0.50*, as it does for median regression, the ratio of positive to negative residuals is one. In the case where residuals around the conditional mean function are distributed independently of *X* (which implies homoskedasticity), only the intercepts in $\mathbf{b}_p$ differ across the quantiles *p*. If this is not the case, then other coefficients in $\mathbf{b}_p$ may differ, including, for example, the coefficients associated with the ethnic origin of workers. We interpret regression coefficients from the p'th quantile regression as the difference in the conditional p'th quantile of log earnings attributable to variation in observable characteristics. We use these coefficients to shed light on the glass ceiling hypothesis.

5. Results

5.1 Conditional Means

In what sense can the presence of a large earnings differential between white and visible minority workers or between white and Aboriginal workers point to discrimination against minorities in labour markets? The first set of differentials we report control for a variety of personal characteristics including age and education, but do not control for any job characteristics, such as occupation, industry, or work hours. Thus, even if all workers in the same occupation and industry groupings get the same hourly wages regardless of their ethnicity, our empirical strategy might find earnings differentials due to the concentration of white workers in higher paying occupations and industries or jobs with longer work hours or weeks compared to non-white workers.

We believe that the job characteristics of workers—such as occupation, industry and hours — are at least as susceptible to ethnic discrimination as the wages paid to workers. In fact, the case is made by Becker (1996) and others that in competitive labour markets, ethnic discrimination by employers, workers or customers results not in wage differentials for workers in identical jobs, but rather in segregation of workers into different jobs by ethnicity. Thus, we present regression results for models which leave out all job characteristics, and for comparison, models which include job characteristics such as full time status, weeks of work, occupation and industry.

Table 2 shows the coefficients on broad ethnicity dummies from regressions controlling for either personal characteristics or personal and work characteristics.[3] Regressions are run separately for males and females for 4 regions (Canada-wide, Montreal, Toronto and Vancouver).

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[3] We do not show results for all ethnic groups in this paper. Tables containing the full set of results are posted on: www.sfu.ca/~pendakur

We run both OLS and quantile regressions. We show output for the conditional mean (OLS regression) and the 20th, 50th, 80th and 90th percentiles (quantile regression). We interpret OLS regression coefficients as the difference in conditional mean of log earnings attributable to broad ethnic category membership. A very large literature has used this as a measure of discrimination.

Figure 1 serves to connect the mean regression results with the historical literature. Here, we show the coefficients for visible minority and Aboriginal status for men and women over the period 1971 to 2001, where the 1971 to 1996 estimates are exactly comparable with the 2001 estimates and are drawn from Pendakur and Pendakur (2002). The coefficients and standard errors corresponding to Figure 1 are presented in Table A1. Here, we see that the patterns at the mean in 2001 are similar to those reported for 1996 in Pendakur and Pendakur (2002) and reinforce their finding that earnings disparity facing visible minorities and Aboriginals has worsened since the 1980s.

Looking at the upper left coefficient reported in Table 2, we see that the log earnings of Aboriginal women are 0.19 lower than of white women conditional on personal characteristics. An approximate interpretation of this is that Aboriginal women earn 19 per cent less than white women with the same personal characteristics. However, if we add work characteristics, this differential shrinks to 6 per cent. We take this as evidence that Aboriginal women have poor access to jobs with work characteristics associated with high earnings. This interpretation of the difference between regressions controlling for personal characteristics and those controlling for both personal and work characteristics will carry through to our discussion of quantile regressions.

Turning to visible minority women, the conditional mean of earnings for these women is about 4% lower than that of white women, regardless of whether or not work characteristics are in the control list. This is consistent with previous research showing small or nonexistent differentials between white and Visible Minority women in Canadian labour markets (see, eg, Pendakur and Pendakur 1998, 2002)

Among males, the patterns in the conditional means are rather different. Aboriginal males earn much less than white males with log-earnings 0.53 less than white males with similar personal characteristics. However, half of this difference in log-earnings is accounted for by the work characteristics attained by Aboriginal men. Thus, access to job characteristics may be an important part of poor labour market attainment for Aboriginal men (see also, George and Kuhn 1994).

Visible minority men earn less than white men, but not nearly to the extent of Aboriginal men. Controlling only for personal characteristics, we see a differential of 13% between Visible minority and white men. The differential drops to 8% if we control for work characteristics.

All earnings disparity associated with broad ethnic origin discussed above is in the conditional average of log-earnings. If glass ceilings are important for ethnic minorities, then the average may hide important variation in the upper and lower tails of the conditional earnings distribution.

5.2 Conditional Distributions

5.2.1 Aboriginal, Visible Minority and White Workers

While the mean difference in log earnings provides us with a global picture of earnings differentials given observable characteristics, it may mask differences across the conditional distribution. We therefore turn our attention to the results from the quantile regressions. For any group, the coefficients on group membership at different quantiles may be correlated with each other. Thus, inspection of the standard errors may not reveal whether or not coefficients at different quantiles are statistically significantly different from each other. In the discussion that follows, most of the results regarding differences across quantiles are statistically significant. We identify those which are not.

Looking at the results for Aboriginal women, we can see that the conditional mean does indeed mask variation across the distribution. Conditional on personal characteristics, the 20th percentile of log earnings for Aboriginal women is 0.34 points lower than that of white women, but the 90th percentile of earnings for Aboriginal women is only .06 points lower. When work characteristics are added to the regression, the magnitudes are 0.06 points at the 20th percentile and 0.03 points at the 90th percentile. Thus, observable work characteristics soak up a great deal of the differential at all points in the distribution, and especially so at the bottom of the distribution. Further, Aboriginal women at the top of the distribution do relatively better than those at the bottom of the distribution. To the extent that Aboriginal women face earnings disparity, it is evident at the bottom of the conditional earnings distribution rather than the top. This is not a story of high-performing Aboriginal women having poor access to good jobs. Indeed, at the top of the distribution, Aboriginal women earn almost as much as white women. This is more a story of low-performing Aboriginal women earning much less than their low-performing white counterparts.

The picture for visible minority women is quite different from Aboriginal women. Visible minority women face an earnings gap of about 2 per cent in comparison with white women regardless of the quantile and regardless of whether or not work characteristics are in the control list. Given that the confidence bands on the point estimates are approximately 4 per cent wide, the 4 per cent differential estimated in the conditional mean is not a puzzle to be explained, but rather an estimate lying roughly within the statistical variation of the quantile estimates. Thus, visible minority women earn almost as much as white women, regardless of their place in the conditional distribution.

Turning to the results for men, we see rather different patterns. Aboriginal men earn much less than white men at every quantile, but there is much variation across quantiles. Compared to white men with similar personal characteristics, the conditional mean of log-earnings of Aboriginal men is 0.53 points lower. However, at the bottom of the conditional earnings distribution, this difference is 0.85 log-earnings points, at the median it is 0.44 log-earnings points and at the top it is ‘only’ 0.21 log-earnings points. Thus, as with Aboriginal women, relative earnings outcomes are much worse at the bottom of the conditional distribution than at the top. However, unlike Aboriginal women, at no point in the conditional distribution are the earnings of Aboriginal men close to those of white men at the same quantile.

Much of the difference in log-earnings between Aboriginal and white men is soaked up by work characteristics. At the bottom of the conditional earnings distribution, the difference in log-earnings shrinks by more than half, and at the top of the distribution, it shrinks by almost half. Work characteristics soak up the largest proportion of the log-earnings difference at the bottom of the distribution. This suggests that, as with Aboriginal women, relative access to good job characteristics may be very poor for Aboriginal men at the bottom of the distribution.

The patterns for visible minority men are similar to those observed for Aboriginal men, but the magnitudes are nowhere near as large. Controlling only for personal characteristics, we see a conditional mean differential of 13 per cent. At the 20th percentile of the conditional earnings distribution, visible minority men earn 15 per cent less than white men, but at the 90th percentile of the distribution, they earn only 10 per cent less. Thus, assessing only the conditional mean differential hides some variation across the quantiles.

If we control for work characteristics, the variation in earnings differentials across the quantiles essentially disappears. Visible minority men earn about 6 per cent less than white men at all the reported quantiles. However, given that quantile regressions which do not control for work characteristics show larger differentials at the bottom of the conditional earnings distribution, this implies that work characteristics soak up more of the earnings differentials at the bottom of the distribution than at the top. Thus, as we observe for Aboriginal men and women, visible minority men may have relatively poorer access to good job characteristics at the bottom of the earnings distribution. Although for visible minority men the largest gap is seen at the bottom of the condition earnings distribution, we do see weak evidence of a glass ceiling at the top. In particular, the earnings differentials at the median and 80th percentile are 8%, but at the 90th, it is 10% (this difference across the quantiles is not statistically significant). Further, a substantial part of this differential is accounted for by work characteristics.

These findings are not suggestive of a glass ceiling in the sense of Albrecht et al (2003). In their view, phrase ‘glass ceiling’ evokes the image of a high-performing minority worker hitting a barrier that limits her earnings or achievement. Instead we observe low-performing minority workers attaining much lower earnings than their low-performing white counterparts. High-peforming minority workers seem to be less affected (though not unaffected).

Two possibilities suggest themselves. First, this conceptualization of the glass ceiling might be wrong. To the extent that glass ceilings are the manifestation of unequal access to rents, there is no reason *a priori* to assume that rents are available only at the top of the earnings distribution. Second, we might imagine that glass ceilings only matter for established workers, because it takes time to hit such ceilings, and that they might only matter for educated workers, because we believe *a priori* that glass ceilings are about opportunities for highly skilled workers.

To assess this second possibility, we ran the same regressions on the subset of workers aged 40 to 64 who have some university education. Table 3 presents these results. As noted above, although Aboriginal men and women have lower labour force participation rates than white men and women in the population as a whole, in this older and more-educated population subsample, the participation rates are about the same for Aboriginals, whites and visible minorities (see Appendix Table A2).

Looking first at Aboriginal women, we see that the disparity in the conditional mean of log earnings is lower than was seen in Table 1 (-.16 versus -.19). Similarly, at the 80th and 90th percentiles, the differentials are actually larger in this subsample than when measured for the whole population. For older, better-educated Aboriginal women, the very large differentials at the bottom of the conditional earnings distribution observed at the level of the whole population do not seem as important. In regressions controlling only for personal characteristics, no pairwise comparison across quantiles is statistically significant. In contrast, when work characteristics are included, a pronounced sticky floor is evident, with a differential of 23% at the 20th percentile and 11% at the upper decile cutoff.

The picture is quite different for visible minority women. While the results from Table 1 suggest that visible minority women as a whole face some small differentials when compared to white women, all of these differences disappear when restricting analysis to the older educated population. In regressions which control either for personal characteristics or for both personal and work characteristics, there are no significant differences between the earnings of visible minority and white women at the mean, or at any quantile.

Turning to older and better-educated Aboriginal men we can see that at the top of the distribution, things look similar to the results from Table 2. However, at the bottom of the distribution the amount of disparity is much smaller in the older educated subsample. For example, at the 20th percentile, the log earnings of Aboriginal men are 0.57 lower controlling for personal characteristics and 0.35 lower controlling for both personal and work characteristics. In contrast at the level of the whole population, these numbers are 0.85 and 0.31 respectively. Thus, to the extent that the older educated population of Aboriginal men faces less earnings disparity as compared to the Aboriginal population as a whole, this occurs only in the lower half of the conditional earnings distribution. This suggests that at the bottom end, well-educated Aboriginal men are more able to overcome the barriers faced their less-educated and younger counterparts. However, the pattern of greater earnings disparity at the bottom of the conditional distribution in comparison with the top of the conditional distribution is still evident.

In the analysis using the whole population, we saw weak evidence of glass ceiling for visible minority men. Using the better-educated and older sub-population, it appears that well educated visible minority men face a glass ceiling. In particular, when we control only for personal characteristics, the earnings differential is increasing from the bottom to the top of the distribution. At the median, the differential is 7 per cent, but at the 90th percentile it is 12 per cent (this difference is only marginally statistically significant---its p-value is 0.08). About half of the differential is soaked up by work characteristics regardless of where one looks in the distribution.

If we focus specifically on the population that might be pre-supposed to face a glass ceiling and define a glass ceiling as large differentials at the upper end, then among men, such a glass ceiling is strongly evident for visible minorities and but not evident for Aboriginals. Among women, it is not evident for either visible minorities or Aboriginals. However, for both Aboriginal men and women, we see a different kind of pattern---the differentials are largest at the bottom of the conditional distributions and smallest at the top of the conditional distributions. This is suggestive of a sticky floor for Aboriginals rather than a glass ceiling.

5.2.2 Visible Minority Ethnic Groups

The visible minority category is an amalgam of a large number of distinct non-European ethnic groups. Our data allow us to identify many of its constituent groups and we have sufficient counts to discuss four groups in particular: Arab/ West Asian, Caribbean, Chinese (including Hong Kong and Taiwan) and South Asian (which encompasses the Indian subcontinent).

Table 4 shows results from regressions with selected detailed ethnic groups. These results are analogous to those reported in table 2, but instead of an ethnic breakdown of three broad ethnic categorizations, (white, visible minority and Aboriginal), we dummy out 37 distinct ethnic categories (22 white, 9 visible minority, and six Aboriginal).[4] In this section we focus on visible minority ethnic groups and compare their outcomes to British origin workers (the left out category).

Inspection of Table 4 shows that the small and nonexistent differentials reported in Table 2 for visible minority women hide important heterogeneity across groups. In particular, Chinese women earn more than British origin women, Arab and West Asian women earn about the same as British-origin women and Caribbean and South Asian women earn less than British-origin women.

Turning to the quantiles, for Chinese women it is evident that most of the action for their earnings premium is at the bottom of the conditional earnings distribution. Chinese women at the 20th percentile earn 15 per cent more than British women with similar personal characteristics. But this premium falls to 4 per cent if work characteristics are included. Thus at the bottom of

[4] The 37 ethnic groups are: British, French, Canadian, American-Australian-NZ, Austrian-German, Hutterite Mennonite or Dukabor, Scandinavian, Belgian, Dutch, Baltic, Jewish, Polish, Czech-Slovak, Hungarian, Russian, Ukrainian, Italian, Portuguese, Greek, Spanish, Balkan, Other European, Latin American, Arab & W. Asian, Black, Caribbean, African Black, S. Asian, Chinese, SE Asian, Other Asian, North American Indian Registered on reserve, North American Indian Registered off reserve, Unregistered North American Indian, Métis, Inuit, Other Aboriginal ancestry. There are also 4 multiple origin groups included in the regressions: European w European, Majority w White, Majority w Visible Minority and multiple origin Aboriginal.

the distribution, Chinese women appear to earn more money and get higher-paying work characteristics than British origin women. At other points in the distribution, these features are much less prominent. For example, Chinese women earn about 4 per cent more than British-origin women at the top of the distribution, and if work characteristics are controlled for, the premium is insignificantly different from zero.

Caribbean women face a very different pattern. Their earnings are lower than British origin women across the distribution, and in regressions which control only for personal characteristics, the disparity is essentially the same at all quantiles. When we add work characteristics the differential falls by half at the 20th percentile and by about a fifth at the 90th percentile. Because work characteristics soak up less variation at the top of the distribution, regressions which control for these characteristics suggest a glass ceiling with an earnings gap of 6% at the bottom growing to a gap of 9% at the top (this difference is marginally significant).

South Asian women face yet another pattern of earnings differences. For them, earnings disparity is much larger at the bottom of the distribution. Controlling only for personal characterstics, South Asian women earn 11 per cent less than British origin women at the 20th percentile. About one-third of this gap is accounted for by work characteristics. In contrast, at the median and above, they earn about the same, regardless of whether work characteristics are included or not.

It appears therefore, that patterns of differentials are very heterogeneous across groups. Chinese women enjoy an earnings premium at the bottom, but South Asian and Caribbean women face a penalty. Caribbean women face earnings gaps from the median to the top of the distribution, but other groups do not. South Asian women face earnings disparity that is largest at the bottom of the conditional distribution. Thus, the results in Table 2 for the visible minority group taken as a whole are somewhat misleading because the small or nonexistent differentials are in fact ‘averages’ of positive and negative effects for different subgroups of the visible minority aggregate.

There are some similarities in the inter-ethnic group patterns observed for men and women. Looking at the conditional means for men, we can see that the spirit of the differentials is roughly similar to that observed for women. In particular, Chinese and Arab/West Asian men earn about the same as British origin men, but Caribbean and South Asian men earn much less (16 percent less when only personal characteristics are included, and about 10 per cent less when work characteristics are added). The patterns across the quantiles for men are also very similar in spirit to those seen for women.

South Asian men face the largest earnings disparity at the bottom of the distribution, whereas Chinese men perform relatively better at the bottom. Chinese men earn about the same as British origin men up to the median. But at the 90^{th} percentile, they earn 5 per cent less. This is consistent with a glass ceiling in the sense of Albrecht (2003) wherein all the action is at the top of the conditional distribution.

South Asian men earn 25 per cent less at the 20^{th} percentile, the lion's share of which is accounted for by work characteristics. At the bottom of the distribution, South Asian men do not get good work characteristics. However, at other parts of the distribution , the differential is much smaller, and is on the order of 10 per cent, and a much smaller amount of the differential is explained by work characteristics. So, at the middle and top of the conditional distribution, South Asian men face less earnings disparity than they do at the bottom of the conditional distribution.

In contrast, there is little variation across the quantiles for Caribbean origin and Arab and West Asian men. In particular, Caribbean origin men earn much less than British-origin men across the distribution. Arab and West Asian origin men earn the same as, or slightly more than, British-origin men across the distribution. Whereas for Chinese and South Asian, the differentials in condition means mask potentially important variation across the conditional distributions, for Caribbean-origin and Arab/West Asian men, this is not the case.

For both men and women, the visible minority aggregate masks important variation across its constituent ethnic groups. For women, the absence of an earnings differential for visible minorities as a whole masks large negative differentials for Caribbean and South Asian women and positive differentials for Chinese women. For men, this same pattern is evident, but relative earnings of all the visible minority groups is lower.

6. Conclusions

Albrecht et al (2003) define a glass ceiling in the context of gender earnings disparity as a situation where women earn less than men at the top of the conditional distribution, but not in other parts of the conditional distribution. We consider glass ceilings in the context of the earnings of ethnic minorities, using a data-base of Canadian-born ethnic minority and majority workers drawn from the 20% sample of the 2001 Census of Canada. We exclusively focus on within-gender comparisons. We find evidence of a glass ceiling in the spirit of Albrecht et al (2003) for older and more educated visible minority men in comparison with similar white men. However, we do not see such a pattern for Aboriginal men or women or for visible minority women in comparison with white men or women. Looking inside the visible minority category, we find evidence of a glass ceiling for Chinese-origin men in comparison with British-origin men, and rough evidence of a similar pattern for Chinese-origin women in comparison with British-origin women.

We see two other patterns in the data, both of which are observed in the context of gender earnings in Europe (Arulampalam et al 2004 and de la Rica et al 2005). First, we observe a pattern of large differentials at the bottom of the conditional distribution but smaller differentials in the middle and at the top for several groups. In particular Aboriginal men face extreme earnings disparity at the bottom of the conditional distribution and smaller but still substantial disparity at the top. For Aboriginal and South Asian women there is considerable earnings disparity at the bottom, but very little at the top. Second, some groups have little or no statistically measurable variation across the quantiles: Caribbean and Arab and West Asian men and women. For these groups, the quantile approach does not reveal anything beyond what is seen in the traditional conditional mean approach.

Our investigation using quantile regression methods reveals features of earnings disparity that are not seen with traditional conditional mean methods. In particular, for many population subgroups, earnings disparity is different at the top of the conditional distribution than at the bottom. For visible minority men taken as a whole, there is evidence of a glass ceiling that binds their earnings at the top of the conditional distribution. Within the visible minority aggregate, there is strong evidence that such a glass ceiling binds Chinese-origin workers. However, South-Asian origin men seem to face the opposite pattern, which has been called a ‘sticky floor’, with the greatest earnings disparity at the bottom of the conditional distribution. Both Aboriginal men and women also face a sticky floor in comparison with white workers.

From the point of view of anti-discrimination policy, such as Employment Equity in the Canadian federal government, these findings are important. The important constraint facing Chinese men would seem to be access to the very best jobs. Employment Equity policy, which focuses on job access, is currently constructed to give minority groups (somewhat) preferential access to all jobs. However, for those groups facing a glass ceiling, access to high-pay and/or managerial jobs is more important, and the policy could conceivably be focused on relaxing this constraint. In contrast, we find that the important constraints facing Aboriginal workers are at the bottom of the conditional distribution. Since federal government workers are on average more educated and better-paid than the population as a whole, equity policy which works entirely through federal employment may be a very weak tool for alleviating the earnings disparity faced by Aboriginals.

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Table 1: **Descriptives -- summary statistics**

			Females	Males
Personal Characteristics	Employment Equity Group	White	95.4%	95.4%
		Visible minority	1.6%	1.6%
		Aboriginal persons	2.9%	3.0%
		Total	100.0%	100.0%
	Marital Status	never married	16.2%	20.3%
		married/common-law	71.4%	72.3%
		divorced	8.2%	5.1%
		separated	3.8%	2.7%
		widowed	1.6%	0.4%
	Official Language knowledge	English	64.0%	64.6%
		French	13.8%	12.8%
		English & French	22.1%	22.6%
	Age	25-29	14.5%	14.4%
		30-34	14.2%	14.5%
		35-39	16.8%	16.7%
		40-44	17.7%	17.0%
		45-59	15.5%	14.6%
		50-54	11.8%	11.9%
		55-59	6.8%	7.3%
		60-64	2.8%	3.5%
	Household size	mean	3	3
	Schooling	Less than gr 5	0.3%	0.5%
		Gr 5-8	1.9%	3.5%
		Gr 9-10	5.0%	7.4%
		Gr 11+ to Highschool	23.9%	23.3%
		Some post sec no certificate	6.8%	6.4%
		Post Secondary certificate	20.2%	13.6%
		Trades certificate	9.2%	17.1%
		Some university	3.2%	3.6%
		Dip < BA	8.3%	6.3%
		BA	15.2%	12.7%
		BA +	2.5%	1.7%
		Ma/PhD	3.4%	4.0%
Work Characteristics	Full-time/part-time status	worked mainly full-time	76.8%	94.3%
		worked mainly part-time	23.2%	5.7%
	Weeks worked	mean	45	47
	Industry	agriculture, forestry	1.3%	2.9%
		mining and oil and gas	0.5%	2.3%
		utilities	0.6%	1.6%
		construction	1.4%	8.9%
		manufacturing	8.3%	21.0%
		wholesale trade	3.3%	6.4%
		retail trade	11.1%	7.9%
		transportation and warehousing	3.1%	8.3%
		information and culture	2.8%	2.9%
		finance and insurance	6.5%	3.0%
		real estate and rental & leasing	1.4%	1.5%
		professional, scientific	5.4%	4.9%
		management of companies	0.1%	0.1%
		administrative and support	3.1%	3.2%
		educational services	12.2%	5.5%
		health care and social assistance	19.5%	3.4%
		arts, entertainment and recreation	1.5%	1.5%
		accommodation and food	6.0%	2.6%
		other services	4.2%	3.8%
		public administration	7.7%	8.7%

	Occupation	Management	8.3%	13.1%
		Professional/financial/admin	32.0%	9.7%
		natural and applied sciences	2.8%	9.9%
		Health	10.5%	1.6%
		Social Science, govt, education	13.4%	5.8%
		Arts, culture recreation and sport	2.2%	1.9%
		Wholesale, retail, personal services	23.5%	16.1%
		Construction, trades	2.2%	28.4%
		Primary	1.1%	4.0%
		manufacturing	4.0%	9.4%
	Annual earnings	mean	28,527	43,821
	log annual earnings	mean	9.90	10.39

Source 2001 public use census microdata file (individual file),

Selection All Canadian-born residents of Canada, 25-64 years of age whose primary source of income is from wages and salaries. The education category Post Secondary certificate includes both certificates and diplomas. In our regressions this category is separated into 2 categories.

Table 2 **Selected Coefficients for log earnings regressions, personal and work characteristics, by sex, minority status, conditional means and quantiles**

			Mean			Quantile												
						20th			50th			80th			90th			
Sex	Group	Model	coef.	*SE*		coef.	*SE*		coef.	*SE*		coef.	*SE*		coef.	*SE*	
females	Aboriginal	Personal	-0.19	*0.01*	***	-0.34	*0.01*	***	-0.12	*0.01*	***	-0.08	*0.00*	***	-0.06	*0.00*	***
		work	-0.06	*0.01*	***	-0.06	*0.01*	***	-0.06	*0.00*	***	-0.05	*0.00*	***	-0.03	*0.01*	***
	Visible Minority	Personal	-0.04	*0.01*	***	-0.02	*0.02*		-0.02	*0.01*	***	-0.02	*0.00*	***	-0.02	*0.01*	***
		work	-0.04	*0.01*	***	-0.03	*0.01*	***	-0.02	*0.01*	***	-0.02	*0.01*	***	-0.02	*0.01*	**
males	Aboriginal	Personal	-0.53	*0.00*	***	-0.85	*0.01*	***	-0.44	*0.01*	***	-0.27	*0.00*	***	-0.21	*0.00*	***
		work	-0.25	*0.00*	***	-0.31	*0.01*	***	-0.22	*0.00*	***	-0.15	*0.00*	***	-0.13	*0.00*	***
	Visible Minority	Personal	-0.13	*0.01*	***	-0.15	*0.01*	***	-0.08	*0.01*	***	-0.08	*0.01*	***	-0.10	*0.01*	***
		work	-0.08	*0.01*	***	-0.07	*0.01*	***	-0.05	*0.00*	***	-0.06	*0.00*	***	-0.06	*0.01*	***

Source 2001 Census main base
Selection All Canadian-born residents of Canada, 25 to 64 years of age, whose primary source of income is from wages and salaries. People without any schooling were dropped from the sample as were those without any earnings.

Significance: ***: 0.01, **: 0.05, *: 0.1

Table 3 **Selected Coefficients for log earnings regressions for Canadian-born workers aged 40+ with university schooling, personal and work characteristics, mean and selected quantiles**

			Mean			Quantile											
						20th			50th			80th			90th		
Sex	Group	Model	coef.	*StErr*		coef.	*StErr*		coef.	*StErr*		coef.	*StErr*		coef.	*StErr*	
females	Aboriginal	personal	-0.16	*0.01*	***	-0.16	*0.03*	***	-0.12	*0.01*	***	-0.14	*0.01*	***	-0.12	*0.01*	***
		work	-0.21	*0.01*	***	-0.23	*0.01*	***	-0.18	*0.01*	***	-0.14	*0.00*	***	-0.11	*0.01*	***
	Visible Minority	personal	0.04	*0.03*		0.05	*0.04*		0.01	*0.01*		-0.01	*0.01*		0.00	*0.02*	
		work	0.00	*0.02*		0.00	*0.02*		0.01	*0.01*		0.00	*0.01*		-0.01	*0.02*	
males	Aboriginal	personal	-0.42	*0.02*	***	-0.57	*0.04*	***	-0.31	*0.02*	***	-0.24	*0.01*	***	-0.25	*0.02*	***
		work	-0.29	*0.01*	***	-0.35	*0.02*	***	-0.23	*0.01*	***	-0.16	*0.01*	***	-0.15	*0.01*	***
	Visible Minority	personal	-0.09	*0.02*	***	-0.06	*0.02*	***	-0.07	*0.02*	***	-0.10	*0.02*	***	-0.12	*0.02*	***
		work	-0.08	*0.02*	***	-0.06	*0.02*	***	-0.04	*0.01*	**	-0.07	*0.01*	***	-0.07	*0.03*	***

Source 2001 Census main base
Selection All Canadian-born residents of Canada, 25 to 64 years of age, whose primary source of income is from wages and salaries. People without any schooling were dropped from the sample as were those without any earnings.

Significance: ***: 0.01, **: 0.05, *: 0.1

Table 4 **Selected Coefficients for log earnings regressions, personal and work characteristics, by sex, ethnic group, mean and selected coefficients, 2001**

			Mean			Quantile											
						20th			50th			80th			90th		
Sex	Ethnic Group	Model	coef	*St Err*		coef	*St Err*		coef	*St Err*		coef	*St Err*		coef	*St Err*	
females	Caribbean	personal	-0.12	*0.03*	***	-0.10	*0.06*		-0.07	*0.02*	***	-0.09	*0.01*	***	-0.11	*0.02*	***
		work	-0.09	*0.02*	***	-0.05	*0.03*	**	-0.06	*0.01*	***	-0.07	*0.02*	***	-0.09	*0.02*	***
	Chinese	personal	0.10	*0.02*	***	0.15	*0.03*	***	0.06	*0.01*	***	0.03	*0.01*	***	0.04	*0.02*	**
		work	0.04	*0.02*	***	0.04	*0.02*	**	0.01	*0.01*		0.01	*0.01*		0.01	*0.01*	
	S_Asian	personal	-0.06	*0.03*	**	-0.11	*0.04*	***	-0.02	*0.02*		-0.01	*0.02*		-0.04	*0.02*	**
		work	-0.05	*0.02*	**	-0.07	*0.02*	***	-0.02	*0.02*		-0.03	*0.02*		0.02	*0.03*	
	Arab_W_Asia	personal	-0.05	*0.03*		-0.10	*0.05*	*	-0.03	*0.02*	*	0.01	*0.02*		0.03	*0.02*	
		work	0.00	*0.03*		-0.06	*0.03*	*	0.01	*0.02*		0.03	*0.02*	**	0.04	*0.02*	*
males	Caribbean	personal	-0.16	*0.02*	***	-0.15	*0.05*	***	-0.13	*0.02*	***	-0.15	*0.02*	***	-0.14	*0.01*	***
		work	-0.09	*0.02*	***	-0.07	*0.02*	***	-0.08	*0.02*	***	-0.07	*0.02*	***	-0.05	*0.03*	*
	Chinese	personal	0.02	*0.02*		0.03	*0.02*		0.01	*0.01*		-0.01	*0.01*		-0.05	*0.02*	***
		work	-0.02	*0.01*		0.01	*0.01*		0.00	*0.01*		-0.03	*0.01*	**	-0.05	*0.01*	***
	S_Asian	personal	-0.16	*0.02*	***	-0.25	*0.05*	***	-0.09	*0.02*	***	-0.07	*0.01*	***	-0.10	*0.02*	***
		work	-0.11	*0.02*	***	-0.07	*0.02*	***	-0.04	*0.02*	***	-0.05	*0.01*	***	-0.08	*0.02*	***
	Arab_W_Asia	personal	0.02	*0.03*		-0.07	*0.04*	*	0.00	*0.01*		0.03	*0.01*	**	0.04	*0.03*	
		work	0.03	*0.02*		0.00	*0.02*		0.03	*0.02*		0.05	*0.02*	**	0.02	*0.03*	

Source 2001 Census main base
Selection All Canadian-born residents of Canada, 25 to 64 years of age, whose primary source of income is from wages and salaries. People without any schooling were dropped from the sample as were those without any earnings.

Significance: ***: 0.01, **: 0.05, *: 0.1

Table A1: Historical comparison of mean earnings disparity for Visible Minority and Aboriginal workers vs White workers, 1971 - 2001

		1971		1981		1986		1991		1996		2001	
sex	variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Females	Aboriginal	-0.20	*0.01*	-0.10	*0.01*	-0.09	*0.01*	-0.17	*0.01*	-0.16	*0.01*	-0.19	*0.00*
	Visible Minority	0.09	*0.02*	0.07	*0.02*	0.04	*0.01*	0.00	*0.01*	-0.06	*0.01*	-0.04	*0.01*
Males	Aboriginal	-0.48	*0.01*	-0.37	*0.00*	-0.44	*0.00*	-0.48	*0.00*	-0.57	*0.00*	-0.53	*0.00*
	Visible Minority	-0.05	*0.01*	-0.03	*0.01*	-0.07	*0.01*	-0.06	*0.01*	-0.15	*0.01*	-0.13	*0.01*

Source 1971 through 1996 drawn from Pendakur and Pendakur, 2002. 2001 figures drawn from 2001 Census mainbase.
Selection All Canadian-born residents of Canada, 25 to 64 years of age. People without any schooling were dropped from the sample as were those without any earnings.

Table A2: Logistic Regression Results on Labour Force Participation

			Coefficient	*Std Error*
Full Sample	Females	Aboriginal	-0.38	*0.03*
		Visible Minority	-0.02	*0.05*
	Males	Aboriginal	-0.20	*0.03*
		Visible Minority	-0.09	*0.06*
Older, More Educated Subsample	Females	Aboriginal	-0.14	*0.11*
		Visible Minority	0.09	*0.15*
	Males	Aboriginal	-0.14	*0.13*
		Visible Minority	0.04	*0.12*

Source 2001 Census public-use micro data (individual file).
Selection All Canadian-born residents of Canada, 25 to 64 years of age. People without any schooling were dropped from the sample as were those without any earnings.
Note that coefficients are related to marginal effects via multiplication by P(1-P) where P is the probability of participation.

Figure 1: Historical comparison of mean earnings disparity for Visible Minority and Aboriginal vs White workers, 1971 - 2001