Employer Learning and Statistical Discrimination in the New Zealand Labour Market

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Abstract

Firms often statistically discriminate in order to lower the cost of recruiting. This behaviour creates different economic opportunities among equally able individuals. We use the New Zealand component of the 2006 Adult Literacy and Life Skills (ALL) survey to test whether statistical discrimination is a factor in wage setting and employment outcomes. We are interested in testing the following hypotheses: (1) whether employers statistically discriminate among potential workers on the basis of education, gender, ethnicity or immigration status, when facing uncertain productivity information, and (2) whether they learn to revise their judgments as new information is revealed. Overall, we find mixed evidence of statistical discrimination over education level and gender for New Zealand born Pakeha, against female Maori and with Asian and Pasifika female immigrants. Significant employer learning behaviour is also found within each group.

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1. Introduction

Decision making is an integral part of human life, an endless stream of situations arise in which one must use limited or scarce information to further themselves. Examples might range from gauging the quality of a used car, boarding an airplane, choosing to spend the rest of your life with someone, or investing in financial markets. These scenarios are diverse but they all demonstrate the problem of uncertainty and asymmetric market information in reality. The decision for a firm to employ a new worker or set the wages of an employee is no different: all available information is scrutinised in order to make the best decision possible. Being human, the correct decision is not always made but over time these initial assessments can be amended as employers, like all of us, learn from our mistakes.

In a perfectly competitive market, wages are be equal to the productivity of workers. However, wage setting is in practice quite difficult when firms cannot observe the true productivity of workers directly. In order to minimise the cost of this process employers tend to statistically discriminate: they estimate the productivity of workers on the basis of statistical regularities of different worker groups. As a result, managers may categorise applicants according to easily observable characteristics such as the gender, race, or ethnic group to which applicants belong. In other words, group averages are applied to individuals. However, a group average is not always close to any given observation and we are faced with a situation where workers of identical ability, but differing in group status, are compensated differently. This can be the cause of much market inefficiency.

If initial mistakes are made, employers can learn in a number of ways. During the hiring process, they are able to learn about the candidates' background and characteristics through documents including school grades, police reports, resumes, and also through job interviews. Once a worker is hired, information about their job performance and productivity can be measured and collected. Employer learning is therefore an important mechanism for correctly adjusting the wage setting and recruitment behaviours of a firm.

Any analysis attempting to understand the driving forces behind wages generally adopts the traditional Mincerian human capital framework. The model has two main implications. First, that investing in education or training enables individuals to acquire knowledge, thereby directly or indirectly increasing their level of proficiency and productivity. The second implication is that better educated, and thus more productive people, receive higher wage compensation. Alternatively, some literature also contemplates a "signalling model" which suggests that education is not the sole mechanism driving productivity enhancing but rather only provides information that signals ability. If it is believed that more years of schooling indicates increased motivation (or other positive attributes) and that motivation affects job performance, then cost minimising firms have incentive to statistically group workers based on their level of education. This information is usually free for employers to use but once new information becomes available in the market, the impact of education on pay decisions should decrease.

The labour economics literature has strived to unveil the determinants of wage gaps between groups of workers. Seemingly equally productive workers of different gender or race are often found to earn different wages. New Zealand is no different. According to Statistics New Zealand (2009), New Zealand women earn 12.2 percent lower average hourly wages in comparison with men. It is also well known that New Zealand has an ethnically diverse population, the ALL survey data show that immigrants earn approximately 6.1 percent less than natives and Maori earn only 80 percent of what New Zealand born Pakeha earn. Oftentimes, the reasons given for immigrants' lower wages include factors such as low proficiency in the destination language or a lack of country-specified labour market skills. However, work such as Stillman (2011) uses regression analysis and shows that even when the education and experience of these groups are considered, minority groups are still worse off. This suggests that it could be statistical discrimination creating wage gaps between these groups and the current thesis aims to test this hypothesis.

This thesis is motivated primarily by the study on testing statistical discrimination and employer learning done by Altonji and Pierret (1996, 2001). Following previous literature, the authors aim to implement a test for statistical discrimination in wages on the basis of education level and race. The researchers first suggest that initial wages are indeed determined by early signals such as education background but as employer learning takes place, wages should become more dependent on new information which is not available to employers at the beginning of workers' careers and become less reliant on the limited information presented at the time of hire. Does this same situation exist in New Zealand? This is what we aim to find out.

The main objectives of this study focus on identifying the effects of education, experience and ability on worker wages. Furthermore, we also examine whether statistical discrimination over education, gender, worker ethnicity or immigrant status inhibit the wages or employment opportunities for these specific groups in the New Zealand labour force. Also, we address whether employers fairly adjust their wage setting and recruitment behaviours regarding these groups over time, thereby searching for the presence of employer learning in New Zealand.

An international data set is used, specifically the New Zealand component of the 2006 Adult Literacy and Life Skill (ALL) survey, which provides both person specific and job specific information. We only include wage/salary employed individuals aged between 25 and 64 to exclude students and those near retiring. Wage measurement difficulties for the self-employed prompt their exclusion. Since paid workers are not a random sample of the overall population, sample selection bias is a potential problem. Further regressions focussing on employment outcomes have been used to deal with the potential sample selection bias.

The results find evidential support for the hypotheses of employer learning and statistical discrimination based on years of schooling for female born New Zealand Pakeha in terms of wage setting and employment outcomes. Substantial evidence for statistical discrimination against Maori females and New Zealand Pakeha females through gender signalling is also found. On the other hand, New Zealand born male Pakeha and all immigrants, except Asian and Pasifika females, seem to face zero statistical discrimination as employers are able to accurately interpret the productivity of these groups. Lastly, we find evidence of employer learning for immigrants originating from heterogeneous cultural backgrounds.

The organisation of this thesis is as follows. Chapter 2 describes the literature on wage setting, statistical theory of discrimination and derives the employer learning models this thesis uses while also presenting international employer learning evidence. Chapter 3 discusses the data source, variable organisation, and presents the descriptive statistics. We then show the estimation results for statistical discrimination and employer learning in wage setting (Chapter 4) and employment outcome (Chapter 5). Lastly, Chapter 6 provides a conclusion of our findings.

2. Literature Review and Background

Decision making is an aspect of life economists strive to model, as lives are shaped through an endless stream of decisions based on limited but available information upon a diverse set of problems. In the context of employment, firms must base their wage setting and recruitment behaviour upon the simple information contained within a job application. Rampant with asymmetric information, employers face both a difficult and costly task if they were to validate the exact characteristics of each job applicant. Understandably, as workers gain experience, the labour market learns the degree of their productivity but upon entry, judgements are only based on the limited observable worker characteristics. These are simple productivity signals, such as the extent of one's education, appearance, previous experiences and possibly interview skills. This scenario sums up the decision making process firms continually face, in a global context, to recruit the best workers and achieve maximum profitability. It is easy to understand that other judgements, besides what an application contains, will be made by firms to minimise the cost of this process. These could range from stereotyping individuals by means of assuming the average productivity of different groups of workers, i.e. grouping all the workers from a specific school to have the same productivity, or to the extent of making gender and race generalisations. Statistical discrimination stems from this behaviour and culminates in generating wage differences between groups of otherwise equally productive workers.

The repercussions leading from statistical discrimination surround market inefficiency and the slowing of economic growth. Farber and Gibbons (1996) were the first to demonstrate that employers may form false expectations of workers but these judgements are updated over time as they learn about the true productivity of discriminated groups. In the process of learning, inefficiency subsides with workers increasingly appropriately remunerated. Kim (2011) introduces a method to test statistical discrimination using employment rates, establishing a testing methodology applicable to employment status regressions. The literature leading into employer learning has been derived from the foundational wage determinant work of Jacob Mincer (1974).

Although a significant amount of research exists regarding why wage differences survive among equally productive individuals in a competitive labour market, no single theory can claim to explain these differences completely. In order to fully understand the characteristic factors driving wage differences amongst individuals, we must first understand the empirically developed determinants of wages and gauge the effects of statistical discrimination. This chapter will introduce the basic wage specifications (2.1), the idea of statistical discrimination (2.2), will review the work done to develop tests for employer learning in the midst of statistical discrimination (2.3), present international employer learning evidence (2.4) and lastly present the wage gaps found in the New Zealand labour force (2.5).

2.1 Wage Determinants

Initially we are concerned with understanding the factors which a firm uses to set worker wages and to understand the basis of human capital models. Common to the labour economics literature, a competitive labour market can be considered efficient when wages reflect the marginal product of workers. However, as introduced earlier, an employer has only a small set of observable worker characteristics to judge when a worker has been newly hired. Studying the decision making process leading to this initial wage allows us to abstract from actual productivity differences between workers and focus in on actual economic discrimination. Over the worker's employment period, firms observe noisy signals of worker productivity and use these for more accurate wage setting. These factors open the possibility of discrepancies between wage and productivity for new workers and provide motivation into the study of wage gaps.

The labour economics literature has ventured into deriving the determinants of wages intensively and various human capital models have been formulated through rigorous empirical work. Mincer (1974) proposed the foundation of human capital theory with the relationship between human capital investments and earnings. Mincer’s work finds that both years of education and experience are key to the analysis of an individual’s lifetime earnings. For us to understand and form models of statistical discrimination or employer learning, we must first understand the basic determinants of wages from the foundational work of Mincer (1974).

Mincer (1974) provided the first empirical evidence to support all of the previous qualitative work backing human capital models with income distributions. He applies basic human capital models to 1960 US census data, restricting the analysis to men aged between 15 and 64. The first Mincer model (1958) used a principle of compensating difference to explain why people with different levels of schooling receive different earnings over their lifetimes. This model assumes that individuals have identical abilities and opportunities, that there is perfect certainty in all aspects of the model except that occupations differ in the amount of formal training required for performance. There is a certain opportunity cost to training or schooling as individuals' who choose schooling will forgo the possible earnings of using that time to work. The model is such that individuals are assumed to be ex ante identical thus they require a compensating differential to work in occupations that require longer training periods. The size of the compensating differential is determined by equating the present value of possible earnings with the different levels of investment required.

Mincer (1974) used age as a proxy for experience and demonstrated that wage compensation will increase as an individual ages through having more labour market experience. However, he also mentions that higher compensation reaches its maximum value at a certain age. That is, earnings should increase with age at a decreasing rate in an age-earning profile, implying a concave earnings curve. Concavity implies that a worker’s human capital starts to depreciate after the peak. The Mincerian wage equation is a log-linear transformation of an exponential function and can be estimated by OLS. Hence, the coefficients have a semi-elasticity interpretation and measure the percentage change in wage for absolute variations in the independent variables. His analysis specified the following equation:

$$\text{Ln } W = \beta_1 SCH + \beta_2 EXP + \beta_3 EXP^2 \qquad \text{(M.1)}$$

(Where EXP stands for labour market experience and SCH represents years of schooling)

By estimating equation (M.1) on cross sectional data from the 1960 census for the US, Mincer (1974) found that an additional year of schooling yields a net increase of 11.5% in annual earnings. Subsequently, the Mincerian wage equation has been estimated for many countries and is used as a benchmark for most labour market work involving wages. Stillman (2011) estimates a similar specification in the context of the New Zealand labour force and Barrett

(2012) examines these Mincerian returns with Australian data whilst also imposing a control for worker cognitive ability. This model will be the foundation for the specifications in the current thesis. Next, measurements of human capital returns will be discussed before developing into the more complex employer learning models.

2.2 Statistical Theory of Discrimination

The above mentioned Mincerian wage models (1974) delve into the determinants of worker productivity through providing a simple framework able to quantify returns to human capital. In reality, workers equal in terms of basic attributes do not always receive equal compensation. Studies into labour market discrimination originate from the fact that different groups of workers, observed to be equally qualified for a certain job, experience different wage compensation and employment outcomes. Many different theories of discrimination exist. However, the present thesis is mainly concerned with the effects of statistical discrimination. The idea of statistical discrimination in the labour force roots from what is known as rational expectations in economic literature. In the absence of full information firms distinguish between individuals by using different characteristics based on what they have defined as statistical regularities. Firms characterise different worker groups in terms of gender, race, ethnicity, age or other differentials that arise because processing the accurate information about these minority groups is difficult, in essence these are signalling models[1] (Spence, 1973). For the purposes of the current thesis, the statistical discrimination literature will be considered with respect to educational attainment, gender, ethnicity and immigration status.

In Becker's employer 'taste' discrimination model (1971), employers lose profits by discriminating, even if they gain in utility. This deviation meant that competitive pressures might reduce or eliminate discrimination. As an empirical fact, the seeming persistence of discrimination cast doubt on Becker's model (1971). An employer who discriminates due to a prejudice is willing to accept lower profits to avoid hiring the group they dislike. A prejudiced employer pays the desired workers more to attract them and to avoid hiring the undesired group, which can lead to lower wages for the undesired workers and lower profits for the

[1] Note: the present thesis will consider the statistical discrimination phenomenon and observable characteristic signalling as being synonymous. It is understood that employers who use signals are statistically discriminating.

discriminating employers (Becker 1971; Stiglitz 1975). Employers who care more about money will profit from hiring the equally productive workers (but ousted via discrimination) at cheaper wages. The model is flawed because tolerant employers have comparatively cheaper costs, increasing their profits and eventually driving their discriminating rivals out of business. Theoretically, the competitive market will drive out prejudice. Also, an increase in the demand for minority workers will lead to more competitive wages and keep them in the labour force. The deviation from the profit maximising assumption prompted much criticism for the 'taste' model.

In response to the shortcomings of the 'taste' model and continual existence of wage gaps between groups, economists developed models of statistical discrimination derived from limited information theories (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). These models assume no prejudice motive by employers, however, employers are assumed to use group characteristics as a cheap proxy of predicting individual worker productivity. A profit-maximising employer wants to hire the worker with the highest expected productivity for a given wage. Instead of gathering information to predict individual productivity, statistical discrimination says that the employer might assume that minority groups are disadvantaged in upbringing, for example, on average 'blacks' attend lower quality high schools than do 'whites'. Or, as employers usually place high value on job attachment due to the great cost in replacing workers, they may discriminate against women on the grounds that women generally have lower labour market attachment than men. Women generally have to leave the labour market for raising children and employers may prefer hiring males over identical female candidates. This is because employers assess higher profitability from hiring a man. These stereotypes are merely statistical correlations and are unlikely to be true in all individual cases, but the process may well lead to worse outcomes for these groups in a number of different ways. Firstly, the job applicant may have a reduced chance of employment. Secondly, wages may be lower for the discriminated group and incentives to make unobservable productivity improvements are also reduced.

Employers that rely on false stereotypes will face a competitive disadvantage similar to employers acting on a taste for discrimination, because they are not hiring the most productive workers available. The stereotypes used are not always false, as it is possible for a group average to be of lower productivity in general. If the stereotypes were always untrue, we would find statistically discriminating employers also driven out in a competitive market but they still exist. The rule applied is as follows; profit maximising employers will statistically discriminate whenever the net gains from using the cheap and available proxies outweighs the net gains of more accurate but more costly individualised information such as lengthy interview processes.

In Aigner and Cain's (1977) prominent model, the group differences arose because an individual productivity test predicted white performance more accurately than black performance, suggesting that employers who maximise profits and discount the risk of worker performance, would favour hiring white workers. However, they were reluctant to over endorse their model due to lacking empirical evidence behind the group differences. The idea of their work is simply based upon black worker test scores being less 'reliable' and thus more risky than their white counterparts. The work of Aigner and Cain (1977) opposed earlier models which assumed an actual productivity difference between worker groups such as the models proposed by Phelps (1972). Phelps (1972) suggested that an employer who seeks to maximise their expected profit will discriminate against 'blacks' if he believes them to be less qualified, or less able, on average compared to 'whites' especially if the cost of gaining accurate information is too great. The same argument can be applied when comparing female and male workers. This a priori belief in potential profitability is based on previous statistical experience with the population groups, formed if the less favourable group proved to be problematic. 'Blacks' are said to be less productive than 'whites' on average and for this reason all 'blacks' are offered lower wages even if they have the same test score on an individual basis. Aigner and Cain (1977) related the Phelps (1972) model to older 'taste' models as if minority groups were wrongly categorised to have lower productivity levels, a competitive market would drive out the discriminating employers in a similar fashion to what has been described with the Becker model (1971) and statistical discrimination wouldn't exist.

Statistical discrimination can also be self-fulfilling, as has been demonstrated by the work of Coate and Loury (1993). The model attempts to formalise many of the ideas Arrow (1973)[2] attempted to convey, but it assumes that wages are set exogenously. Coate and Loury's (1993) model follows the signalling literature with the assumption that a worker's costly skill investment may not be perfectly observed by firms. Thus, firms may rely on the race of the worker as a useful source of information regarding the worker's skill. If the firms believe that workers from a certain racial group or minority group are less likely to be skilled, due to factors such as more difficult upbringings, it will be more difficult for these groups to obtain higher paying jobs. Consequently, workers from these groups will be less likely to partake in costly' investment incentives. The cyclic nature of this theory is self fulfilling; if minority workers reduce their education or training investments they are in fact rationalising the firms' initial pessimistic belief.

The story thus far presented might seem to adhere with an economic mindset, as it seems that statistical discrimination increases overall efficiency by allowing individual employers to maximise their individual profits. In a world of imperfect information, statistical discrimination indeed helps to place workers in jobs where their expected productivity is most valued. But statistical discrimination, by holding individuals to group averages that are not always accurate, creates an externality reducing overall economic output and efficiency. Employers are using average product valuations of worker groups, rather than awarding marginal valuations which are necessary for efficient resource allocation. Individual incentives for minority workers can be eroded. In the Aigner and Cain (1977) model, workers are paid a weighted average of their individual predicted productivity and their group average productivity this can lead to poor outcomes. Workers in such a model invest too little in training, because they are not completely remunerated for individual increases in productivity. As Lundberg and Startz (1983) show, statistical discrimination tends to magnify such market distortions. While 'white' workers could be encouraged to receive more training, this can be more than offset by the discouragement of 'blacks' to receive training, similar to the self fulfilling work of Coate and Loury (1993).

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[2] Arrow (1973) derived a theoretical labour market racial discrimination framework using rational expectations and neo-classical theory, however he did not apply his work empirically.

One empirical issue with the Lundberg and Startz (1983) model is that the returns to education are assumed to be lower for 'blacks' than 'whites' while recent literature fails to confirm this. Long (2010) shows that the return to years of education on log of wages has increased more for 'blacks' than 'whites' using NLS data between 1972 and the year 2000. Higher education returns for minority groups contradict the disincentive hypothesis proposed by statistical discrimination but could also reflect changes in the population demographic for 'black' education as the growing gap between pay of skilled and unskilled workers. The stereotypes placed upon 'black' workers are derived from older and less educated cohorts of workers. Modern society has driven the cost of obtaining training down such that more workers, in general, are formally educated. It could be the case that employers are increasingly aware of the productivity signals of 'black' workers, but the fact that wage gaps still exist between equally productive workers from these groups (Long, 2010), suggests statistical discrimination is still present.

Cornell and Welch (1996) show that discrimination can also occur in a multi-cultural setting, even when group characteristics do not differ and 'taste' models are not in effect. The model used implies that employers judge job applicants' unknown qualities better when the candidates are from the same background as the employer. Employers screen candidates under asymmetric information by culture type, broadly defined groups set by language, religious belief, ethnic background, sex or schooling. Their model intuition flows from employer knowledge, they assume that if an applicant is from a similar background to the employer, the employer will be in a better position to gauge the ability of this candidate. It follows that applicants of other backgrounds will more easily be grouped as average ability, allowing those judged to be of high ability (homogenous background) to have better employment outcomes. It is important to acknowledge discrimination can exist on a cultural basis, this idea reflects the struggles immigrants have in finding employment in new countries. Also, the literature outlines that immigrants face imperfect transferability of education credentials as a result of limited information and thus employers place greater risk premiums with hiring immigrants. As a result, on entry, immigrants are often found in jobs for which they are clearly overqualified for and they receive lower remuneration for both their qualifications and labour market experience (Chiswick, 1978; Chiswick and Miller, 2001).

Schwab (1986) investigates the efficiency effects of statistical discrimination. He presents evidence pointing towards allocation inefficiency in labour supply. In his model, workers can choose to work in an individualised market, opting for self-employment, such that individual productivity can be recognised. Workers can also choose to work in a ‘factory’ scenario where only average worker ability is acknowledged. The framework employed exposes a distortion in labour supply. Suppose some workers, who are of high productivity in the factory market setting, inefficiently choose to work in the individualised market in avoidance of receiving an 'average' wage. If factory employers statistically discriminate on group status, the disfavoured group are likely to opt out of factory work and favoured workers are likely to partake. This dynamic can create inefficiency as the number of discouraged workers may outweigh the encouraged. For example, employers may statistically discriminate against women because of their greater labour dropout rates. Following the above logic, women may seek self employment in hope of marginal productivity rewards as opposed to staying in employee positions. However, if men are likely to remain in employee positions, regardless of statistical discrimination (more inelastic labour supply), the discouragement of women can outweigh the encouragement of men. Here, statistical discrimination over gender forces high ability females from working in the standardised labour market such that society may be less productive.

In general, the statistical discrimination literature attempts to model the behaviour of employers to account for the wage gaps we find amongst different races and genders. We can also see that statistically discriminating employers create inefficiency in both labour supply and firm output while also discouraging training investments for certain groups. The previous research is not naive. Even when allowing for workers to seek individual productivity compensation a market inefficiency still exists under a statistical discrimination framework. In essence, the issues caused by discrimination surmount to stagnating economic growth. Such repercussions need to be addressed but most of the literature reviewed lacks an empirical testing framework. In order to identify the presence of statistical discrimination, a testing framework needs to validated. The following section will develop the employer learning and tests of statistical discrimination which have been developed by Farber and Gibbons (1996) and Altonji and Pierret (2001). These allow us to gauge whether statistical discrimination is present and which groups are affected.

2.3 Theory of Employer Learning

The statistical discrimination literature reviewed acknowledges the fact that employers will eventually bear witness to the potential inaccuracies of their initial worker categorisation. Whether or not employers decide to change their recruiting behaviour or wage allocation towards those discriminated against is key to avoiding potential market inefficiency. Empirically, it is important to be able to test for the presence of statistical discrimination and hence whether future wage setting and recruiting behaviour reflects any learning. With regard to the literature on testing the employer learning phenomenon, the pioneering work has been done by Farber and Gibbons (1996), and further developed by the likes of Altonji and Pierret (2001) and Kim (2011). The following section examines the alternative frameworks pivotal to testing for employer learning under statistical discrimination.

Farber and Gibbons (1996) present a dynamic model in which education (and other easily observable worker characteristics) are used by firms as an initial signal about a potential employee's innate ability or productivity. The employee assessments are modelled by wage expectations conditional on the observable characteristics and could contain error. The developed model takes into consideration a series of subsequent observations of worker productivity (performance history) that employers would observe. If these observations invalidate the firms initial assessment, learning can occur. In terms of information, Farber and Gibbons (1996) assume a 'public learning' model, where all the observed worker outcomes by the current employer are also observed by all market participants such that performance history can carry over and worker assessments will become more accurate with greater experience. These assumptions are foundational to all of the employer learning literature and subsequent work tends to build on this specification. The data in their study comes from the National Longitudinal Survey of Youth (NLSY). The derived model considers two types of variables that affect productivity; an easily observable and possible discriminated upon variables such as schooling (SCH) or race, and secondly, variable (AB) is used as a proxy for workers' unobserved ability characteristics. Armed Forces Qualification Test (AFQT) scores and possession of a library card at age fourteen are used as AB variables. The key to their specification is the prediction that the partial effect of education on earnings is independent or even declines with the labour market experience of a worker. The following model is estimated:

$$\text{Ln } W = \beta_1 SCH + \beta_2 AB + \beta_3 (SCH*EXP) + \beta_4 (AB*EXP) + H(t)$$

(FG.1)[3]

Theoretically, the model implies that the estimated effect of schooling on the level of wages should be independent of worker experience; the coefficient on an interaction between schooling and experience will then equal zero. Farber and Gibbons (1996) propose that as employers observe worker productivity, on average it will confirm their initial assessment of the relation between expected productivity and the educational attainment for new labour market entrants thus the coefficient will equal zero. Also, the model predicts AB variables should be increasingly correlated with wages over an experience profile. The ability variable is assumed to be correlated with worker productivity, increasingly attributed to determining wages as education signals become irrelevant. Technically, in order to observe the relationship between ability and wages over the experience profile of a worker, an interaction between the AB variable and experience is introduced. In essence, this variable captures the 'employer learning' effect if wages are increasingly related to the ability measure.

The framework constructed by Farber and Gibbons (1996) allows one to empirically determine whether employers wage setting behaviour adjusts in accordance to what they actually observe. However, statistical discrimination is not investigated. Altonji and Pierret (2001) build on this foundational work and additionally implement an actual test for statistical discrimination. The point of difference being SCH and AB variables are allowed to be correlated with each other, this means that SCH is informative about AB. This assumption controls for the experience profile of the effect of all of AB, not just the part of AB uncorrelated with SCH, on wages such that that this alters the interaction between experience and SCH. It is shown that if SCH and AB are positively correlated then statistical discrimination implies that the coefficient on SCH will drop with experience and the interaction between SCH and EXP will enter with a negative sign. Also, a logarithm wage function is implemented such that level independent variable coefficients represent percentage

[3] Note: H(t) is the experience profile of a worker (first or higher orders of experience) and is crucially assumed to be independent of all other variables (defined such that it fully captures the effects of on-the-job training). Also, EXP is the variable measuring worker experience.

point changes in wage. The Altonji and Pierret (2001) specification allows one to test for both employer learning and statistical discrimination, the present research aims to identify statistical discrimination and will thus adopt a similar framework.

Altonji and Pierret (2001) use the same equation as Farber and Gibbons (1996) for estimation, and this same specification will be adopted for the present thesis.

$$\text{Ln W} = \beta_1 SCH + \beta_2 AB + \beta_3(SCH*EXP) + \beta_4(AB*EXP) + H(t) \qquad (AP.1)$$ [4]

Altonji and Pierret are able to derive three propositions from their theoretical work to test for the presence of statistical discrimination within a dataset and whether employer learning is taking place.

Proposition 1: The estimated effect of SCH on LnW should be non-increasing in labour market experience, with schooling entered in the equation both in level form and interacted with experience. On the other hand, the estimated effect of AB on LnW should be non-decreasing in labour market experience. Also AB is entered as a level and with an experience interaction.

The interaction between SCH and EXP is non-increasing because an observable variable (SCH) will get less of the credit for an association with worker productivity over time as, initially, AB is unobserved by employers but SCH is easily observed. However, given that SCH and AB are correlated, when that unobserved variable (AB) is present in the wage equation, it will claim the credit over time (Altonji and Pierret, 2001). The same logic explains an increase in the return to the unobserved ability variable over time.

Proposition 2: If employers have full information about the productivity of new employees or employers do not learn over time, then $\beta_3 = \beta_4 = 0$. When either of the above cases are true, then both schooling and ability variables will not change with experience and the proposed interaction terms (from proposition 1) will have coefficients equal to zero.

[4] Note: SCH, AB, EXP and H(t) represent schooling, ability, experience and experience profile variables respectively.

Proposition 3: Altonji and Pierret (2001) also propose that: $(\partial \mathrm{LnW}/\, \partial \mathrm{SCH})/\, \partial \mathrm{EXP} = -\theta((\partial \mathrm{LnW}/\, \partial \mathrm{AB})/\, \partial \mathrm{EXP}))$.

Firstly, this implies that the effects of schooling and ability over time are related by θ, which represents an auxiliary regression of AB on SCH. Also, this implies that the effect of learning on coefficient β_3 has two components. One comes from the relationship between SCH and AB, which is captured by θ, the other is due to the fact that employers gradually learn about AB.

The specification presented in equation AP.1 will form the basis of our employer learning under statistical discrimination model, the current thesis will apply this to the New Zealand segment of the Adult Literacy and Life Skills (ALL) survey dataset. In order to detect the presence of discrimination over certain minority groups and whether employers learn, a similar framework will be applied to what has be described above. The exact specifications used will be further explained as they are implemented in chapter 4.

In terms of replicating Altonji and Pierret's (2001) work, it is important to note that their propositions about the signs rely on the assumption that the effect of on-the-job training and other complementary interactions between education and ability are fully captured by the experience profile, such that on-the-job training has no effect on the time paths of SCH and AB. However, if more educated and more able workers tend to receive more training, it is possible that both coefficients are positive (Bauer and Haisken-DeNew, 2001). To mitigate this problem, researchers include dummy variables which indicate whether the worker has ever received on the job training. However this dummy would not be sufficient to remove all the effects of human capital accumulation on the time paths of returns to schooling and ability. With respect to this effect, bold conclusions of statistical discrimination must be treated with caution.

The testing methods described thus far involve scarcely available information such as the productivity test scores of workers. Also, the analysis has only studied the wage setting behaviour of workers and neglected the employment decision. Statistical discrimination over minority groups may inhibit worker employment as well as wages. Kim (2011) develops a test that does not rely on these specific variables and can be performed with simple employment status data. Experience, together with the variables which are normally discriminated upon, such as race, gender and education are also required with Kim's specification. The theoretical model of Kim suggests that unemployment rates for the discriminated groups can capture both statistical discrimination and employer learning, with testable implications for employment rates. When employers statistically discriminate, the discriminated group's unemployment rate will be larger than the non-discriminated group's unemployment rate at the time of labour market entry (proposition 1). The theory of statistical discrimination, accompanied by the employer learning hypothesis, predicts that the discriminated group's unemployment rate will decrease at a faster rate than the non-discriminated group's unemployment rate as workers become more experienced (proposition 2). Kim estimates the following specification, where the variable OBS is a vector of easily observable variables such as race, gender and education, Y is a dummy variable for employment status, equal to one for the employed and zero otherwise, and EXP is labour market experience.

$$Y = \beta_1 OBS + \beta_2 OBS*EXP \qquad \text{(SK.1)}$$

Empirical findings support statistical discrimination on the basis of race and education. The test, however, is not suitable for the case of gender discrimination because gender-specific labour force participation decisions affect female employment rates. Kim also compares high school graduate workers with university graduate workers; it is found that less educated workers and African American workers face initially worse labour market employment opportunities but the employment rates do improve with learning. As an extension of the Altonji and Pierret (2001) model, it seems Kim's work (2011) would provide additional evidence and support for any endeavour to find the effects of statistical discrimination. For these reasons, the current thesis will apply Kim's specifications (2011), using employment status, as a robustness check against the sample selection bias associated with wage analysis of only an employed group, after estimating wage specifications.

2.4 Evidence of Employer Learning

Literature using the employer learning framework has emerged in a variety of contexts and augmented to capture specific nuances. Empirical evidence of employer learning found in the

US, Germany and Britain is presented below along with alternate testing specifications hoping to find the speed and type of learning along with the importance of specific skills in the screening process.

Farber and Gibbon's (1996) find that the estimated effect of education on the wage level is approximately 9%. However, there is no conclusive or significant indication that the impact of education varies with labour market experience and thus the results do not present any evidence towards statistical discrimination. Secondly, the estimated coefficients on the interactions between test score and experience, as well as between library card and experience, are statistically significantly and positive: 0.1848 (0.06) and 0.6169 (0.192), respectively.[5] This is consistent with the prediction of the learning model. The reason is that the initially unobserved information which is correlated with the ability of the workers will have an increasingly positive effect on the wage as experience accumulates.

Altonji and Pierret (2001) present evidence suggesting that employers learn about productivity. The coefficient on education interacted with experience variable is estimated at -0.0032 (0.0094) indicating that wages are less driven by education over the experience profile and thus statistical discrimination is present. Moreover, the coefficients on AFQT and AFQT interacted with experience at -0.0060 (0.0360) and 0.0752 (0.0286) respectively, imply that the return to an individual's unobserved ability will increase over time. They further present evidence on statistical discrimination on the basis of education. When AFQT*experience is added into the equation, the coefficient on education*experience becomes more negative. It drops significantly, from -0.0032 (0.0094) to -0.0234 (0.0123). Discrimination over race is also explored, 'black' workers are found to be statistically grouped but it is inconclusive as to whether employers learn over time.

The employer learning specifications used above all assume that all employers learn at the same rate and information is equally available. Schonberg (2007) considers this to be symmetric employer learning but also considers asymmetric employer learning where current employers are assumed to have superior information about the productivity of their employees than the rest of the market. He argues that the type of learning has important consequences

[5] Note: Standard errors are recorded in parentheses.

mainly in terms of statistical discrimination as productivity signals will have much longer lasting implications as opposed to symmetric learning. The methodology adopted to distinguish between the types of learning involves using the same tests as Altonji and Pierret. If both ability and education variables have the same impact on wage offers from incumbent and outside firms a learning is symmetric. However, if ability has greater effect (and schooling weaker) for incumbent firms, he argues this shows that incumbent firms are better informed thus learning is asymmetric. Introducing tenure as the measure of experience, within the standard interaction terms and controlling for actual experience interactions as well, allows Schonberg to compare the offered wages from both incumbent and outside firms. using the same dataset used by Altonji and Pierret. His results suggest that learning is mostly symmetric but the results for college graduates are potentially consistent with an asymmetric learning model. Galindo-Rueda (2003) also adopts the asymmetric learning approach, providing evidence towards incumbent employers having greater learning prowess over blue collar workers within the British labour market.

Arcidiacono, Bayer and Hizmo (2010) split the education variable into two groups, college graduates versus high school graduates and proceed to argue that attending college plays a direct role into revealing productivity to employers. Their results suggest that having college education allows individuals to completely reveal their own ability to the labour market as returns to ability for this group are large upon entry to the labour market and do not change with experience. This leads to zero employer learning for college graduates. However, the measured ability returns for high school graduates rise steeply from near zero with labour market experience, suggesting that employers receive much weaker signalling from such qualifications. The authors proceed to explain racial gaps with this finding, as 'blacks', with equivalent test scores, are found to earn relatively more than 'whites' in the college market but up to 10 percent less with high school education. If employers have imperfect information when dealing with high school graduates, it is more likely they will discriminate against race and this finding is consistent in explaining the fact that 'blacks' obtain more education than 'whites' (Johnson and Neal, 1998). Understandably, facing wage penalties in the high school labour market, 'blacks' would seek higher education to better signal their ability to employers.

Besides type of learning being considered, the previous literature has also delved into whether the employer learning process depends on the type of skill being learned as well as the importance of that skill. Light and McGee (2012) separate skills into various types and propose that some simpler skills such as language skills may be easily signalled to employers through an interview process but more intricate skills such as the ability to find patterns of numbers quickly might only be revealed over time. The importance of the skill is also considered. If a particular skill is critical to job performance it could be that employers cultivate their screening process around that particular skill. Their results demonstrate that employer learning varies across skill types and across education type, similar to the work of Arcidiacono et al. (2010). The effect of skill importance is found to be relevant depending on skill types. For some skills screening increases and learning decreases in skill importance and vice versa for other types. It can be understood that the nature of job and type of skills involved heavily affects the role of employer screening. The relevance of statistical discrimination in terms of market inefficiency is an important question to address. Clearly employers do learn about their initial judgement mistakes and correct employee wages but the speed of this process determines how badly the market will be inhibited.

Lange (2007) investigates the speed of employer learning by first creating a framework of estimating speed and and estimates the actual speed of employer learning using 1979 NSLY data. It is suggested that employers do learn quickly as he estimates that, on average, it takes 3 years for the initial misjudgement to decline by 50 percent. The faster employers manage to accurately compensate workers, the less the damage will be done in terms of market inefficiency, labour supply distortion and disincentive for human capital acquisition.

Bauer & Haisken-DeNew (2001) replicates, the previously discussed, US employer learning studies using a large German panel data set. In contrast to the existing empirical work for the US, the evidence of this study finds employer learning insignificant for Germany when using the basic specification defined in the existing US literature. The results reveal the usual positive relationship between education and wages with the interaction variable between own education and experience entering positively and significant, suggesting that the effect of education on wages increases with experience. This result is inconsistent with previous literature as it should have a negative coefficient. When employers initially statistically discriminate over the workers observable education credentials but wages are decreasingly related to education as ability information becomes available. When the interaction variable between parents' education and experience is added, the usual effect of unobserved ability on wages increasing with the labour market experience is found. However, since the interaction term between education and experience is positive, the statistical discrimination hypothesis is not justified. Bauer & Haisken-DeNew then splits the sample into blue collar and white collar workers. It is revealed that employer learning does indeed take place for blue collar workers but not at all for white collar workers. A very simple explanation suggests that firms may struggle to observe the productivity of white collar workers and thus cannot learn about true productivity. Or, this could be due to the nature of the hiring process; employers have sufficient information on the productivity of white collar workers because they invest more in screening for higher paying jobs.

Overall, the previous employer learning literature confirms that employers tend to statistically discriminate over observable worker characteristics when faced with little information. The screening process can be specific in that it searches for specific skills or it can be broader and group workers by education level or race. Workers who have invested heavily in education may see benefits not only through educational screening but evidence has also shown that employers seem to better interpret the productivity signals of college grads leading to more representative wages.

2.5 New Zealand Background

Study into employer learning under statistical discrimination has not been conducted with New Zealand data previously. However, a great deal of literature exists estimating the returns to Mincerian wage models to quantify the wage returns for education and experience variables. Also, wage gaps between genders and for immigrants have been identified and examined.

Boyd (2003) establishes that immigrants are generally more educated than the New Zealand born. Her work suggests that in 2001 24 percent of recent immigrants who had immigrated within the last five years had university qualifications compared to only 10 percent of New Zealand born. Despite this, Winkelmann & Winkelmann (1998) show that migrants are likely to earn lower wages than their native counterparts, estimated to be 20 percent less.

Stillman (2011) uses survey data from the 1997–2009 New Zealand Income Survey (NZIS) to examine the differences in labour market outcomes between immigrant and non-immigrant populations in New Zealand. Specifically, he looks at the differences in returns to human capital for the two population groups and whether the returns vary over time. Stillman (2011) uses regression analysis to estimate the relationship between education and employment, hours worked, and wages for immigrants and the New Zealand born, separately for men and women using the Mincer specification. In terms of results, taking account for education; the average wage for immigrants are 4 percent to 8 percent lower than the average wage for equivalent New Zealand born workers. This gap in wages, is found to be largest among less educated workers, declining as education accumulates. Following the usual immigration literature, Stillman (2011) suggests the found wage gaps occur due to the fact that immigrants, particularly those with less education, have worse job networks, or lower effective human capital (perhaps because of poor language skills), or are subjected to labour market discrimination.

The paper also breaks down immigrant groups to be more specifically defined, allowing for detailed analysis into whether ethnic group characteristic differences lead to different labour market outcomes. Differences in educational attainment are found to explain most of the large employment gap between New Zealand born Maori, New Zealand born Pasifika and New Zealand born Pakeha/Europeans. However, Foreign born Pasifika, Asian-born Asians, Pasifika born Asians and other foreign born, still have lower employment rates than the New Zealand born Pakeha. Stillman's findings suggest that labour market discrimination plays an important role in wage setting among less educated Maori, Pasifika, and Asians in New Zealand.

Previous literature has also examined whether convergence of both immigrant labour force participation rates and wages occurs. Winkelmann and Winkelmann (1998) suggest that immigrant earnings gaps are likely to exist between 10 and 30 years while participation is expected to take between 5 and 15 years for convergence. Stillman and Maré (2009) suggest that the convergence time is dependent on the education level of immigrants. Their findings suggest that those with university qualifications are likely to reach equivalent income levels within 10 years, however the picture is much harsher for unqualified immigrants. Convergence is, for them, expected only after 20 years in the labour force.

Dixon (2000) examines the changes in the gender earnings gap in New Zealand between 1984 and 1998. The shift in men and women skill sets and employment distributions were considered in quantifying the actual earnings gap. She finds that women at all levels of the female earning distribution experienced some growth in real earnings. However, it was found that the earnings of lower paid men declined. Overall, she finds that the wage gap is contracting, mostly attributed to a lack of increase in male wages during the period studied. When studying specific age groups, she finds that younger women also experienced much greater earnings than that of older women. This is an interesting result, it suggests that younger birth cohorts of women enter the labour force less disadvantaged than older women did. This claim is backed with younger women gaining more similarity to their male counterparts in terms of employment rates and paid work patterns. Wage regressions of the change in the male-female wage gap attributed increases in the relative educational levels of women to be responsible for 15 percent of the reduction in the wage gap. A gender gap is still present in the New Zealand labour force, but Dixon (2000) has demonstrated that convergence is occurring with equal compensation a potential future outcome.

Acknowledging that wage gaps have been found in the New Zealand labour market; between immigrants, gender and various ethnic groups presents grounds to examine statistical discrimination. In a modern day labour context, workers of equal productivity deserve equal pay whether they are female or of a minority ethnic background. However, even if these minority groups are being discriminated against, we have seen that employers can learn about their initial mistakes by altering their wage setting behaviour. Because employer learning literature within the context of the New Zealand labour market is non-existent, an application of the Altonji and Pierret framework seems to be justified considering the significant wage gaps present.

3. Data

Imperative to the study of employer learning is the measurement of both observable worker correlates of productivity and, unobserved by employers, worker ability. The Adult Literacy and Life Skills (ALL) survey is an international study, involving 12 countries, and the survey collects information about the participants' literacy, numeracy and demonstrated workplace ability. This is measured through their problem solving skill and aptitude with information and communication technology. The ALL survey also collects information needed for labour market analysis such as wage data, household characteristics and schooling information. The relationships between the individual skill level, human capital and wage can be examined with this data set, making it relevant to the study of employer learning.

This thesis uses data from the New Zealand component of the ALL Survey which had been collected between May 2006 and March 2007. The survey collected data from an area based representative sample of 7,131 respondents aged between 16 and 65 with a response rate of 64 percent. One eligible member from each randomly selected private household was arbitrarily chosen to partake in the face to face interview. In terms of individual characteristics, information has been collected on: the individuals residence, education, immigration status, language skills, parental characteristics, labour force activities, literacy, work place training, social participation, health, proficiency with information and communication technologies, household characteristics and many measures of individual income and wage (Barrett, 2012).

In order to undertake our human capital analysis, measuring years of education, years of experience and cognitive ability will be required. Education is easily defined as the ALL survey asked each respondent about the number of years of formal education in which they had partaken. Experience proves to be more difficult as no measure of actual is experience is collected. For the purposes of analysis, the variable potential experience is created (age-schooling-5) as is standard with labour market literature.[6] The lack of experience measures collected from the ALL survey represent a potential weakness of the data set in comparison to the NSLY data used by most of the international employer learning literature. Farber and Gibbons (1996) are able to use longitudinal information to precisely determine when workers

[6] Note: in general New Zealanders' start school at age five, thus our potential experience calculation accounts for this.

made their first long term transition into the labour force thus can accurately compute actual labour force experience. A measure of potential experience assigns the same amount of experience to workers of the same age and educational status even though their working histories may be completely different. However, actual experience is an outcome measure in itself as the intensity of work experience, not just quantity, may be conveying information to employers about worker quality. Altonji and Pierret (2001) decide that actual experience must be treated as an endogenous variable and investigate the effects associated with the experience terms through actual experience instrumented by potential experience. The ALL data does allow accurate measures of workers tenure [2007-(job start date)]. This variable will be used both separately and in conjunction with the potential experience variable to capture additional worker experience characteristics. Specifications including tenure and potential experience both together and separately will be used in order to extend our experience measures beyond just potential experience.

It is easily understandable that women have different labour force participation cycles due to reasons such as child rearing (Stillman, 2011) prohibiting comparisons of male and female potential experience measures. Women tend to take breaks from the labour force for child rearing and will have comparatively less tenure and experience than men. For this reason potential experience is likely to be a more accurate measure of actual experience for men but using tenure measures can be also useful to in capturing the effects for women. Analysed in separate gender groups, the relative comparison of potential experience within the female sample will hold more validity as similar measurement bias affects each observation. For these reasons, some of the analysis will focus on male and female groups separately.

The ALL survey assesses four main literacy skill domains (Barrett, 2012).These domains are:

1. **Prose Literacy:** the ability to understand and use various kinds of information from texts including editorials, news stories and instructions manuals.
2. **Document Literacy**: the ability required to locate and use information contained in various formats including job applications, transportation schedules, maps, tables and charts.
3. **Numeracy:** the ability required to effectively manage and respond to the mathematical demands of diverse situations.

4. **Problem Solving**: the ability required for goal-directed thinking in situations for which no routine solution procedure is available.

Collectively, the assessment tasks used were representative of workplace situations. The tasks in each domain drew on cognitive skills used in work place activities, defining the skills measured as demonstrated ability as opposed to innate ability. The exercises used for assessing prose literacy ranged from reading product labels to dissecting information from company memorandums. In terms of document literacy, tasks included reading simple price charts and deriving information from complex consumer magazines. Numeracy ranged from simple arithmetic to more difficult compound interest calculations and problem solving skills involved respondents being faced with real-life projects and working through various logistics. These measures do not equate to the pre-employment skill measures adopted in previous work through AFQT scores (Altonji and Pierret, 2001); the ALL measures are designed to capture workplace ability and could be positively related to tenure and experience. The employer learning model adopted by Altonji and Pierret (2001) assumes that the experience profile is independent of all other measured variables including worker ability. This could add a positive bias over the employer learning tests.

The Main Task Booklet was used to assess these domains and, due to time constraints, each participant received a booklet containing two, out of a set of possible eight, blocks of questions with each block assessing a single skill domain (Barrett, 2012). The ALL survey generated five proficiency scores in each domain for each respondent, as each set of questions allocated had been representative of the entire set of questions. The generated values can all be considered equally valid estimates of the respondent’s skill level.

Proficiency, in each domain, is measured along a continuous scale ranging from 0 to 500. However, as is standard when dealing with test score literature, the proficiency scores have been standardised, [(prose score-mean)/standard deviation of prose score], to ease the interpretation in the following regression analysis. It is also notable that each domain of ability cannot be interpreted as an individual component of skill such that there could be validity in conclusions of particular expertise in one domain significantly affecting wage returns. The literacy scores across the four domains are highly correlated, thus each score within each domain can be considered an equally valid representation of the participant's ability. To reduce the computational demands associated with separately regressing each model with each different test score, the first plausible value reported for prose literacy is used and standardised for the purposes of creating the ‘cognitive ability’ variable. This approach is adopted from Barrett (2012), as he justifies that prose ability can be considered as valid as each other domain in measuring 'cognitive' ability.

The ALL survey uses multiple mechanisms to gauge participant income. Wages have been computed from a series of questions asked, resulting in the hourly wage (before taxes). As we are dealing with returns to variables such as education; hourly return provides the most interpretable unit. The ALL survey allowed pre-tax income to be expressed in nine different ways such as: per hour, per day, per week, per year, etc. Therefore necessary steps were taken to convert each of these into hourly wages by using the unit in which wage was specified and dividing this by the reported amount of hours worked during that unit, until an hourly wage return has been extracted. In order to minimise missing wage observations, those who were missing wage measurements after completing the process mentioned above, were allocated wages from the information collected through a series of annual personal net income estimation questions. Observations still missing wage values after these processes or missing other key information were then set to missing. Income from any other source such as rent or dividends have been excluded to allow for direct comparisons between education and income from wages or salary.

The analysis conducted will be restricted to the adult population aged between 25 and 64 in order to exclude students and those near retiring. Only those who were employed at the time of the survey and earn income from wages and salary are included with those reported as only earning income from self-employment being excluded. The studied sample excludes self-employed individuals from the analysis as is standard in papers looking at returns to human capital, because their wages are often difficult to measure (Stillman, 2011). Those reporting an hourly wage of greater than $500 have also been excluded to eliminate any bias from positive measurement error. As a result of these restrictions, the sample size of this analysis is 4162 with 1050 (25.23%) of whom are foreign born. This sample is comprised of 2006 men and 2156 women.

3.1 Descriptive Statistics

Table 1 provides the means and percentages for all of the variables used in the regression analysis including wages, ethnicity, potential experience and standardised ability. [7] The average age of the employed sample was 43.29 years which remained relatively constant across both genders as can be seen in Table 1. The ethnic composition of the employed sample was dominated by New Zealand Europeans making up 72.15 percent of the total sample size with 6.36 percent Maori, 3.57 percent from the Pacific Islands, 8.32 percent Asian and 9.59 percent a variety of other ethnicities not fitting in the above groups. Looking at total education, measured in years of schooling, the employed sample have approximately one year more education than the non-wage/salary employed group on average which is 7.1 percent more schooling. It is also found that on average, foreign born workers have 8.85 percent more schooling than native born sample.[8] Immigrants having greater levels of formal education which is similar to what had been found by Stillman (2011), where he found immigrant men to have an average of three to six months more education than their New Zealand counterparts. The wage gaps are also confirmed with men earning 15.1 percent more than women in general and New Zealand born workers earning 6.1%, or one dollar and 50 cents more per hour than their foreign counterparts.[9]

Table 2 presents detailed information about the schooling characteristics of New Zealand born; allowing us to compare schooling levels between ethnicities and genders. Interestingly, examining the total number of years spent within formal education, we can see that males and females share very similar mean levels of education with females found to have 0.43 percent lesser education than males. In terms of ethnicity, the Asian and the 'Other' group are the most educated groups with Maori and Pacific Islanders being less qualified than the New Zealand Europeans. When looking at the highest level of qualification attained, the 'Other' group are found to have pursued the greatest level of qualification with 3.46 percent of them reaching PhD level as opposed to 0.73 percent of New Zealand Europeans. The Maori demographic

[7] Note that both Tables 1 and 2 as well as all of the figures presented in this descriptive section use the population weight variable (POPWT) created with the ALL data. This adjusts survey population estimates according to known population totals. I considered using population weights for the regression analysis as well, but since the following analysis controls for the variables which enter the weighting formula, specifically gender, age and ethnicity, weights are unnecessary and lead to potentially less efficient estimates than when just controlling for variables that enter the weighting formula.
[8] See Table A.1 comparing the mean levels of education between immigrants and NZ born found Appendix A.
[9] See Table A.2 containing the average wages for New Zealand born and immigrants found in the Appendix A.

appear to be the least qualified with only 10 percent attaining any University level qualification.

	Table 1:Means and Percentages of Variables Used in Multivariate Analysis								
Variable	Not Wage/Salary Employed			Employed but Wage Missing			Employed		
	Pooled	Female	Male	Pooled	Female	Male	Pooled	Female	Male
% Employed	5.39	5.13	5.97	100.00	100.00	5.97	100.00	100.00	100.00
Male	30.75	0.00	100.00	48.25	0.00	100.00	53.82	0.00	100.00
Age	43.61	42.59	45.89	4503.19	45.27	45.89	43.29	43.36	43.22
NZ European/Pakeha	59.96	60.48	58.79	65.74	69.56	58.79	72.15	73.72	70.81
Maori	9.83	9.86	9.75	3.91	5.36	9.75	6.36	6.15	6.55
Pasifika	6.60	6.79	6.19	1.79	1.74	6.19	3.57	3.10	3.97
Asian	13.30	12.93	14.12	13.10	10.94	14.12	8.32	7.53	9.00
Other	10.31	9.94	11.15	15.46	12.39	11.15	9.59	9.50	9.67
Wage	-	-	-	-	-	-	24.17	21.96	26.07
Total Education Years	12.95	12.90	13.05	13.95	13.58	13.05	13.93	13.90	13.96
Potential Experience	25.66	24.69	27.83	26.08	26.69	27.83	24.36	24.46	24.26
Standardised Ability	-0.29	-0.20	-0.49	0.15	0.05	-0.49	0.18	0.25	0.11
Tenure	-	-	-	8.25	7.77	8.77	7.61	6.66	8.42
Foreign born	31.28	31.95	29.79	29.88	22.35	29.79	25.23	23.73	26.52
YSM	5.28	5.34	5.13	5.05	3.27	5.13	4.48	4.23	4.70
Sample size (n)	1497	1096	401	301	174	127	4162	2156	2006

Notes: Table 1 includes both immigrants and New Zealand born participants. A population weight (POPWT) has been applied to Table 1. Also, PG stands for post graduate.

Table 2: Highest Level of Educational Attainment for New Zealand Born by Gender and Ethnic Group

Education Level	Entire Sample	Female	Male	NZ European	Maori	Pasifika	Asian	Other
Up to Year 11	23.55	25.56	21.77	23.08	30.89	17.18	19.802163	18.11
Year 12 or 13	14.04	14.71	15.09	13.91	16.03	24.17	0	6.85
Level 1, 2 or 3 Certificate	14.87	12.56	19.00	14.11	22.59	26.04	13.538329	8.37
Level 4 Certificate	11.97	5.82	19.59	11.83	10.57	9.16	18.423169	25.61
Level 5, 6 or 7 Certificate	13.62	18.58	10.34	14.20	9.93	4.06	0	12.75
Bachelor Degree	10.57	10.28	12.16	10.88	6.43	12.09	6.3305947	14.38
Professional Degree	2.38	2.42	2.63	2.56	0.13	0.79	13.200804	3.09
Bachelor Degree (Honours) or PG Diploma	5.68	7.08	4.98	5.94	2.46	1.24	28.704942	5.90
Masters Degree	2.61	2.62	2.91	2.76	0.97	5.27	0	1.48
PHD	0.71	0.38	1.13	0.73	0.00	0.00	0	3.46
Years of Total Schooling	13.93	13.9	13.96	13.79	12.53	12.68	15.46	15.08
Sample Size (n)	3172	1494	1678	2794	266	41	12	59

Notes: This Table includes only New Zealand born participants. A population weight variable has been used in calculating Table 2.

Figure 1: Gender comparison of the relationship between standardised prose ability and education level for New Zealand born Pakeha

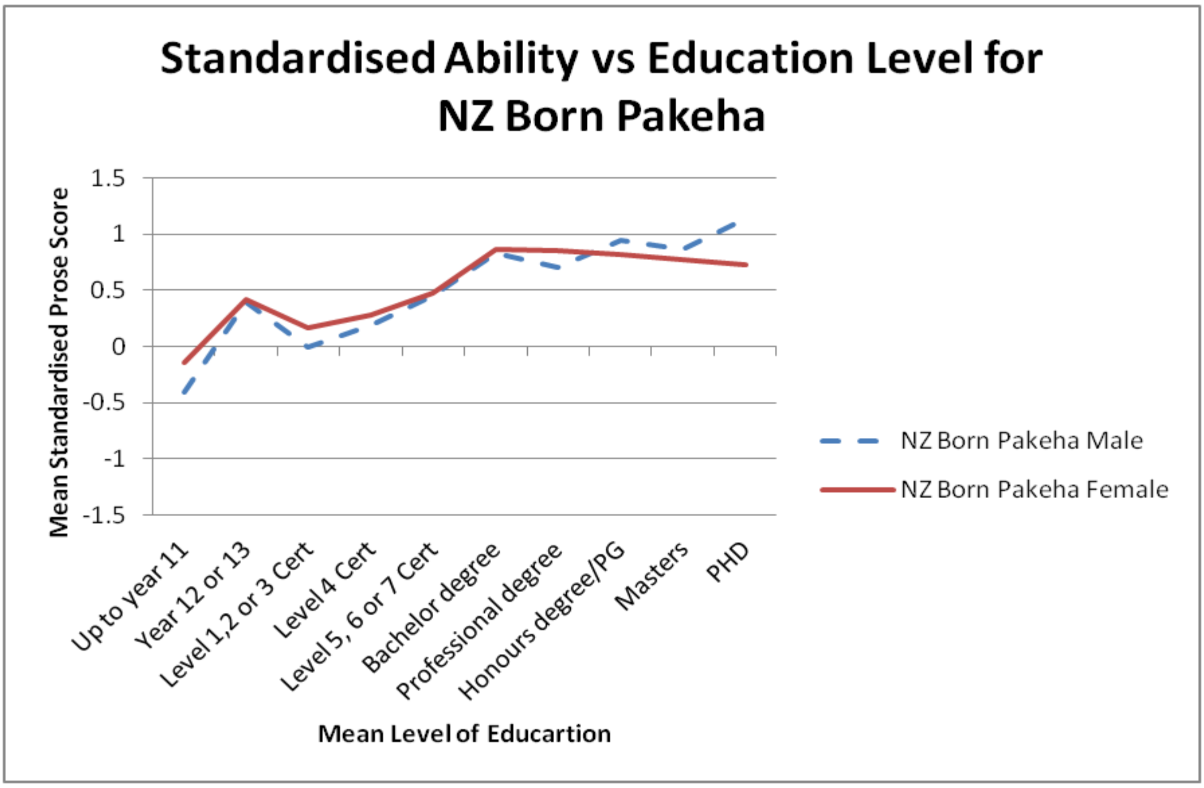


Figure 1 portrays the relationship between level of qualification attained and standardised prose ability for New Zealand born Pakeha males and females. As expected, male and female ability is highly correlated across each qualification level. When considering education is used as an ability signal by employers, a positive relationship between cognitive ability and qualification can justify this usage. Figure 1 clearly shows that for men and woman, a participant's standardised prose score is positively related to the level of education they have attained. It can be concluded that figure 1 justifies educational qualifications as an equally good signal of ability for both male and female New Zealand born workers. It is common for higher ability individuals to seek greater levels of education but as the ability measure used in this analysis is workplace ability, a positive relation between education and ability represents the complementary benefits of education. Education directly increases worker productivity through knowledge but it also drives more efficient and sensible workers; adding to other workplace productivity.

Figure 2 and 3 interestingly show that both male and female Maori generally have lower 'skills' than Pakeha at all levels of education except for Maori females with Post-Graduate degrees, also the difference is relatively consistent. The difference found here could reflect different quality of schooling or different post-school experiences for the Maori population. Considering the measure of ability used is standardised prose score, it is possible that language barriers could account for the lower scores collected amongst the Maori sample. However, when the numeracy scores collected by the ALL survey are used for the same comparison; we find the same results.[10] Each of the ALL survey testing domains requires a certain level of English ability in order to score well, as they aim measure demonstrated work force ability. Maori who are less competent with their English will find each domain equally as difficult, not specifically the prose score testing.

The same explanation can be used to explain figures 4 and 5, where again, we find that New Zealand born Pakeha have greater average prose scores, across education levels, in comparison with the foreign born for both males and females. Here, we are considering a pooled immigrant group thus the average level of English language competence is much lower than that of native New Zealanders, which could be inhibiting immigrant proficiency in each of the testing domains conducted by the ALL survey.

[10] See Figures B.1 and B.2 in Appendix B.

Figure 2: Ethnic comparison of the relationship between standardised ability and education level for New Zealand born males

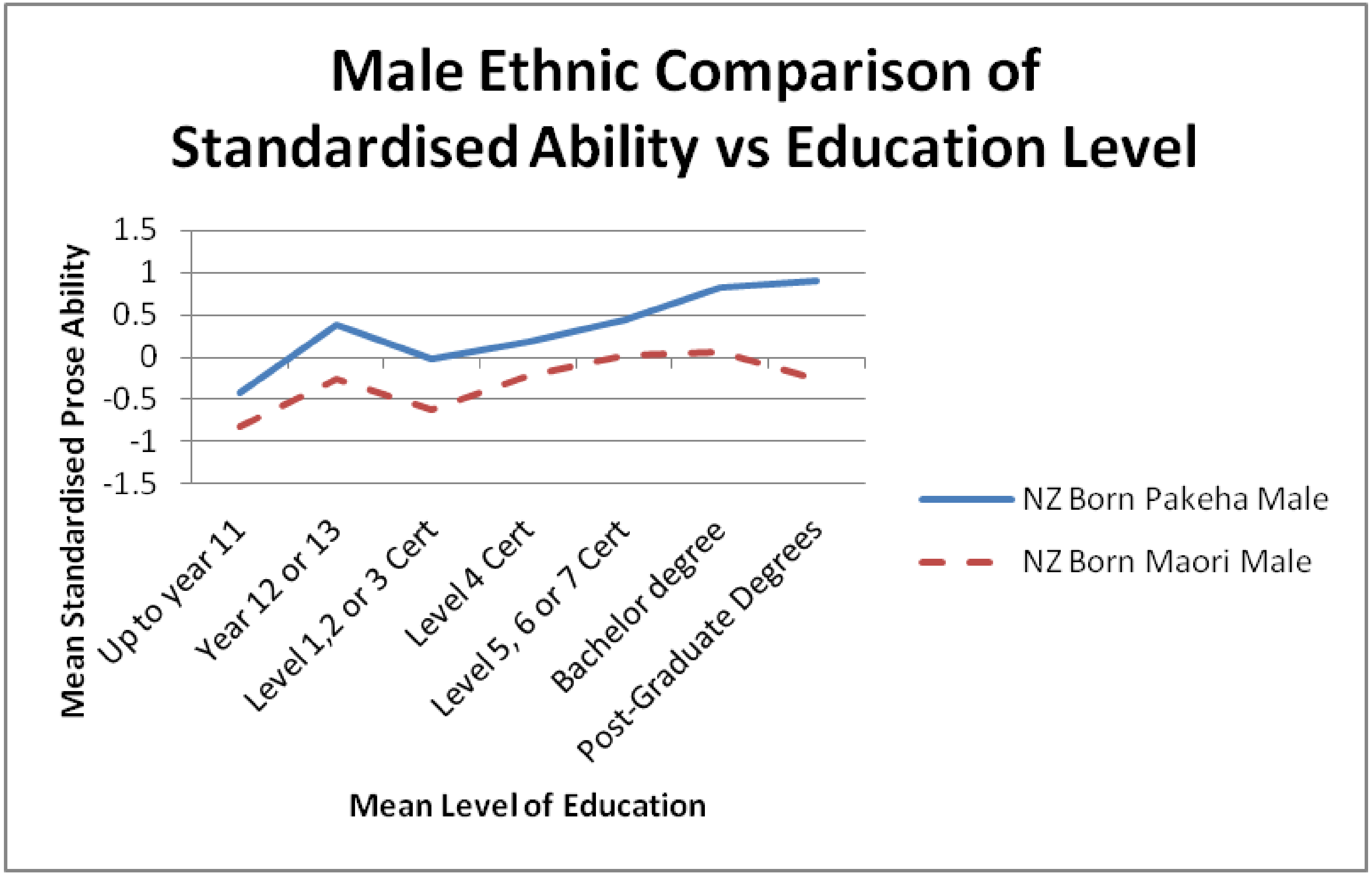


Figure 3: Ethnic comparison of the relationship between standardised ability and education level for New Zealand born females

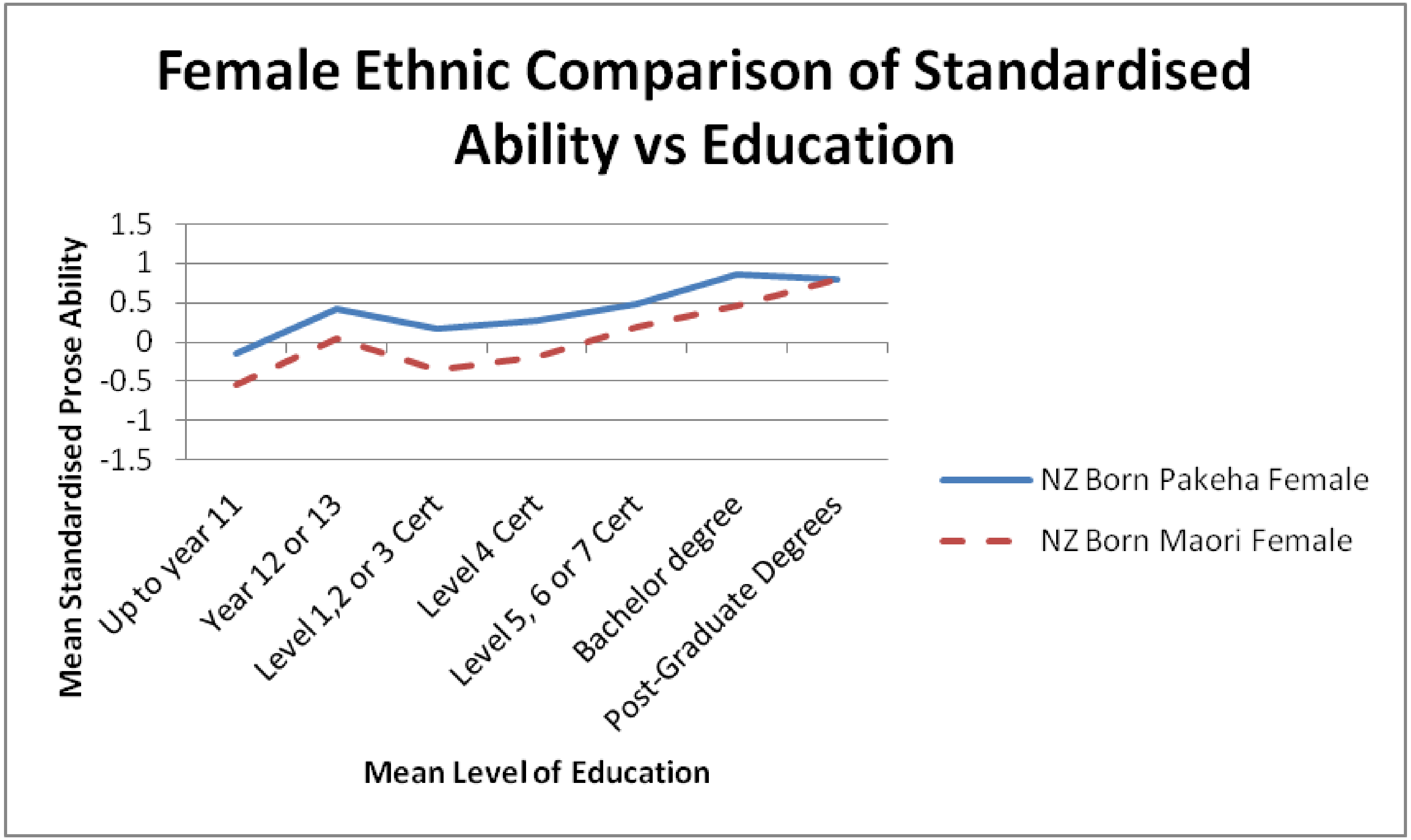


Figure 4: Immigrant comparison of the relationship between standardised ability and education level for New Zealand born males

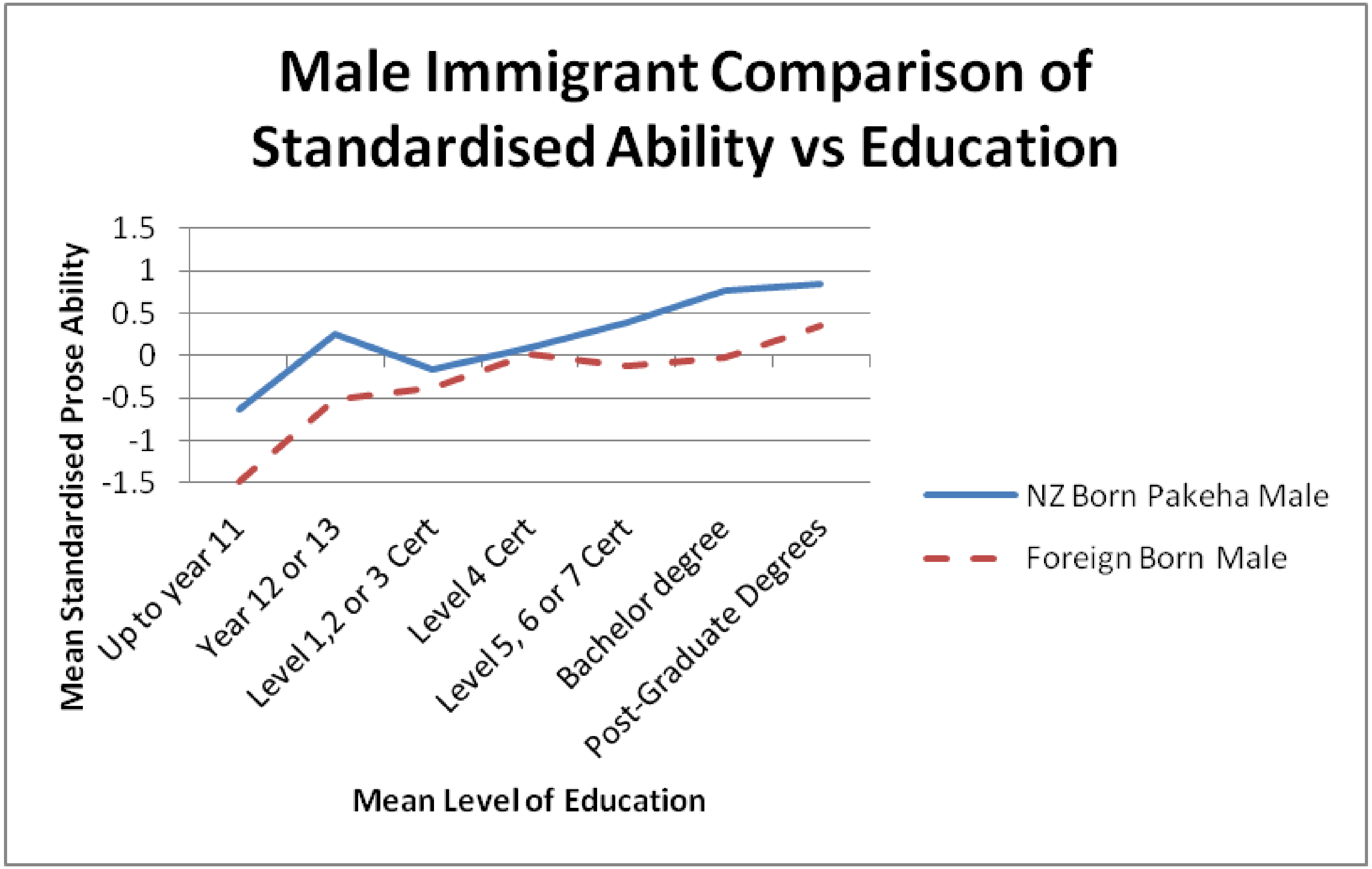
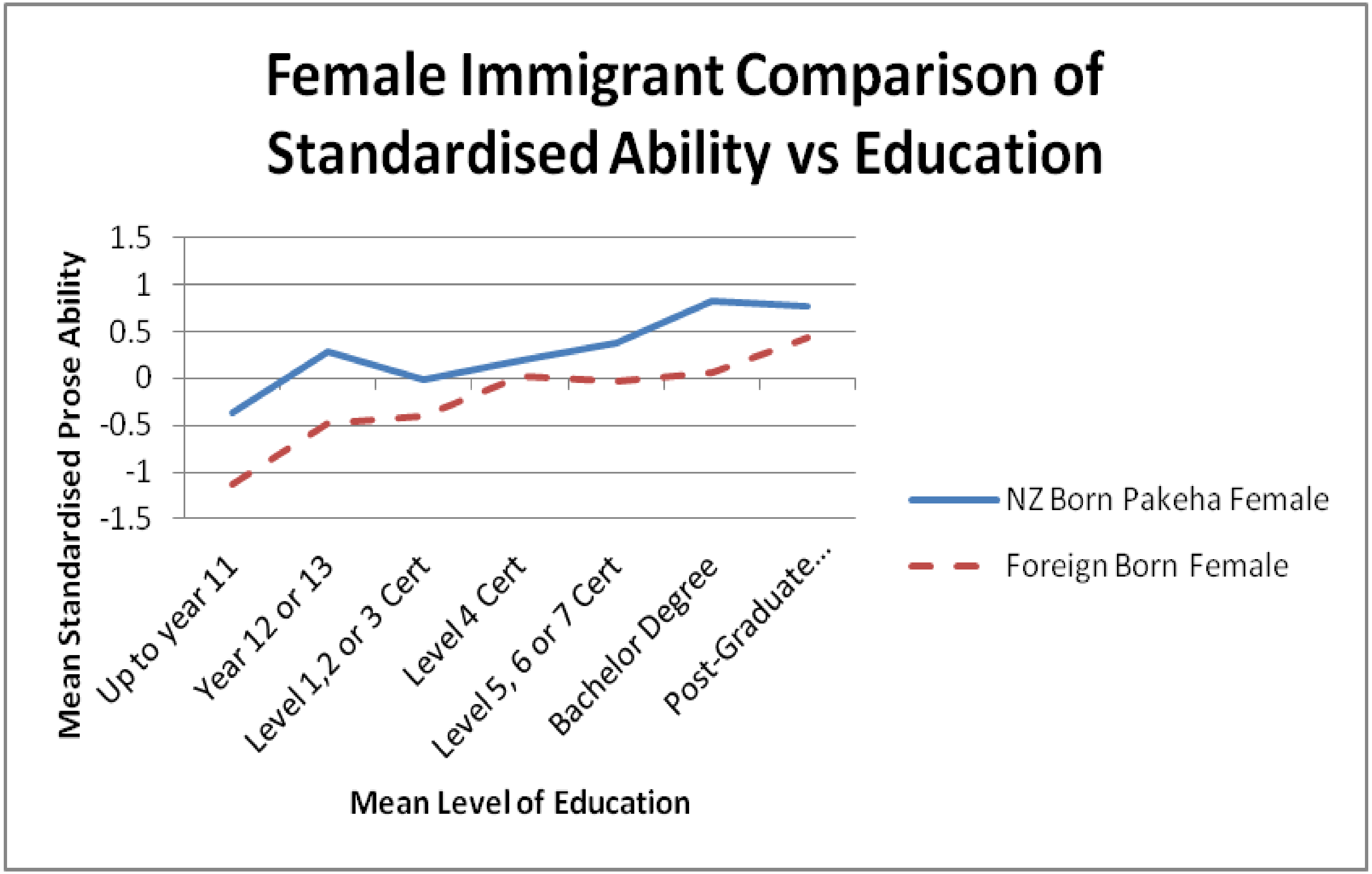


Figure 5: Immigrant comparison of the relationship between standardised ability and education level for New Zealand born females



4. Empirical Model and Results

The ALL data are consistent with previous New Zealand labour economics literature and confirms that multiple wage gaps exist within the labour force. Men have been shown to earn 15.1 percent more than their female counterparts and New Zealand born workers earn 6.1 percent more than foreign born workers. It is also found that New Zealand born Pakeha are earning 20 percent more than New Zealand born Maori, with significant wage gaps present between genders for both the NZ Pakeha and Maori groups (males earning more than females). Recognising such significant wage gaps creates the question of how and why they exist. After delving into the statistical discrimination literature, one may question whether it is in fact employer stereotyping driving the lower wage setting for females, immigrants and Maori within a New Zealand context.

Any work which looks to quantify discrimination between two groups needs to be conducted with care. A multitude of factors dictate wage setting within a labour context and could justify wage differences. The specification established through the work of Altonji and Pierret (2001) basically relies on the information contained within measurements of employee education, experience and testable ability to derive notions of statistical discrimination. Within a labour force, we have workers of completely different backgrounds, gender and knowledge; assuming level measurements of the generic characteristics of these workers will result in misspecification. In order of gathering meaningful results, analysis must take place such that worker differences are controlled for in a broad to specific manner. Analysis is initially conducted for only the New Zealand born sample as they form the largest group within the ALL survey, also it is plausible that this group have all been subject to more similar levels of education and general nurture than those of different origin. Within the New Zealand born population, previous research has revealed that mean wages for Maori and Pacific Islanders (Stillman, 2011) is very different to that of New Zealand Born Pakeha, thus it makes sense to look at the New Zealand born Pakeha sample for an initial standpoint.[11] The labour force participation cycles of men and women differ greatly, as discussed earlier, women tend to spend large amounts of time absent from the labour force (Stillman, 2011). Conducting

[11] When studying only the New Zealand born Pakeha sample, we are avoiding possible complications involved with other forms of discrimination, such as racial, that are separate from our initial education focus.

analysis separately by gender allows the measurement error of variables such as potential experience, stemming from different labour characteristics between genders, to hold validity and allow for relative comparisons of returns within separate gender groups.

The following empirical analysis will be conducted on New Zealand born wages, similar to the work of Altonji and Pierret, the present thesis will firstly be investigating the impacts of statistical discrimination over level of formal education separately for both male and female workers (4.1). This will be followed with an investigation into possible gender discrimination (4.2) and ethnic discrimination accompanied with being of Maori origin (4.3). Lastly, we this chapter will examine any statistical discrimination over immigration status in wages (4.4).

4.1 Statistical Discrimination and Employer Learning over Education

While maintaining the crucial assumptions of a competitive labour market and public learning across all firms, as is standard with the Altonji and Pierret model, the first part of estimation focuses on the role of education and experience in a wage function. That is, education level (ED) is used as an easily observable characteristic and adding the experience (EXP) quadratic into the estimation equation to capture the phenomenon of diminishing return to experience. The experience coefficient is expected to be positive and the experience square coefficient is expected to be negative.

Before beginning the empirical analysis, it is important to understand that our sample is not randomly selected as only the market wage rate for employed individuals is observed. The estimated results in this section only capture the wage differences among working people rather than the wage rate they could earn if employment status decisions were included that determine labour force participation. Kim (2011) deals with this issue by using an employment independent variable to test for discrimination and employer learning behaviour associated with employment outcome and the present thesis will include such estimation for robustness purposes in Chapter 5. Specifications will initially only involve potential experience as the EXP variables capture inter-firm experience effects.[12] A secondary model including both potential experience and tenure for level EXP effects, with tenure measures for the interaction terms, will be used to capture intra-firm specific experience effects.

[12] Potential experience is defined as 'age-schooling-5', commonly used throughout labour economic literature.

A total of 5 wage equations will be estimated in looking for employer learning and statistical discrimination amongst level of education for the New Zealand Pakeha sample and will be conducted for both males and females:

(a) $\text{Ln W} = \beta_1 \text{EXP} + \beta_2 \text{EXP}^2 + \beta_3 \text{ED} + v$ (E.1a)

Where v is the random error term and is assumed to be uncorrelated with other variables in the model.

(b) The second step is adding an ability variable (AB) into the estimation:

$\text{Ln W} = \beta_1 \text{EXP} + \beta_2 \text{EXP}^2 + \beta_3 \text{ED} + \beta_4 \text{AB} + v$ (E.1b)

(c) Next, we add schooling interacted with experience to account for the effect of experience over time:

$\text{Ln W} = \beta_1 \text{EXP} + \beta_2 \text{EXP}^2 + \beta_3 \text{ED} + \beta_4 \text{AB} + \beta_5 (\text{ED*EXP}) + v$ (E.1c)

(d) Also, we estimate an equation which includes both the interactions of schooling and ability with experience.

$\text{Ln W} = \beta_1 \text{EXP} + \beta_2 \text{EXP}^2 + \beta_3 \text{ED} + \beta_4 \text{AB} + \beta_5 (\text{ED*EXP}) + \beta_6 (\text{AB*EXP}) + v$

(E.1d)

(e) Lastly, we estimate an equation which includes both the interactions of schooling and ability with experience and an interaction between prose ability and education.

$\text{Ln W} = \beta_1 \text{EXP} + \beta_2 \text{EXP}^2 + \beta_3 \text{ED} + \beta_4 \text{AB} + \beta_5 (\text{ED*EXP}) + \beta_6 (\text{AB*EXP}) + \beta_7 (\text{ED * AB}) + v$ (E.1e)

Our testable hypotheses are as follows, firstly, LnW is non-decreasing in AB and non-increasing in ED. Second, if employers have full information about the new workers' productivity, the coefficients are such that $\beta_5 = \beta_6 = 0$.

4.1.1 Statistical Discrimination and Employer Learning over Education for Males

Table 3 reports the OLS estimates of the specifications noted above in equation E.1 for the New Zealand born Pakeha sample using potential experience as the experience measure and standardised prose score for ability. Throughout the present thesis robust standard errors are used because they do not rely on normality assumptions, these are reported in parenthesis. It is important to note that the coefficients of level variables have a semi-elastic interpretation and interaction variables noted here reflect the slope of the return over time such that an estimate for the variable, Education*Experience, reflects the average return for an extra year of education over the potential experience profile.[13] Marginal effects for the interactions will be calculated, using first differentials, in the following analysis at the 25th, 50th and 75th percentile of the potential experience distributions to add meaning to the interaction coefficients.[14]

In column (1) of Table 3 we can see the returns for a basic Mincerian wage model are as expected, with the estimate on Potential Experience found as positive (approximately 2.98 percent point increase in wages for first year of potential experience) and statistically significant. It is consistent with concavity of the experience profile as the squared experience term has a negative coefficient and these findings are regular throughout Table 3. These estimates conform to what is found in previous labour economic literature (Mincer, 1974); as an individual's wages increase with years of potential experience at a decreasing rate, reaching a peak return at approximately 33 years ((∂LnW / ∂Poten Exp = 0.0298 – 0.000904t = 0). The marginal analysis shows that the wage return for an extra year of potential experience at 12 years of potential experience is 53 percent smaller than the return received for an employee's first year of potential experience. The implied return to an extra year of education is approximately 7.47 percent for New Zealand born Pakeha males, which is slightly smaller than the return found by Stillman (2011). Interestingly, comparing the standard human capital returns from the NZ Pakeha male sample with the ALL data and the Australian labour force work conducted by Barrett (2012); the New Zealand returns are very similar for education but returns to experience follows a different profile.[15] Barrett (2012) finds the marginal effects to experience to be 0.011, 0.00828 and 0.00542 at 12, 22 and 33 years of experience respectively, indicating that returns for men with very high levels of experience are greater in the Australian labour force.

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[13] Because the dependent variable in the regression model is log hourly wage, these coefficients can be converted to percent changes using the formula: percent change =100*[exp(coefficient) – 1]. This formula is applied throughout the thesis.
[14] For the experience distribution, the 25th, 50th and 75th percentile represents 12, 22 and 33 years of potential experience respectively.
[15] Barrett estimates a standard human capital model including only education and an experience quadratic for males, the coefficient for education is estimated at 0.062 and 0.014 for experience.

Table 3: The Effects of Standardised Prose Score and Schooling on Wages for Male NZ born Pakeha

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.0298***	0.0285***	0.0245	0.0266*	0.0238
	(0.00637)	(0.00624)	(0.0150)	(0.0147)	(0.0149)
Potential Experience Squared	-0.00045***	-0.00042***	-0.00039**	-0.00038**	-0.00036**
	(0.000126)	(0.000123)	(0.000165)	(0.000166)	(0.000168)
Education	0.0719***	0.0553***	0.0505***	0.0559***	0.0494***
	(0.00603)	(0.00659)	(0.0152)	(0.0156)	(0.0164)
Standardised Prose Score		0.128***	0.128***	0.0858*	-0.0501
		(0.0203)	(0.0203)	(0.0498)	(0.0995)
Education*Experience			0.000189	-0.0000070	0.000105
			(0.000615)	(0.000630)	(0.000634)
Prose Score*Experience				0.00156	0.00233
				(0.00177)	(0.00183)
Prose Score*Education					0.00912
					(0.00591)
N	1247	1247	1247	1247	1247
R^2	0.114	0.138	0.138	0.139	0.14

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

In column (2) the standardised prose ability variable is added into the wage equation, as has been well established through previous literature, measures of employee ability have a significant association with wages. The measure of prose score has been standardised to have a standard deviation of one, thus the estimate implies that a one standard deviation increase in ability is related to an increase of wages by 13.7 percent. Also, the estimate for mean returns to years of education declines by 23 percent with the inclusion of this term. This implies that 23 percent of the estimated return to education in column (1) is due to the higher level of ability associated with an extra year of education thus 77 percent of the return to education can be attributed to additional unmeasured skills generated by the educational process (Barrett, 2012). Whereas the return to years of potential experience declines less, implying that ability is only weakly related to experience unlike education. This result suggests that schooling may play a greater role than post-school or on-the-job training in generating workplace ability (Barrett, 2012).

Column (3) introduces a term for the interaction between education and experience, a slightly positive coefficient is found but it is not statistically significant from zero. Even when the model is augmented to include the prose score and potential experience interaction (column (4)), we find that the coefficient on education*experience remains insignificant. In effect, the Altonji and Pierret test for statistical discrimination finds no significant evidence and the basic hypothesis of employers using education as an easily observable productivity measurement and using the average group ability of different education levels to determine worker wages is rejected. The coefficients of 0.00156 on the interaction between prose score and experience is also estimated to be statistically insignificant from zero confirming that as we have no signalling over educational credentials present, no employer learning can be exhibited. The results for NZ male Pakeha could indicate that employers have near perfect information in regards to the productivity of this group such that signalling is no factor.

4.1.2 Statistical Discrimination and Employer Learning over Education for Females

As we would expect, Table 4 confirms that potential experience is a much less reliable measure of experience for the female population. We find the usual positive sign for potential experience along with concavity but potential experience does fail to enter the equation with

Table 4: The Effects of Standardised Prose Score and Schooling on Wages for Female NZ Born Pakeha

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.00720	0.00533	0.0102	0.0143	0.0140
	(0.00692)	(0.00697)	(0.0146)	(0.0148)	(0.0146)
Potential Experience Squared	-0.000117	-0.0000716	-0.000103	-0.0000704	-0.0000685
	(0.000134)	(0.000134)	(0.000152)	(0.000151)	(0.000150)
Education	0.0737***	0.0641***	0.0699***	0.0828***	0.0810***
	(0.00647)	(0.00670)	(0.0188)	(0.0197)	(0.0193)
Standardised Prose Score		0.0863***	0.0865***	-0.0249	-0.0742
		(0.0229)	(0.0230)	(0.0574)	(0.137)
Education*Experience			-0.000238	-0.000755	-0.000745
			(0.000666)	(0.000715)	(0.000710)
Prose Score*Experience				0.00432**	0.00461**
				(0.00199)	(0.00205)
Prose Score*Education					0.00318
					(0.00840)
N	1397	1397	1397	1397	1397
R^2	0.0871	0.0954	0.0955	0.0982	0.0983

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

statistical significance at any level. In column (1), the educational return represents a 7.37 percentage point increase in wages per year of additional education which happens to be very similar to what was found for the male sample and education retains statistical significant at the one percent level. The educational returns found for women remain consistently higher than that for males through every specification. This finding could represent the lack of an appropriate experience measure entering the wage equation thus the education coefficient is also capturing the miss-specified experience returns. A one standard deviation increase in prose ability is estimated to increase wages by 8.6 percent which is substantially lower than what has been estimated for the male sample. The interaction of education and potential experience, column (4), is estimated to have a negative sign but fails to enter with statistical significance.

Interestingly, the interaction between prose ability and experience finds statistical significance at the 5 percent level for New Zealand born females. This can be interpreted as the wage return, to a one standard deviation increase in prose ability, is increasing by 0.43 percent per additional year of potential experience. This result is in accordance with the previous employer learning literature, suggesting that employers learn about the true productivity of workers over time and compensate them for this. We can see the R squared values are significantly lower for Table 4 in comparison with Table 3 and thus much less of the variance in earnings have been captured. Further examination into the female sample is justified as the presence of employer learning suggests signalling may also exist, but the potential experience specification is unable to correctly capture all the labour market features of a female sample causing our model to lack power. We can further examine these phenomena by augmenting the model with a measure of tenure in the hope of capturing what has been missed by potential experience.

It is widely accepted that potential experience is less adequate of a measure for females due to their particular labour force participation cycles (Stillman, 2011). Tenure captures the effect of firm specific experience, it is important to recognise that examining the wage coefficient associated with tenure can also represent 'choice' models. Workers with short tenure either left for a higher wage elsewhere or did not fit with that particular firm. The interpretation for the coefficient on tenure is not straightforward, it is not directly comparable with wage returns

Table 5: The Effects of Standardised Prose Score, Schooling and Tenure on Female NZ Pakeha Wages

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.00506	0.00358	0.00551	0.00548	0.00536
	(0.00687)	(0.00692)	(0.00708)	(0.00704)	(0.00708)
Potential Experience Squared	-0.000130	-0.0000888	-0.000127	-0.000127	-0.000125
	(0.000132)	(0.000133)	(0.000137)	(0.000136)	(0.000137)
Tenure	0.0212***	0.0197***	0.0324**	0.0406***	0.0405***
	(0.00634)	(0.00637)	(0.0131)	(0.0132)	(0.0132)
Tenure Squared	-0.000365*	-0.000338*	-0.000346*	-0.000352*	-0.000354*
	(0.000206)	(0.000205)	(0.000202)	(0.000201)	(0.000202)
Education	0.0707***	0.0625***	0.0689***	0.0750***	0.0756***
	(0.00658)	(0.00680)	(0.00939)	(0.00948)	(0.00992)
Standardised Prose Score		0.0758***	0.0748***	0.0176	0.0342
		(0.0233)	(0.0234)	(0.0307)	(0.112)
Education*Tenure			-0.000913	-0.00171*	-0.00171*
			(0.000885)	(0.000910)	(0.000914)
Prose Score*Tenure				0.00773**	0.00773**
				(0.00304)	(0.00304)
Prose Score*Education					-0.00126
					(0.00834)
N	1397	1397	1397	1397	1397
R^2	0.101	0.107	0.108	0.112	0.112

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

associated with potential experience as the general level of worker experience is not captured. To account for worker overall experience, we must leave the potential experience measures[16] in the equation. When including tenure interactions with education and ability variables, we can capture the effects associated with within firm experience. As potential experience is less accurate for females, looking at interactions with tenure for females may be of more interest. As can be seen in Table A.3 in Appendix A, the specification including both tenure and potential experience for males lacks significance for the measures of tenure however, as can be seen in Table 5 above, the female specification finds statistical significance for tenure as an experience measure and is thus examined.

Column (1) in Table 5 presents the estimates for a basic human capital model for the female New Zealand born Pakeha population, however, both tenure and potential experience are included as measures of worker experience to form an extended model. The marginal returns presented are again estimated at the 25th, 50th and 75th percentile of the tenure distribution, which correlate to 2, 5 and 10 years of worker tenure. The basic specification in column (1) estimates tenure to be statistically significant at the 1 percent level with the first year of tenure associated with a 2.1 percentage point increase in employee wages.

The tenure squared term is also significant at the 10 percent level and adheres to the previous experience literature with a negative return. The potential experience measures do not enter with statistical significance but follow the usual sign pattern with a positive return for potential experience and concavity over the experience profile with diminishing returns. The marginal effects of tenure are also of interest, we can calculate that the marginal effect of an additional year of tenure falls by 29 percent between 2 to 10 years of tenure. The return to education is estimated at 0.0707, implying that an additional year of education increases female wages by 7.3 percent which is very similar to the returns found for both the male and female potential experience models above (7.2 and 7.4 percent respectively). It seems New Zealand Pakeha approximately earn a 7 percent increase in wage compensation per additional year of formal education, slightly greater than what Barrett (2012) found for Australians. Section 4.3 will compare these New Zealand Pakeha returns with other ethnic groups in order to investigate further forms of signalling present in the New Zealand labour force.

[16] These are the level potential experience and potential experience squared variables.

The standardised prose score variable enters the equation in column (2) with a statistically significant wage return of 7.9 percent per one standard deviation increase in prose score. The returns for education and prose ability are smaller in Table 5, with tenure specified. The greater R squared value with tenure included provides evidence that this specification also has greater explanatory power. The tenure term is capturing the effects of worker experience additional to the potential experience measure, in the previous specification the education and ability variables were capturing some of the tenure returns. However, it is interesting to note that the standardised ability return is significantly smaller for females as opposed to males (40 percent larger for males) within New Zealand Pakeha. Statistical discrimination literature has substantially studied the effects of gender signalling in labour forces, females are grouped as workers with higher dropout rates (Aigner and Cain, 1977) thus pose a greater risk for employers. It is quite likely gender signalling is present in the New Zealand labour force and this will be investigated later in section 4.2. The finding that female workers receive lower returns for their ability measures poses the question that gender signalling could be a factor.

Columns (3) and (4) clearly demonstrate evidence towards statistical discrimination over education, the interaction between education and tenure enters the equation with a negative sign but coupled with the standardised prose ability*tenure variable, in column (4), the return to education*tenure declines to a statistically significant value of -0.00171. The marginal effect of an additional year of education declines from 0.072 to 0.058 between two and ten years of tenure, a decline of approximately 19 percent. These estimates suggest that employers statistically group the productivity of workers according to the group average associated with their education levels, as it is evident that the association between education and wage diminishes over the employees tenure period. Statistical discrimination presents the idea that New Zealand born Pakeha females, given the same level of productivity, may receive different wages when only differing in education level. Evidence of employer learning is also present as column (4) estimates the interaction between standardised prose score and tenure to be statistically significant at the five percent level, with a coefficient of 0.00773. We can calculate that over a tenure period of two to ten years, the marginal wage return for a one standard deviation increase of prose ability increases from 3.3 to 9.5 percent points.[17] This result also conforms to the work of Altonji and Pierret (2001) , where an increased return to correlates of employer productivity are observed as employers learn about the actual productivity of workers. Using the basic assumptions of the Altonji and Pierret model, the ALL data presents significant evidence of employer learning under statistical discrimination of education level for the female New Zealand Pakeha population.

4.2 Statistical Discrimination and Employer Learning over Gender Signals

It has been long established that females receive lower wages in the New Zealand labour force as for example men are found to earn 15.1 percent more than their counterparts in the ALL data. As is discussed above, a statistically discriminating employer may use employee gender as well as education and other information to predict the productivity of potential workers. Altonji and Pierret (2001) have proposed that over the experience profile of a worker, their real productivity will be revealed. Firms will adjust the compensation for that worker according to this new information as opposed to using their initial information for wage setting. If statistical discrimination based on employee gender is relevant, then adding interaction terms for an ability*experience and female dummy*experience will follow a similar pattern of results to what has been established above in section 4.1. A gender intercept term (FEM) will be introduced to capture the percentage point wage difference associated with being female given equal ability, education and experience. The following equation G.1 will be the focus of our analysis.[18]

$$\text{Ln W} = \beta_1\text{FEM} + \beta_2\text{EXP} + \beta_3\text{EXP}^2 + \beta_4\text{ED} + \beta_5\text{AB} + \beta_6(\text{ED*EXP}) + \beta_7(\text{FEM*EXP}) + \beta_8(\text{AB*EXP}) + v \qquad \text{(G.1)}$$

The analysis below, in Table 6, pools both genders into one regression sample with the addition of a female dummy to capture the intercept for females. Again, the analysis is only conducted for the New Zealand born Pakeha participants of the 2006 ALL survey. For the

[17] A specification including the interactions of ability and education with both tenure and potential experience was also run, however this model lacked significance for all the important interactions. Implementing tenure interactions only is feasible as long as potential experience measures are included to capture cohort effects contained in age. The full specification for both genders can be found in Tables A.4 and A.5 in Appendix A.

[18] Where EXP, ED and AB refer to experience, education and ability as before.

Table 6: The Effects of Standardised Prose Score, Schooling and Gender on Wages						
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.175***	-0.189***	-0.189***	-0.0478	-0.0395	-0.148
	(0.0244)	(0.0242)	(0.0241)	(0.0587)	(0.0581)	(0.150)
Potential Exp	0.0180***	0.0162***	0.0169	0.0192*	0.0227**	0.0223**
	(0.00475)	(0.00472)	(0.0104)	(0.0104)	(0.0104)	(0.0103)
Potential Exp Squared	-0.000276***	-0.000233**	-0.000237**	-0.000237**	-0.000220*	-0.000222**
	(0.0000923)	(0.0000917)	(0.000112)	(0.000112)	(0.000112)	(0.000112)
Education	0.0731***	0.0602***	0.0610***	0.0599***	0.0695***	0.0641***
	(0.00442)	(0.00470)	(0.0121)	(0.0120)	(0.0126)	(0.0127)
Standardised Prose Score		0.107***	0.107***	0.107***	0.0283	0.0525
		(0.0152)	(0.0152)	(0.0152)	(0.0383)	(0.0403)
Education*Experience			-0.0000324	0.00000479	-0.000355	-0.000320
			(0.000453)	(0.000452)	(0.000478)	(0.000474)
Female*Experience				-0.00552**	-0.00584***	-0.00570**
				(0.00217)	(0.00215)	(0.00226)
Ability*Experience					0.00296**	0.00284**
					(0.00134)	(0.00134)
Female*Ability						-0.0422
						(0.0305)
Female*Education						0.00859
						(0.00936)
N	2644	2644	2644	2644	2644	2644
R2	0.110	0.124	0.124	0.126	0.128	0.128

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

female population, we have established that a tenure variable is able to capture more of the experience dynamics in comparison to potential experience. In order to investigate the employer learning effects under statistical discrimination on the basis of gender; we will firstly estimate equation G.1 using only potential experience as the EXP measure (Table 6) and further estimate the equation using tenure and potential experience to measure EXP with only tenure interactions (Table 7).

Between column's (1) and (2) of Table 6 we can see that education, again, enters the wage equation with a positive coefficient and the wage effect for potential experience has positive returns with diminishing returns over the experience profile. The models we estimate for gender signalling pools both male and female wages together such that if females do receive lower wages, a female dummy will capture such effects. Previously, in section 3.1, the female population from the 2006 ALL survey were found to receive lower wages than males and this fact is again realised in Table 6. Column (1) shows that females earn 19.1 percent lower hourly wages, upon labour market entry, than males when controlling for education and experience. Standardised prose ability is added in column (2), similar to the earlier research, a workers ability is positively related to their hourly wage with a one standard deviation in prose ability being associated with a 11.3 percent increase in worker wages. When the prose ability variable is added to the specification in column (2), the female intercept becomes slightly more negative but not significantly different. An initial wage gap of 20.8 percent holds significance in its own right, after controlling for the workers ability, education and experience, female workers are still at a sizeable disadvantage in comparison to their identical male counterparts. We can see in column (5), that the Female*Experience interaction term enters negatively (-0.0058) with statistical significance however females now do not face any significant wage penalty for their first year of experience. The estimate suggests that the female wage gap will widen as they gain more experience, this contradicts our screening hypothesis. Potential Experience captures the effect of age, these are effects such as characteristics and policy differences for different cohorts of workers through time. There are still issues with this, for example older cohorts of women may have displayed much different labour force participation patterns in comparison to younger cohorts but the calculation of potential experience would not take this into consideration and this could be creating bias in the estimates found here.

Table 7: The Effects of Standardised Prose Score, Schooling, Tenure and Gender on Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.159***	-0.175***	-0.175***	-0.209***	-0.203***	-0.408***
	(0.0244)	(0.0241)	(0.0241)	(0.0326)	(0.0322)	(0.119)
Potential Experience	0.0148***	0.0136***	0.0143***	0.0148***	0.0147***	0.0148***
	(0.00477)	(0.00474)	(0.00490)	(0.00492)	(0.00491)	(0.00491)
Potential Experience Squared	-0.000249***	-0.000213**	-0.000226**	-0.000236**	-0.000235**	-0.000238**
	(0.0000923)	(0.0000916)	(0.0000948)	(0.0000951)	(0.0000951)	(0.0000951)
Tenure	0.0138***	0.0117**	0.0163*	0.0139	0.0189**	0.0171*
	(0.00461)	(0.00461)	(0.00860)	(0.00870)	(0.00885)	(0.00880)
Tenure Squared	-0.000254*	-0.000205	-0.000211	-0.000176	-0.000164	-0.000163
	(0.000141)	(0.000140)	(0.000140)	(0.000141)	(0.000140)	(0.000140)
Education	0.0709***	0.0588***	0.0616***	0.0619***	0.0656***	0.0566***
	(0.00453)	(0.00476)	(0.00618)	(0.00621)	(0.00632)	(0.00758)
Standardised Prose Score		0.102***	0.102***	0.101***	0.0711***	0.0918***
		(0.0154)	(0.0154)	(0.0154)	(0.0199)	(0.0241)
Education*Tenure			-0.000330	-0.000357	-0.000781	-0.000652
			(0.000532)	(0.000536)	(0.000564)	(0.000562)
Female*Tenure				0.00407	0.00331	0.00355
				(0.00313)	(0.00307)	(0.00308)
Ability*Tenure					0.00341*	0.00312*
					(0.00174)	(0.00175)
Female*Ability						-0.0357
						(0.0305)
Female*Education						0.0157*
						(0.00898)
N	2644	2644	2644	2644	2644	2644
R2	0.116	0.129	0.129	0.130	0.131	0.132

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Further down in column (5) we can see that employer learning is confirmed, the interaction between ability and potential experience is estimated at 0.00296 suggesting that New Zealand Pakeha wages are adjusted to reflect actual worker productivity as it is revealed to employers. It is plausible that the potential experience interactions are capturing erroneous cohort effects through age measurements. These could be returns from elder women which have not worked during their middle age but enter the work force with a low wage reception job, they would be measured to have a high level of potential experience (age-education-5) thus their returns per year of experience are relatively low. As an extension of the model using only potential experience, Table (8) also includes level tenure variables and uses only tenure interactions to test whether firm specific experience measures can capture any gender signalling.

We can see in Table 7 column (5), above, when controlling for the tenure profile and tenure interactions, females face wages 22.5 percent smaller than equivalent males per first year of firm tenure. Evidence on employer learning is, again, confirmed with the interaction between Ability and Tenure found to have a significant and positive coefficient (0.00341). The finding of a significant wage penalty for New Zealand born Pakeha females for their first year of tenure, that does not significantly change over the tenure profile, suggests that gender signalling may exist. Employers under-compensate female workers that are considered equally as productive as their male counterparts, with our prose ability measure, for a variety of reasons. As reviewed in section 2.2 earlier, females are most commonly discriminated upon because their labour force dropout rates are viewed as an added risk to employers, discounting wages (Aigner & Cain, 1977). However, it is important to understand the limitations of the applied model, such that differences in the accuracy of potential experience in measuring actual experience for the female population and complications in prose score as a measure of ability could be causing the level difference in wages between the genders.

4.3 Statistical Discrimination and Employer learning over Ethnic Group

The 2006 ALL survey collected a diverse set of employee characteristics, including identifying the ethnic groups in which the participants related to. The survey allowed the participants to identify up to five different ethnic groups, however for the purposes of the following analysis the first two mentioned groups were coded together to group workers into five different ethnic bands. These were New Zealand European, Maori, Pasifika, Asian and an 'other' group.[19] Theorising about the determinants of wages directs one to study the various different inputs of training a worker has undertaken throughout their lives. Employers, after all, are human and can only make decisions with the information given to them, these are observable productivity signals. Our work thus far follows a standard labour economics assumption; wages are assumed equal to worker productivity, but we have argued that employers use signals to gauge worker productivity.

The previous analysis has focussed solely on workers which have been born in New Zealand under the assumption that they would have partaken in fairly similar educational and training opportunities. Also, being born in New Zealand, should identify a group of workers which understand the workplace culture and habits common to New Zealand employers. The idea behind our framework has been to keep all worker characteristics equal such that when we analyse statistical discrimination over either education or gender, these variables should be the only variables causing differences in the wage returns. When searching for ethnic group signalling, we must keep this same mindset because including foreign born workers would obviously introduce a multitude of different characteristics creating increased heterogeneity amongst workers. These could range from extreme language difficulties, cultural workplace differences, different quality standards of education or lack of qualification transferability between countries. To remove all of these different bias, we will focus our study on just the New Zealand born workers and see whether there are different returns for being of different Ethnicity whilst having been born in New Zealand. Thus all the ethnic groups, listed above, will be pooled.

When looking at the employed sample of the ALL data, clearly New Zealand Europeans made up the largest group with 72 percent of all employed workers belonging to this category. Maori workers make up the 6.36 percent of all employed workers, making them one of the largest other ethnic groups. For this reason, the following discriminatory analysis will focus around the wage returns for male and female Maori workers. In order to investigate whether Maori workers are discriminated upon in the New Zealand labour force and whether

[19] Individuals are assigned to one ethnicity using the prioritisation scheme, which works as follows: an individual who answers Maori in any choice is Maori, an individual who answers Pacific Islander in any choice but not Maori is a Pacific Islander, an individual who answers Asian in any choice but not Maori or Pacific Islander is Asian, an individual who answers Other in any choice but not Maori, Pacific Islander, or Asian is Other, and all remaining individuals are Pakeha/European (Stillman, 2011).

employers learn about their true productivity over time, regressions will be run similar to the framework introduced in section 4.1. Male and female workers will be analysed separately to keep measurement errors between variables, such as potential experience, constant within groups and basic human capital models will be estimated with a Maori dummy term (MAORI), introduced to capture any intercept differences. The analysis will focus on the following equation:

$$\text{Ln W} = \beta_1\text{MAORI} + \beta_2\text{EXP} + \beta_3\text{EXP}^2 + \beta_4\text{ED} + \beta_5\text{AB} + \beta_6(\text{ED*EXP}) + \beta_7(\text{MAORI*EXP}) + \beta_8(\text{AB*EXP}) + v \qquad \textbf{(ETH.1)}$$ [20]

Similar to the work Altonji and Pierret (2001) conducted over race signalling between 'black' and 'white' workers, we will be looking at introducing interaction terms to capture how the returns to being Maori change over experience and if returns to a workers ability changes over the experience period. The analysis presented initially uses only the measures of potential experience in testing for statistical discrimination, but specifications using both tenure and potential experience as experience measures with tenure interactions for both genders are also examined as an extension of the model.

4.3.1 Statistical Discrimination and Employer Learning over Ethnic Group for Males

Table 8, below, presents the estimates surrounding returns to human capital variables for the New Zealand born male population, we can see in column (1) that the Maori population start significantly lower than the rest as the Maori intercept is -0.109. This can be interpreted as being of Maori ethnicity penalises wage by 11.5 percent on average. Education enters the wage equation with significance and workers earn 7.2 percent more on average per additional year of education, prose score also follows the established pattern with a statistically significant positive return. Once standardised prose ability is added to the equation, the Maori return loses significance and drops, the male sample lacks statistical significance for the Maori dummy after column (1). Each of the interaction terms added in columns (3), (4) and (5) are estimated to be statistically insignificant from zero. With standardised prose ability driving the Maori intercept into insignificance, it can be interpreted that once we account for

[20] As earlier defined, EXP, ED and AB stand for experience, education and ability respectively. Also note that potential experience will initially be used as the experience measure followed with an extended specification including both tenure and potential experience as level EXP measures and only tenure for interaction terms.

Table 8: The Effects of Standardised Prose Score, Schooling and Ethnic Group (Maori/non-Maori) on Male Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.109**	-0.0412	-0.0414	-0.0272	-0.0574	0.132
	(0.0504)	(0.0508)	(0.0508)	(0.119)	(0.121)	(0.332)
Potential Experience	0.0279***	0.0259***	0.0225*	0.0229*	0.0255*	0.0263*
	(0.00582)	(0.00571)	(0.0134)	(0.0135)	(0.0134)	(0.0135)
Potential Experience Squared	-0.000418***	-0.000371***	-0.000347**	-0.000350**	-0.000343**	-0.000345**
	(0.000117)	(0.000114)	(0.000151)	(0.000151)	(0.000152)	(0.000152)
Education	0.0695***	0.0531***	0.0490***	0.0494***	0.0558***	0.0583***
	(0.00559)	(0.00600)	(0.0136)	(0.0135)	(0.0139)	(0.0143)
Standardised Prose Score		0.130***	0.130***	0.130***	0.0775*	0.0685
		(0.0194)	(0.0194)	(0.0193)	(0.0463)	(0.0478)
Education*Exp			0.000164	0.000150	-0.0000930	-0.000139
			(0.000556)	(0.000556)	(0.000573)	(0.000574)
Maori*Experience				-0.000615	0.000632	0.000292
				(0.00499)	(0.00503)	(0.00514)
Prose Score*Poten Exp					0.00202	0.00219
					(0.00173)	(0.00175)
Prose Score*Maori						0.0373
						(0.0777)
Maori*Education						-0.0134
						(0.0204)
N	1502	1502	1502	1502	1502	1502
R2	0.112	0.138	0.138	0.138	0.138	0.139

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

the male Maori workers standardised prose ability scores being lower, there is no longer any negative return to being of Maori ethnicity. If no gap exists between groups, the statistical discrimination and employer learning literature is not confirmed in the New Zealand context and employers will have adequate information as to the workers ability. This explanation conforms with the fact that all the Altonji and Pierret (2001) interaction terms lack significance with the Male Maori group. Following uniform methodology, we repeat the male specification including both potential experience and tenure for experience measures and including tenure interaction terms to investigate firm specific dynamics. However, as can be seen in Table A.6 in Appendix A, the difference in wages between male Maori and Pakeha is explained through differences in worker productivity and employers do not statistically discriminate as they have full information about productivity.

4.3.2 Statistical Discrimination and Employer Learning over Ethnic Group for Females

The effects for the female Maori population are of much greater statistical significance, we can see from column (4) Table 9 that including experience interactions in the human capital model finds female Maori workers penalised by 31.3 percent for their first year of experience with the interaction between Maori and experience decreasing this 'gap' by 0.97 percent per year of additional experience. This result clearly aligns with the Altonji and Pierret (2001) model of statistical discrimination. The signalling result is further confirmed with the addition of an interaction between standardised prose score and potential experience in column (5). The inclusion of this interaction, increases the slope of return to being Maori over the experience period thus the gap for female Maori workers closes more quickly when the returns to ability are allowed to change with experience. The marginal return to being Maori is calculated to increase from -0.18 at 12 years of potential experience to Maori earning approximately 6 percent more than other workers at 33 years of potential experience. The point in which female Maori catch up is at 27.7 years of potential experience. The coefficient for the standardised prose score*potential experience interaction is statistically significant and positive thus the return to prose ability increases by 0.4 percentage points per year of additional potential experience for female Maori workers. We can see in column (5) that the return to ability for first entering the labour force is extremely small (0.00812) and calculated to increase to 0.1379 after 33 years of potential experience, these results support the employer learning under statistical discrimination hypothesis, as employers are increasingly

Table 9: The Effects of Standardised Prose Score, Schooling and Ethnic Group (Maori/non-Maori) on Female Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.0749*	-0.0369	-0.0371	-0.272**	-0.313***	0.619**
	(0.0443)	(0.0431)	(0.0430)	(0.112)	(0.109)	(0.246)
Potential Experience	0.0137**	0.0108*	0.0230*	0.0179	0.0225*	0.0229*
	(0.00617)	(0.00617)	(0.0125)	(0.0128)	(0.0131)	(0.0130)
Potential Experience Squared	-0.000225*	-0.000161	-0.000239*	-0.000207	-0.000187	-0.000172
	(0.000120)	(0.000120)	(0.000136)	(0.000137)	(0.000136)	(0.000134)
Education	0.0707***	0.0581***	0.0729***	0.0685***	0.0809***	0.0889***
	(0.00569)	(0.00605)	(0.0158)	(0.0161)	(0.0174)	(0.0176)
Standardised Prose Score		0.107***	0.107***	0.107***	0.00812	-0.0207
		(0.0214)	(0.0214)	(0.0213)	(0.0561)	(0.0530)
Education*Experience			-0.000612	-0.000431	-0.000928	-0.000997
			(0.000571)	(0.000582)	(0.000642)	(0.000637)
Maori*Experience				0.00965**	0.0113***	0.00818**
				(0.00415)	(0.00406)	(0.00396)
Prose Score*Poten Exp					0.00393**	0.00414**
					(0.00198)	(0.00191)
Prose Score*Maori						0.216***
						(0.0758)
Maori*Education						-0.0661***
						(0.0183)
N	1670	1670	1670	1670	1670	1670
R2	0.0871	0.101	0.101	0.104	0.106	0.114

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

compensating workers for their actual productivity as it is revealed.

Table 10, further below, investigates the firm specific effects of statistical discrimination over ethnicity. We can see in column (5) that female Maori face 13 percent smaller wages upon entry into a firm and wages will converge with that of other New Zealand born non Maori after 8.7 years of firm tenure as the Maori penalty decreases by 0.0145 per additional year of firm tenure. This result confirms initial statistical discrimination by firms against Maori that diminish over time. Also, employer learning is again confirmed as the Ability*Tenure variables enters positively. Together with Table 9, we can confirm that statistical discrimination against Maori females occurs at both an intra and inter-firm levels with employer learning.

Comparing the returns for female Maori to that found in Table 5 for female Pakeha born in New Zealand, we can see that female Maori receive slightly higher returns for their first year of formal education (8.1 compared to 7.5 percent), this could reflect the weight placed on ethnic signalling. Employers may place more weight on the education level of Maori applicants in comparison to New Zealand Pakeha, being Pakeha may comfort employers with a less risky investment option. A potential limitation surrounding this finding stems from the fact that prose score is used as a correlate of worker productivity. It is important to note that the ability measure employed is derived from the ALL survey questions and relates directly to prose ability demonstrated in work place scenarios. This measure does not directly reflect the innate ability of the workers but is just a reflection of the workers ability to complete specific tasks (Barrett, 2012). Maori results could be bias in this measure as they may not have received valid workplace training in forms they could understand through cultural differences or miss-communication. However, as can be seen in Tables A.7 and A.8 in Appendix A, using an alternate measure of ability (numeracy) leads to the same result.

Our results provide strong evidence of employer learning under statistical discrimination for the female Maori ethnic group in the New Zealand labour force. Employers find Maori women to be of more employment risk than other female workers on average and apply a wage penalty accordingly. Over time, employers learn that their initial productivity assessments were wrong and female Maori eventually catch up. It is understandable,

Table 10: The Effects of Potential Experience, Tenure and Ethnic Group (Maori/non-Maori) on Female Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.0665	-0.0333	-0.0348	-0.111*	-0.126**	0.857***
	(0.0435)	(0.0425)	(0.0424)	(0.0643)	(0.0622)	(0.247)
Potential Experience	0.0114*	0.00907	0.0114*	0.0110*	0.0112*	0.0102*
	(0.00612)	(0.00612)	(0.00620)	(0.00621)	(0.00619)	(0.00613)
Potential Experience Squared	-0.000238**	-0.000181	-0.000227*	-0.000218*	-0.000221*	-0.000204*
	(0.000118)	(0.000118)	(0.000120)	(0.000120)	(0.000120)	(0.000119)
Tenure	0.0203***	0.0181***	0.0354***	0.0306**	0.0396***	0.0432***
	(0.00600)	(0.00598)	(0.0115)	(0.0124)	(0.0125)	(0.0124)
Tenure Squared	-0.000298	-0.000259	-0.000267	-0.000253	-0.000278	-0.000288
	(0.000208)	(0.000204)	(0.000200)	(0.000195)	(0.000189)	(0.000187)
Education	0.0675***	0.0564***	0.0651***	0.0638***	0.0698***	0.0784***
	(0.00579)	(0.00614)	(0.00829)	(0.00837)	(0.00852)	(0.00887)
Standardised Prose Score		0.0955***	0.0941***	0.0938***	0.0403	0.0155
		(0.0217)	(0.0217)	(0.0215)	(0.0290)	(0.0282)
Education*Tenure			-0.00126	-0.00102	-0.00183**	-0.00207**
			(0.000795)	(0.000818)	(0.000849)	(0.000850)
Maori*Tenure				0.0127	0.0145**	0.00970
				(0.00829)	(0.00740)	(0.00663)
Prose Score*Tenure					0.00755***	0.00799***
					(0.00289)	(0.00283)
Maori*Prose Score						0.203***
						(0.0737)
Maori*Education						-0.0740***
						(0.0196)
N	1670	1670	1670	1670	1670	1670
R2	0.103	0.114	0.115	0.117	0.120	0.129

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

following from the findings of gender signalling in section 4.3, female Maori face statistical discrimination over both ethnicity and gender.

Table 8 presented evidence such that controlling for the ability of male Maori removed any significant wage gap between the groups, implying that any wage difference is explained by the lower prose ability of Maori. These findings reflect the information presented in figure 2 earlier, as Maori males were shown to have lower ability across the entire education distribution with a fairly similar ability average at each point. As discussed, ability is gauged using prose testing and this method may bear more difficulty for the Maori population creating bias in the results, but this result doesn't change when using alternative ability measures. The difference in signalling results between genders can only be explained through female productivity being considered more noisy than that of males, with employers initially allocating wages based on observable characteristics.

4.4 Statistical Discrimination over Immigrant Status

The economics literature has generally acknowledged poor labour market outcomes for immigrants. Stillman (2011) confirms the harsh outlook immigrants face within the context of the New Zealand labour market with equally educated migrants receiving wages 4 to 8 percent lesser than their native counterparts. The present thesis confirmed the existence of such wage gaps within the New Zealand ALL survey data, with wage gaps of 7.8 and 4.1 percent estimated between groups for men and women respectively in Table A.2, Appendix A. Immigration literature ventures into the determinants of such wages, suggesting immigrants face an uphill battle when treading into foreign labour markets. Information is always a most valuable commodity, when one seeks to find employment, having inside information as to the opportunities available is a competitive advantage. Locals have much better job networks than migrants plainly because local knowledge reduces job searching costs (Stillman, 2011). When it comes to judging the proficiency associated with the unknown quantities contained within a foreigner's education and experience credentials, employers are also more likely to accurately predict the ability of a local worker. Language and cultural barriers may also plague those hoping to secure jobs when moving to a new country (Stillman, 2011).

Job productivity is the key to our analysis. If workers who are identical in productivity, only differing by birth country, receive different wages, we can postulate statistical discrimination. Quantitative productivity differences can result if foreign workers lack the ability to adequately conduct work within local New Zealand cultural norms or accurately communicate within their workplace. In order to test whether statistical discrimination is a factor in the presented wage differentials between New Zealand born Pakeha workers and those born outside, we will use immigrant status as the observable characteristic to apply statistical discrimination and employer tests in a similar fashion to what has been done above. We will first explore immigrant status signalling within wages (this section) followed by employment outcomes later on in section 5.4. In both sections, immigrants will first be examined as a whole but sequentially broken into the following smaller groups: foreign born Europeans and a group containing Pasifika and Asian immigrants.[21]

In order to examine statistical discrimination over immigrant status, we will use the Altonji and Pierret (2001) interaction variable tests as we have done in earlier sections. An intercept term will be introduced to capture the wage gap between foreign born (FB) and New Zealand Born Pakeha. The main equation we will look at to investigate wage effects is as follows:

$$\text{Ln W} = \beta_1 FB + \beta_2 EXP + \beta_3 EXP^2 + \beta_4 ED + \beta_5 AB + \beta_6 (ED*EXP) + \beta_7 (FB*EXP) + \beta_8 (AB*EXP) + v \qquad \textbf{(IM.1)}^{22}$$

4.4.1 Statistical Discrimination and Employer Learning over Immigrant Status for All Immigrants

Table 11, similar to what Phillips, Poot and Roskruge (2011) found, suggests that it is differences in the ability of immigrant causing wage gaps between groups. In column (1), male immigrants (of all origins) have 8.8 percent lower hourly wages. However, when ability is added in column (2), the foreign born intercept terms becomes insignificant suggesting that differences in worker ability between the groups explains the found wage penalty and no evidence of statistical discrimination is found. Table 12, following typical immigration

[21] Even though Pasifika and Asian culture is different, they have been joined to increase the sample size and due to the fact that both cultures are dissimilar to that of western (New Zealand Pakeha) culture.

[22] Where EXP, ED and AB refer to experience, education and ability as before.

Table 11: The Effects of Standardised Prose Score and Schooling on Male Wages of NZ Born Pakeha vs. All Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.0845***	-0.0124	-0.0103	-0.0598	-0.0444	0.152
	(0.0304)	(0.0325)	(0.0325)	(0.0641)	(0.0668)	(0.198)
Potential Experience	0.0282***	0.0258***	0.0182	0.0178	0.0163	0.0178
	(0.00514)	(0.00498)	(0.0121)	(0.0121)	(0.0121)	(0.0122)
Potential Experience Squared	-0.000410***	-0.000364***	-0.000308**	-0.000304**	-0.000303**	-0.000312**
	(0.000101)	(0.0000982)	(0.000134)	(0.000133)	(0.000133)	(0.000133)
Education	0.0686***	0.0508***	0.0423***	0.0432***	0.0401***	0.0446***
	(0.00462)	(0.00534)	(0.0119)	(0.0119)	(0.0123)	(0.0135)
Prose Ability		0.122***	0.123***	0.122***	0.145***	0.156***
		(0.0170)	(0.0170)	(0.0170)	(0.0353)	(0.0413)
Potential Exp*Education			0.000345	0.000322	0.000443	0.000403
			(0.000493)	(0.000493)	(0.000517)	(0.000526)
Potential Exp*Foreign				0.00209	0.00152	-0.0000446
				(0.00248)	(0.00261)	(0.00293)
Potential Exp*Ability					-0.000928	-0.00101
					(0.00133)	(0.00139)
Ability*Foreign						-0.0169
						(0.0373)
Foreign*Education						-0.0112
						(0.0114)
N	1751	1751	1751	1751	1751	1751
R2	0.114	0.142	0.143	0.143	0.143	0.144

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 12: The Effects of Experience on Male Wages of NZ Born Pakeha and YSM for ALL Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.0335	0.0364	0.0307	0.131**	0.141**	0.425***
	(0.0349)	(0.0368)	(0.0372)	(0.0551)	(0.0565)	(0.150)
Potential Experience	0.0159***	0.0154***	0.00408	0.00588	0.00413	0.00768
	(0.00455)	(0.00444)	(0.00808)	(0.00797)	(0.00847)	(0.00866)
Potential Experience Squared	-0.000210**	-0.000208**	-0.000144	-0.000166*	-0.000164*	-0.000175*
	(0.0000889)	(0.0000873)	(0.0000973)	(0.0000950)	(0.0000951)	(0.0000952)
Education	0.0659***	0.0476***	0.0340***	0.0323***	0.0293***	0.0396***
	(0.00449)	(0.00531)	(0.00851)	(0.00847)	(0.00932)	(0.0108)
Prose Ability		0.123***	0.124***	0.127***	0.148***	0.150***
		(0.0173)	(0.0172)	(0.0172)	(0.0292)	(0.0291)
Potential Exp*Education			0.000592*	0.000674*	0.000803**	0.000625
			(0.000355)	(0.000356)	(0.000408)	(0.000416)
Potential Exp*Foreign				-0.00452**	-0.00486**	-0.00599**
				(0.00222)	(0.00228)	(0.00240)
Potential Exp*Ability					-0.000930	-0.000915
					(0.00119)	(0.00119)
Ability*Foreign						-0.0141
						(0.0428)
Education*Foreign						-0.0159
						(0.0119)
N	1751	1751	1751	1751	1751	1751
R2	0.104	0.133	0.134	0.136	0.136	0.138

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. Potential Experience is defined as YSM for immigrants and remains as Potential Experience for natives. The regression model also includes a constant.

literature, defines years since migrations (YSM) as the relevant experience measure for immigrants but potential experience remains for locals which assumes foreign experience has zero return in the New Zealand labour market. YSM can be considered a more relevant measure for immigrants as additional time in New Zealand would allow learning of the accepted workplace culture, social norms and allow foreign workers to become accustomed with various job networks (Phillips et al., 2011). Using this newly defined experience variable in Table 12, we again find no statistically significant evidence of wage differentials between male immigrants and natives in column (1). Interestingly, in column (5), we find that foreign born male immigrants receive wages 15.1 percent larger than New Zealand born Pakeha during their first year of migration.[23] It is likely that self-selection is causing the greater intercept for migrants, the New Zealand Government aims to bring immigrants which have already secured jobs in the country. Such immigrants will tend to have previous work experience in their home countries invalidating comparisons to New Zealanders just entering the labour force. Further evidence towards this explanation is found with the Potential Exp*Foreign variable significantly entering the equation with a negative sign (-.00486) This suggests that the return to being a foreigner reduces with time in New Zealand, contradictory to our statistical discrimination hypothesis. Consistent with self selection theory (Chiswick, 1999), the negative coefficient implies that New Zealand born Pakeha male wages eventually converge with foreigners as their experience builds.

The female labour population already seem to be subject to greater levels of both ethnic and education credential signalling compared with males, The basic model presented in Table 13 conforms with female deficits, as foreign born female immigrants face a wage deficit of -0.112. This basic model presented finds no further evidence of statistical discrimination or employer learning. However, we can see that potential experience as a measure of worker experience does not enter with much significance in this model.

As we have earlier, this model is extended to include tenure and potential experience as experience measures with only tenure interactions. We can see in column (5) of Table 14 that female immigrants do also face a penalty estimated to set foreigners 8.9 percent smaller

[23] Note that this is comparing the wage returns for immigrants in their first year of migration to the returns of the first year of potential experience for New Zealand born Pakeha males.

Table 13: The Effects of Standardised Prose Score and Schooling on Female Wages of NZ Born Pakeha vs. All Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.112***	-0.0463	-0.0465	-0.126*	-0.147*	0.224
	(0.0346)	(0.0348)	(0.0351)	(0.0763)	(0.0768)	(0.201)
Potential Experience	0.00553	0.00269	0.00381	0.00355	0.00555	0.00863
	(0.00569)	(0.00563)	(0.0119)	(0.0119)	(0.0121)	(0.0120)
Potential Experience Squared	-0.0000681	-0.00000820	-0.0000159	-0.0000125	-0.00000766	-0.0000289
	(0.000112)	(0.000110)	(0.000128)	(0.000128)	(0.000128)	(0.000128)
Education	0.0703***	0.0556***	0.0568***	0.0586***	0.0633***	0.0751***
	(0.00541)	(0.00546)	(0.0142)	(0.0144)	(0.0151)	(0.0157)
Prose Ability		0.123***	0.123***	0.122***	0.0817*	0.0272
		(0.0179)	(0.0179)	(0.0177)	(0.0456)	(0.0466)
Potential Exp*Education			-0.0000532	-0.000106	-0.000305	-0.000451
			(0.000513)	(0.000517)	(0.000553)	(0.000543)
Potential Exp*Foreign				0.00337	0.00414	0.00262
				(0.00284)	(0.00288)	(0.00301)
Potential Exp*Ability					0.00164	0.00233
					(0.00157)	(0.00152)
Ability*Foreign						0.0995***
						(0.0355)
Education*Foreign						-0.0243**
						(0.0116)
N	1883	1883	1883	1883	1883	1883
R2	0.0904	0.111	0.111	0.112	0.112	0.116

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 14: The Effects of Schooling and Tenure on Female Wages of NZ Born Pakeha vs. All Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.101***	-0.0407	-0.0409	-0.0632	-0.0850*	0.315**
	(0.0342)	(0.0345)	(0.0346)	(0.0471)	(0.0473)	(0.159)
Potential Experience	0.00310	0.000639	0.00114	0.00114	0.00158	0.00200
	(0.00566)	(0.00561)	(0.00584)	(0.00584)	(0.00585)	(0.00582)
Potential Experience Squared	-0.0000811	-0.0000242	-0.0000340	-0.0000352	-0.0000438	-0.0000599
	(0.000111)	(0.000110)	(0.000114)	(0.000114)	(0.000114)	(0.000114)
Tenure	0.0256***	0.0234***	0.0268**	0.0260**	0.0323***	0.0361***
	(0.00565)	(0.00560)	(0.0110)	(0.0111)	(0.0113)	(0.0112)
Tenure Squared	-0.000508***	-0.000460**	-0.000465**	-0.000447**	-0.000439**	-0.000460**
	(0.000189)	(0.000185)	(0.000183)	(0.000185)	(0.000185)	(0.000185)
Education	0.0667***	0.0532***	0.0548***	0.0549***	0.0592***	0.0708***
	(0.00551)	(0.00554)	(0.00777)	(0.00778)	(0.00790)	(0.00865)
Prose Ability		0.116***	0.115***	0.115***	0.0768***	0.0235
		(0.0181)	(0.0181)	(0.0181)	(0.0246)	(0.0283)
Tenure*Education			-0.000240	-0.000267	-0.000907	-0.00114
			(0.000707)	(0.000710)	(0.000750)	(0.000746)
Tenure*Foreign				0.00362	0.00700	0.00693
				(0.00421)	(0.00432)	(0.00436)
Tenure*Ability					0.00585**	0.00703***
					(0.00255)	(0.00249)
Ability*Foreign						0.117***
						(0.0353)
Education*Foreign						-0.0288***
						(0.0106)
N	1883	1883	1883	1883	1883	1883
R2	0.106	0.124	0.124	0.124	0.127	0.132

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

wages when looking at a model including tenure. The interaction between tenure and immigrant status does not enter with significance and we cannot confirm any statistical discrimination over immigrant status when looking at all immigrants. Employer learning is found, with wage setting behaviour increasingly adjusting to reflect worker productivity. As we can see in column (5), the interaction between tenure and ability enters with a positive sign (0.00585). In column (6) we find some interesting results, we control for the effect of being foreign born over both the education and ability profiles. The interaction between prose ability and immigrant status enters with a significant positive coefficient, this suggests that higher ability female foreigners earn greater wages than high ability New Zealand born. A negative coefficient is found for the Education*Foreign variable, this implies that higher educated foreigners earn lower wages than higher educated natives.[24]

4.4.2 Statistical Discrimination and Employer Learning over Immigrant Status by Immigrant Groups

We further split immigrant groups by ethnicity in order to quantify any possible cultural signalling. As we can see in Tables A.9 and A.10 in Appendix A, immigrants of European decent are not subject to any wage penalty for males or females. As the foreign born intercept does not enter with any significance, no evidence of statistical discrimination and employer learning is found. This result makes sense, as European immigrants do not face the same work force barriers that those of different cultural background would face. When looking at immigrants of foreign culture, grouping Asian and Pasifika migrants together, we find that the difference in worker ability is again unable to explain wage penalties faced by females.[25] Firstly, in Table 16 we can see that when using only potential experience as an experience measure for female Asian and Pasifika immigrants, we find no significance for the immigrant wage gap. In order to extend the model, Table 17 uses tenure and potential experience to measure worker experience and tenure interactions are used. We can see in column (5) of Table 17, foreign born Asian and Pasifika initially face wages 21.3 percent smaller than New Zealand born Pakeha. Statistical discrimination evidence is presented with the

[24] A model using an experience variable constructed with YSM for immigrant experience and potential experience for native females can be seen in Table A.11 in Appendix A, the results are indifferent to what is found with using just potential experience measures.

[25] Similar to the entire migrant group population, males from the Asian and Pasifika groups were not subject to any wage penalties. The results for this estimation are presented in Table (15).

Tenure*Foreign variable effect estimated at approximately 1.15 percent with significance, this implies that the negative wage effect of being a foreign born Asian or Pasifika female is lessening with tenure and the slope is equal to 0.0114. Calculating the change in the marginal effect of being foreign born, over the tenure profile, we can see that it drops from -0.17 to -0.079 between 2 and 10 years of tenure with convergence after 17 years. It can be inferred that employers have less information about foreign born Asians and Pasifika when setting wages due to cultural differences. Employers are more comfortable in accurately judging the productivity of European workers which have experienced more familiar education and work institutions to what is in place in New Zealand. However, female workers from Asian and Pacific background are more unfamiliar, creating an added risk for employers. Facing uncertain information, employers form group averages about the productivity of workers from these groups and remunerate all workers accordingly (Cornell and Welch, 1996). Employer learning does occur, with the interaction between Tenure and Ability estimated to be significant and positive (0.00704).

It is clear that female Asian and Pasifika immigrant workers do face significantly harsher labour force conditions in comparison to their native counterparts but when employers are able to observe real worker productivity, wages are adjusted. In particular, those of cultural heterogeneity are most likely to face statistical discrimination and receive unfair wages.

Table 15: The Effects of Human Capital on Male Wages of NZ Born Pakeha vs. Foreign Born Asian and Pasifika

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.229***	-0.0815**	-0.0775*	-0.0591	-0.0744	0.519*
	(0.0346)	(0.0413)	(0.0415)	(0.0768)	(0.0926)	(0.270)
Potential Experience	0.0275***	0.0259***	0.0186	0.0189	0.0195	0.0242*
	(0.00562)	(0.00549)	(0.0132)	(0.0133)	(0.0132)	(0.0132)
Potential Experience Squared	-0.000420***	-0.000384***	-0.000329**	-0.000333**	-0.000332**	-0.000359**
	(0.000111)	(0.000109)	(0.000149)	(0.000149)	(0.000149)	(0.000149)
Education	0.0661***	0.0495***	0.0411***	0.0410***	0.0425***	0.0531***
	(0.00517)	(0.00587)	(0.0129)	(0.0129)	(0.0134)	(0.0140)
Prose Ability		0.116***	0.117***	0.117***	0.105**	0.122***
		(0.0174)	(0.0174)	(0.0174)	(0.0408)	(0.0445)
Potential Exp*Education			0.000339	0.000338	0.000281	0.0000883
			(0.000533)	(0.000534)	(0.000554)	(0.000552)
Potential Exp*Foreign				-0.000861	-0.000271	-0.00665
				(0.00312)	(0.00376)	(0.00436)
Potential Exp*Ability					0.000455	0.000228
					(0.00152)	(0.00154)
Ability*Foreign						-0.0292
						(0.0401)
Education*Foreign						-0.0339**
						(0.0146)
N	1470	1470	1470	1470	1470	1470
R2	0.123	0.146	0.146	0.146	0.146	0.152

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 16: The Effects of Human Capital on Female Wages of NZ Born Pakeha vs. Foreign Born Asian and Pasifika

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.255***	-0.129**	-0.131**	-0.165*	-0.226**	0.756**
	(0.0465)	(0.0516)	(0.0521)	(0.0871)	(0.0916)	(0.295)
Potential Experience	0.00449	0.00282	0.0110	0.0101	0.0119	0.0149
	(0.00619)	(0.00616)	(0.0135)	(0.0136)	(0.0136)	(0.0135)
Potential Experience Squared	-0.0000743	-0.0000297	-0.0000846	-0.0000751	-0.0000560	-0.0000792
	(0.000120)	(0.000119)	(0.000141)	(0.000142)	(0.000142)	(0.000141)
Education	0.0669***	0.0549***	0.0646***	0.0643***	0.0705***	0.0820***
	(0.00618)	(0.00619)	(0.0169)	(0.0169)	(0.0171)	(0.0174)
Prose Ability		0.105***	0.105***	0.105***	0.0503	0.0195
		(0.0210)	(0.0209)	(0.0210)	(0.0525)	(0.0526)
Potential Exp*Education			-0.000393	-0.000375	-0.000625	-0.000729
			(0.000599)	(0.000598)	(0.000615)	(0.000612)
Potential Exp*Foreign				0.00164	0.00413	-0.00150
				(0.00342)	(0.00362)	(0.00515)
Potential Exp*Ability					0.00219	0.00262
					(0.00180)	(0.00178)
Ability*Foreign						0.118**
						(0.0571)
Education*Foreign						-0.0571***
						(0.0164)
N	1606	1606	1606	1606	1606	1606
R2	0.0910	0.104	0.104	0.104	0.105	0.106

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 17: The Effects of Human Capital on Female Wages of NZ Born Pakeha vs. Foreign Born Asian and Pasifika

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.239***	-0.124**	-0.124**	-0.135**	-0.193***	0.674***
	(0.0460)	(0.0510)	(0.0511)	(0.0661)	(0.0689)	(0.200)
Potential Experience	0.00211	0.000741	0.00149	0.00137	0.00138	0.00172
	(0.00617)	(0.00614)	(0.00633)	(0.00638)	(0.00636)	(0.00639)
Potential Experience Squared	-0.0000827	-0.0000409	-0.0000559	-0.0000535	-0.0000540	-0.0000641
	(0.000119)	(0.000118)	(0.000122)	(0.000122)	(0.000122)	(0.000123)
Tenure	0.0227***	0.0211***	0.0266**	0.0262**	0.0338***	0.0402***
	(0.00595)	(0.00595)	(0.0123)	(0.0125)	(0.0126)	(0.0125)
Tenure Squared	-0.000412**	-0.000384**	-0.000388**	-0.000384**	-0.000383**	-0.000414**
	(0.000195)	(0.000192)	(0.000190)	(0.000191)	(0.000190)	(0.000190)
Education	0.0637***	0.0529***	0.0555***	0.0554***	0.0608***	0.0730***
	(0.00631)	(0.00631)	(0.00873)	(0.00874)	(0.00874)	(0.00924)
Prose Ability		0.0964***	0.0961***	0.0963***	0.0477*	0.0155
		(0.0213)	(0.0213)	(0.0213)	(0.0288)	(0.0300)
Tenure*Education			-0.000389	-0.000380	-0.00114	-0.00154*
			(0.000831)	(0.000835)	(0.000860)	(0.000856)
Tenure*Foreign				0.00213	0.0114*	0.0128**
				(0.00628)	(0.00676)	(0.00636)
Tenure*Ability					0.00704**	0.00803***
					(0.00293)	(0.00290)
Ability*Foreign						0.147***
						(0.0548)
Education*Foreign						-0.0565***
						(0.0133)
N	1606	1606	1606	1606	1606	1606
R2	0.105	0.116	0.116	0.116	0.120	0.127

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

5. Testing for Statistical Discrimination and Employer Learning through Employment Rates

Kim (2011) proposes a methodology in which variables such as worker ability are not required in the test for statistical discrimination and employer learning. Employment status is used as the outcome variable instead of wages. The framework proposes that if employers statistically discriminate among inexperienced workers, but show learning over time, then the unemployment rates for discriminated groups will be higher than those for non-discriminated groups at the point of labour market entry. Also, unemployment rates will decline faster for discriminated groups as employers observe a group's actual productivity. Thus far, the regression analysis conducted has focussed on the employed section of the data, looking to see whether the marginal wage return to human capital variables change over an experience profile. When looking to analyse labour force dynamics, it is also important to consider the unemployed.[26] When employers statistically discriminate, it is not just with respect to wage setting but it also changes the employment rates for different worker groups. In the present thesis, the specific Altonji and Pierret (2001) interaction tests will be used in human capital models that have employment status as an outcome variable.

Measuring of the employment rate for a particular group also reflects that particular groups choice to partake in employment. It may be the case that members of these minority groups, the less educated, female, Maori or immigrants, generally choose to have less employment due to their particular preference function shape. An example of this phenomenon can be drawn with female employment rates. Older cohorts of female workers generally did not seek to join the labour force and chose to take care of their families from home. The preferences and role of women in the workforce has drastically changed over the last 50 years with females undertaking similar levels of formal education to males in a present day context (Dixon, 2000). This can explain drastic increases in female employment rates over this period, as it is changing utility functions within the group not statistical discrimination causing changes. Employment 'search' models also explain employment rate differences between

[26] Important to note that the unemployed group is made up of all participants who did not report themselves as being employed or self-employed in the ALL survey aged between 25-64, excluding those self-employed and those reporting wages greater than $500 per hour.

groups (Kim, 2011). Search models assume that every worker of equal characteristics is offered the same amount of jobs per period but will only accept if the pay is greater than their reservation wage. Again, differing preferences will determine reservation wages and could cause differences in employment rates between equally productive workers. Even when considering these other human capital hypotheses, our methodology is still relevant. If preferences were completely dictating the difference between group employment rates, these differences would be consistent throughout the entire experience profile. We are testing whether the employment rates between groups converge with experience to justify statistical discrimination as a relevant factor because the discriminated group's employment rate would be rising at a faster rate than the other groups.

By specifying employment status as an outcome, a dummy variable set to equal 1 for the employed and zero for unemployed, allows a larger sample group for the analysis as both employed and unemployed survey participants data are included. Our New Zealand born sample size has now increased from 3112 participants as can be calculated from Table 1 of section 3,[27] to 4352 New Zealand born[28] (total number of NZ born from all three groups in Table 1). The increased sample allows analysis into whether statistical discrimination on the basis of either education, gender or ethnicity has an effect on employment rates. We can also look at whether, over time, the employment differentials between these worker groups converge such that employers learn about the true productivity of the groups.

In order to be consistent, the following analysis follows the same format as the above wage models; firstly New Zealand born Pakeha will be examined for signalling over levels of attained education separately for males and females (sections 5.1), followed by a pooled gender model looking for gender signalling (section 5.2). Also ethnic signalling will be looked at for the New Zealand born Maori population, again, separately for each gender (section 5.3) and lastly we will investigate any employment outcome statistical discrimination associated with immigrant status (5.4).

[27] Calculated multiplying the percentage New Zealand born (1-% foreign born) with the total employed population (4162).
[28] Calculated multiplying the percentage New Zealand born (1-% foreign born) with the total employed population for each of the three groups and adding these together .

5.1 Statistical Discrimination Over Education and Employment Outcomes for New Zealand Born Pakeha

OLS regressions of the same human capital models used above are run separately for male and female New Zealand born Pakeha, as the models include the calculated measure of potential experience it is important that the female group is treated by itself. The following specification in equation (SK.2) will be the centre of our analysis. Note that Y is the dummy dependent variable equal to one for employed and zero for unemployed.

$$Y = \beta_1 EXP + \beta_2 EXP^2 + \beta_3 ED + \beta_4 AB + \beta_5 (ED*EXP) + \beta_6 (AB*EXP) + v \qquad \text{(SK.2)}$$ [29]

5.1.1 Statistical Discrimination and Employer Learning over Education Level for Male Employment Outcomes

As we can see in column (1) of Table 18 all the normal human capital variables are found to have statistically significant effects on male employment. Potential experience enters the equation with a positive coefficient, implying that the first year of potential experience increases male employment rates by approximately 1.34 percent. Concavity over the potential experience estimates are present with the potential experience squared term estimated to have a negative sign and we can calculate the marginal effect of potential experience and 12, 22 and 33 years of potential experience to be 0.0061, 0.00006 and -0.0068 respectively. The coefficient on education suggests that the mean effect of an extra year of education is associated with a small 0.9 percent increase in the likelihood of employment.

Column (2) augments the model to include the effect of standardised prose ability which increases the likelihood of employment by 7.7 percent with a one standard deviation change in prose ability. This result confirms that worker ability is an important factor when understanding employer recruitment behaviour as a one standard deviation increase in worker ability results in a 7.7 percent greater employment rate. The results for male Pakeha are overall quite weak, however when an interaction between standardised prose score and education is added we find statistically significant results for the Altonji and Pierret (2001) interaction tests. Column (5) estimates the potential experience*education variable to have a negative association with employment suggesting that over time employers place increasingly

[29] As earlier defined, EXP, ED and AB stand for experience, education and ability respectively. Also note that potential experience will be used as the EXP measure. It is important to note that tenure interactions cannot be considered in these specifications by definition as if tenure is equal to zero, so is employment.

Table 18: Employment Outcomes for New Zealand Born Male Pakeha

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.0134***	0.0124***	0.0159**	0.0191**	0.0219***
	(0.00345)	(0.00346)	(0.00762)	(0.00772)	(0.00775)
Potential Experience Squared	-0.000306***	-0.000277***	-0.000302***	-0.000280***	-0.000303***
	(0.0000679)	(0.0000675)	(0.0000819)	(0.0000804)	(0.0000805)
Education	0.00854***	-0.00197	0.00223	0.0118	0.0173*
	(0.00304)	(0.00322)	(0.00875)	(0.00941)	(0.00978)
Standardised Prose Score		0.0741***	0.0740***	-0.000319	0.104*
		(0.0113)	(0.0113)	(0.0288)	(0.0627)
Potential Experience*Education			-0.000164	-0.000501	-0.000616*
			(0.000329)	(0.000351)	(0.000351)
Potential Experience*Prose Score				0.00266***	0.00208**
				(0.000992)	(0.00105)
Prose Score*Education					-0.00712**
					(0.00356)
N	1512	1512	1512	1512	1512
R2	0.0364	0.0688	0.0690	0.0746	0.0776

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

smaller weighting on a potential candidate's level of educational attainment. The effect of prose ability is estimated to increase over time with a positive coefficient of 0.00208 found for the potential experience and prose score interaction. In the context of employment for male Pakeha, we can conclude that employers do statistically discriminate over the level of applicant education when looking to employ but adjust their recruitment bias over time as they gauge the actual productivity of workers with lower levels of education.

5.1.2 Statistical Discrimination and Employer Learning over Education Level for Female Employment Outcomes

Table 19 presents the estimates for the female Pakeha population born in New Zealand, we can immediately see from column (1) that female employment rates change more than males with both experience and education than the male sample (55 percent larger coefficient for their first year of experience and 72 percent larger per additional year of education). Prose score enters the equation with a very similar estimate to the male sample, a 7.7 percent increase in employment is associated with a one standard deviation increase in standardised prose ability. As found with the male sample, the Altonji and Pierret interaction tests become significant in column (5) when the interaction between prose score and education is added to the equation. Statistical discrimination is significantly present with the interaction between potential experience and education estimated with a negative slope, we can calculate that the marginal effect of education decreases by 44 percent between 12 and 33 years of potential experience. However, there is no significant evidence found to support employers increasingly adjusting recruitment processes towards worker ability over time as no learning is confirmed. The results suggest that employers discriminate over the education credentials of potential female employees during the hiring process such that less educated candidates face weaker employment opportunities given equal levels of ability.

Table 19: Employment Outcomes for New Zealand Born Female Pakeha

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.0298***	0.0281***	0.0364***	0.0384***	0.0422***
	(0.00378)	(0.00376)	(0.00808)	(0.00825)	(0.00818)
Potential Experience Squared	-0.000514***	-0.000475***	-0.000530***	-0.000526***	-0.000546***
	(0.0000708)	(0.0000709)	(0.0000846)	(0.0000850)	(0.0000843)
Education	0.0305***	0.0210***	0.0309***	0.0356***	0.0461***
	(0.00354)	(0.00378)	(0.00963)	(0.0105)	(0.0107)
Standardised Prose Score		0.0742***	0.0744***	0.0427	0.267***
		(0.0124)	(0.0124)	(0.0318)	(0.0642)
Potential Experience*Education			-0.000411	-0.000596	-0.000776**
			(0.000350)	(0.000388)	(0.000385)
Potential Experience*Prose Score				0.00122	-0.000110
				(0.00113)	(0.00118)
Prose Score*Education					-0.0150***
					(0.00355)
N	2060	2060	2060	2060	2060
R2	0.0592	0.0752	0.0759	0.0765	0.0821

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Having established the market dynamics for statistical discrimination through both a wage setting and employment outcome context for the New Zealand born Pakeha population, it can be concluded that New Zealand employers display statistical discrimination over the educational credentials of workers. It is rational behaviour for employers to use only the given observable characteristics for either wage setting or hiring decisions when faced with scarce information in the scenario of hiring workers which have newly entered the labour force. Employers attempt to maximise their productivity and profits through hiring productive workers, and in a competitive market, efficiently paying the workers accordingly. It is often noted that an economy with statistical discrimination is more efficient than one where employers neglect the available information (Arrow, 1973). However, equally productive workers should not be faced with either lower employment opportunity or wage when their true productivity has been displayed through actual performance history. The research presented confirms evidence of statistical discrimination over education in the labour force with partial employer learning and any policy reform should take this into consideration. There are risks involved with enforcing a discrimination law forcing equal pay as if the worker groups are of actual lower productivity, market inefficiencies will be created. It is important for new labour force participants to understand the signalling accompanied with their education and factor this into their training investment decisions.

5.2 Statistical Discrimination Over Gender and Employment Outcomes for New Zealand Born Pakeha

To further investigate the statistical discrimination found over gender in wage setting for New Zealand born Pakeha, we can formulate employment status equations and test whether females face labour force statistical discrimination in comparison to males given equal levels of experience, education and prose ability. It is important to note that tenure interactions cannot be considered in these specifications by definition as if tenure is equal to zero, so is employment. The following analysis will focus on the interactions with potential experience and introduce a female intercept (FEM), in the following equation:

$$Y = \beta_1 FEM + \beta_2 EXP + \beta_3 EXP^2 + \beta_4 ED + \beta_5 AB + \beta_6 (ED*EXP) + \beta_7 (FEM*EXP) + \beta_8 (AB*EXP) + v \qquad (SK.3)$$[30]

[30] As earlier defined, EXP, ED and AB stand for experience, education and ability respectively. Also note that potential experience will be used as the EXP measure.

The gender gap is significant with a female dummy variable entering column (1) of Table 20 with a negative coefficient of -0.123, implying that the employment rate is 13 percent less for females in comparison to males. The pooled gender model finds the female intercept to be significant for all five specifications where as in Table 6 the female wage differential lost significance after an interaction variable of potential experience*female was added. An explanation could follow such that female wages tend to converge with male wages rather quickly as time passes rendering the wage differential insignificant. However, we can calculate that it would take approximately 72 years of potential experience for females to catch up with male employment probabilities (using the female intercept in column (5) of Table 20). Without convergence, females always have lower employment rates. As has been introduced, differences in the employment rates between genders also reflects the preferences of these groups which could be the case here. It is the interaction between potential experience and the female dummy which captures any signalling.

We can see that employers do statistically discriminate over employee gender, the interaction between potential experience and female dummy enters the equation with a statistically significant and positive coefficient of 0.00287 in column (5). This estimate does suggest the gap lessens over time providing evidence consistent with gender signalling models. Adding this interaction implies a 23 percent lower employment rate for female workers entering the labour force even though they have the same levels of education and ability. The interaction between potential experience and prose scores is estimated to have a significantly positive slope, employers continually learn that their initial assessment of female worker ability is inaccurate and increasingly change their recruitment behaviour towards reflecting actual worker ability.

Considering the signalling females are facing in terms of employment rate and unfair wages,[31] it can be argued that policy reform is justified. It is unfair for females to face both employment and wage differentials given equal levels of productivity, a discrimination law could be put in place such that unequal pay is made illegal. There are risks with this idea

[31] We saw earlier in Table 7 that New Zealand born Pakeha females face 22.5 percent smaller wages upon labour market entry compared to males.

Table 20: Employment Outcomes for New Zealand Born Pakeha

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.123***	-0.132***	-0.132***	-0.213***	-0.208***	-0.550***
	(0.0126)	(0.0124)	(0.0124)	(0.0321)	(0.0320)	(0.0823)
Potential Exp	0.0226***	0.0212***	0.0294***	0.0272***	0.0301***	0.0276***
	(0.00261)	(0.00260)	(0.00575)	(0.00571)	(0.00579)	(0.00569)
Potential Exp Squared	-0.000423***	-0.000389***	-0.000445***	-0.000443***	-0.000432***	-0.0004***
	(0.0000497)	(0.0000496)	(0.0000605)	(0.0000603)	(0.0000604)	(0.0000598)
Education	0.0201***	0.0101***	0.0200***	0.0195***	0.0265***	0.0136*
	(0.00237)	(0.00253)	(0.00671)	(0.00670)	(0.00720)	(0.00735)
Standardised Prose Score		0.0740***	0.0739***	0.0734***	0.0223	0.0210
		(0.00848)	(0.00847)	(0.00847)	(0.0221)	(0.0235)
Potential Exp*Education			-0.000395	-0.000374	-0.000638**	-0.00057**
			(0.000247)	(0.000246)	(0.000266)	(0.000261)
Potential Exp*female				0.00309***	0.00287**	0.00502***
				(0.00117)	(0.00116)	(0.00123)
Potential Exp*Prose Score					0.00190**	0.00185**
					(0.000771)	(0.000767)
Prose Score*Female						0.00680
						(0.0167)
Education*Female						0.0213***
						(0.00494)
N	3572	3572	3572	3572	3572	3572
R2	0.0656	0.0860	0.0867	0.0887	0.0906	0.0963

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

however, as firms may respond to such regulation by hiring only males which could further reduce the incentives for the disadvantaged group (females) to make skill investments (Lundberg, 1991). Also, regulation can be used to maintain a certain gender ratio but this also carries risk. Workers may not always be of equal productivity, thus enforced ratios may actually create a situation where firms are forced to hire less productive workers creating a more difficult market environment.

5.3 Statistical Discrimination Over Ethnicity and Employment Outcomes for New Zealand Born

Earlier in section 4.3 our wage specifications found significant statistical discriminatory behaviour over ethnicity such that Maori females are facing up to 31 percent smaller wages upon labour market entry than their equivalent New Zealand born counterparts. Investigating whether Maori also face signalling in the employment decision is of great interest. We will investigate the following equation, that includes a Maori intercept term (MAORI):

$$Y = \beta_1 MAORI + \beta_2 EXP + \beta_3 EXP^2 + \beta_4 ED + \beta_5 AB + \beta_6 (ED*EXP) + \beta_7 (MAORI*EXP) + \beta_8 (AB*EXP) + v \qquad \textbf{(SK.4)}$$

Table 21: Employment Outcomes for New Zealand Born Male Maori

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.0947***	-0.0646**	-0.0647**	-0.0573	-0.0824	-0.542***
	(0.0294)	(0.0304)	(0.0304)	(0.0750)	(0.0770)	(0.193)
Potential Experience	0.0147***	0.0134***	0.0156**	0.0158**	0.0182**	0.0163**
	(0.00328)	(0.00327)	(0.00698)	(0.00713)	(0.00719)	(0.00717)
Potential Exp Squared	-0.000320***	-0.000290***	-0.000306***	-0.000307***	-0.000296***	-0.000289***
	(0.0000645)	(0.0000641)	(0.0000770)	(0.0000775)	(0.0000773)	(0.0000774)
Education	0.0111***	0.00225	0.00485	0.00506	0.0111	0.00568
	(0.00288)	(0.00303)	(0.00791)	(0.00810)	(0.00855)	(0.00858)
Prose Score		0.0635***	0.0635***	0.0635***	0.0166	0.0317
		(0.0105)	(0.0105)	(0.0105)	(0.0265)	(0.0273)
Potential Exp*Education			-0.000105	-0.000113	-0.000338	-0.000241
			(0.000301)	(0.000308)	(0.000325)	(0.000325)
Potential Exp*Maori				-0.000305	0.000687	0.00248
				(0.00295)	(0.00305)	(0.00317)
Potential Exp* Prose Score					0.00175*	0.00147
					(0.000952)	(0.000958)
Prose Score*Maori						-0.0622*
						(0.0348)
Education*Maori						0.0321**
						(0.0127)
N	1862	1862	1862	1862	1862	1862
R2	0.0430	0.0646	0.0646	0.0647	0.0669	0.0716

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

5.3.1 Statistical Discrimination and Employer Learning over Ethnic Group for Male Employment Outcomes

Similar to the analysis conducted with wages, male Maori face a significant negative employment differential until column (4) of Table 21 where the Potential Experience*Maori term is added. This interaction captures the effect that being Maori has over the potential experience profile and allows the Maori dummy to represent the employment gap a male Maori faces upon entry into the labour force. This result suggests that Maori males do not face any significantly different employment rate when first entering the New Zealand labour force after controlling for the Maori effect over time. We can see that Maori males have a significant 6.7 percent lower employment rate in column (2) when the specification controls for education, experience and prose ability. The wage model presented earlier in Table 8 suggested that prose ability explained the difference in wages between Maori male and other New Zealand born males, however column (2) of Table 21 reveals that given equal levels of prose ability the Maori still face weaker employment prospects. Overall, we do not find any evidence towards statistical discrimination or employer learning for male Maori in terms of employment rates.

5.3.2 Statistical Discrimination and Employer Learning over Ethnic Group for Female Employment Outcomes

Female Maori are found to have significant employment gaps throughout all of Table 22, similar to the results we found earlier, in Table 9, using wage as the dependent variable. When controlling for both the time varying effects of being Maori and prose ability in column (5), it is estimated that Maori females face a 24.5 percent lower likelihood of employment when first entering the labour force in comparison to an equal ability non Maori New Zealand born worker. A significantly positive interaction is found between the Maori dummy and potential experience such that statistical discrimination is present. The employment deficit for female Maori is decreasing over time with a gradient of 0.006 with an 88 percent decrease in the Maori employment gap calculated between 12 and 33 years of potential experience. Employer learning can also be confirmed with employers learning the true productivity of Maori workers throughout the time period. We see this with a significantly positive coefficient on the interaction between potential experience and prose score. It can be ascertained that female Maori face both significantly harder employment opportunities and wage signalling.

Table 22: Employment Outcomes for New Zealand Born Female Maori

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.100***	-0.0764***	-0.0762***	-0.198***	-0.219***	-0.387**
	(0.0273)	(0.0275)	(0.0275)	(0.0651)	(0.0653)	(0.184)
Potential Exp	0.0287***	0.0268***	0.0361***	0.0327***	0.0367***	0.0365***
	(0.00345)	(0.00344)	(0.00721)	(0.00734)	(0.00750)	(0.00750)
Potential Exp Squared	-0.000477***	-0.000435***	-0.000496***	-0.000473***	-0.000465***	-0.000466***
	(0.0000650)	(0.0000652)	(0.0000769)	(0.0000770)	(0.0000773)	(0.0000773)
Education	0.0337***	0.0235***	0.0346***	0.0317***	0.0407***	0.0388***
	(0.00327)	(0.00354)	(0.00865)	(0.00876)	(0.00956)	(0.00968)
Prose Score		0.0752***	0.0754***	0.0766***	0.0164	0.0186
		(0.0114)	(0.0114)	(0.0114)	(0.0287)	(0.0288)
Potential Exp*Education			-0.000471	-0.000356	-0.000714**	-0.000700*
			(0.000317)	(0.000321)	(0.000357)	(0.000357)
Potential Exp*Maori				0.00518**	0.00613**	0.00688***
				(0.00240)	(0.00241)	(0.00257)
Potential Exp*Prose Score					0.00236**	0.00234**
					(0.00103)	(0.00103)
Prose Score*Maori						-0.0150
						(0.0345)
Education*Maori						0.0119
						(0.0123)
N	2560	2560	2560	2560	2560	2560
R2	0.0704	0.0858	0.0866	0.0886	0.0907	0.0907

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

In terms of market dynamics, the analysis conducted exposes a great inefficiency in the New Zealand labour force. Under compensating equally productive workers of different groups and providing them with weaker employment possibility will certainly induce a change in the groups behaviour. Education and training investment will be more costly for female Maori as they will be under compensated in comparison. In the wage estimation work, the marginal return to being Maori increased over the experience profile such that female Maori wages converged with the wages of other New Zealand born workers after approximately 28 years of potential experience. However, when investigating the effects of employment outcomes, we can see that female Maori employment probability does eventually converge but over a longer period of 36 years of employment. These are both rather large employment periods. For an equally productive worker to face up to 36 years of an employment deficit will change the incentives for younger Maori, in terms of investment in education. Regulatory steps may be necessary to help reduce unequal wage setting in New Zealand. Our government places value on Maori education by providing various funding mechanisms to incentivise higher education. With unequal compensation, the effect of these educational scholarships are negated as Maori may not be able to achieve a justified employment outcome or wage return upon labour force entry.

5.4 Statistical Discrimination Over Immigrant Status and Employment Outcomes

In order to be consistent and thorough, we finally investigate whether immigrants face weaker employment prospects in comparison with the New Zealand born Pakeha sample. Again, similar to chapter 6, employment status is specified as the dependent variable (Y). The following equation will be used as the basis of the employment outcome analysis for immigrants:

$$Y = \beta_1 FB + \beta_2 EXP + \beta_3 EXP^2 + \beta_4 ED + \beta_5 AB + \beta_6 (ED*EXP) + \beta_7 (FB*EXP) + \beta_8 (AB*EXP) + v \qquad \text{(IM.2)}$$ [32]

[32] As earlier defined, FB, EXP, ED and AB stand for foreign born, experience, education and ability respectively. Also note that potential experience will be used as the EXP measure.

Table 23: Male Employment Outcomes for NZ Born Pakeha vs. All Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	0.0141	0.0541***	0.0520***	0.162***	0.132***	0.586***
	(0.0158)	(0.0162)	(0.0162)	(0.0382)	(0.0393)	(0.109)
Potential Exp	0.0205***	0.0189***	0.0273***	0.0273***	0.0296***	0.0309***
	(0.00237)	(0.00237)	(0.00539)	(0.00537)	(0.00544)	(0.00543)
Potential Exp Squared	-0.000399***	-0.000365***	-0.000426***	-0.00043***	-0.000424***	-0.000428***
	(0.0000455)	(0.0000454)	(0.0000565)	(0.0000564)	(0.0000565)	(0.0000561)
Education	0.0158***	0.00723***	0.0169***	0.0150**	0.0202***	0.0264***
	(0.00216)	(0.00234)	(0.00614)	(0.00613)	(0.00653)	(0.00669)
Prose Ability		0.0600***	0.0604***	0.0618***	0.0247	0.0270
		(0.00737)	(0.00736)	(0.00732)	(0.0183)	(0.0196)
Potential Exp*Education			-0.000395*	-0.000340	-0.000543**	-0.000576**
			(0.000228)	(0.000228)	(0.000244)	(0.000243)
Potential Exp*Foreign				-0.00450***	-0.00347**	-0.00679***
				(0.00156)	(0.00161)	(0.00172)
Potential Exp*Prose Score					0.00142**	0.00149**
					(0.000661)	(0.000664)
Prose Score*Foreign						-0.00659
						(0.0162)
Education*Foreign						-0.0262***
						(0.00612)
N	4244	4244	4244	4244	4244	4244
R2	0.0368	0.0525	0.0534	0.0556	0.0568	0.0633

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 24: Male Employment Outcomes for New Zealand Born Pakeha vs. Foreign Born Asian and Pasifika

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.109***	-0.0365	-0.0391*	0.0391	-0.0318	0.325**
	(0.0208)	(0.0230)	(0.0232)	(0.0460)	(0.0520)	(0.150)
Potential Exp	0.0203***	0.0191***	0.0233***	0.0247***	0.0278***	0.0295***
	(0.00244)	(0.00244)	(0.00547)	(0.00551)	(0.00557)	(0.00557)
Potential Exp Squared	-0.000390***	-0.000361***	-0.000392***	-0.000408***	-0.000397***	-0.000411***
	(0.0000467)	(0.0000466)	(0.0000581)	(0.0000585)	(0.0000586)	(0.0000586)
Education	0.0174***	0.00924***	0.0141**	0.0138**	0.0214***	0.0257***
	(0.00225)	(0.00247)	(0.00625)	(0.00625)	(0.00671)	(0.00680)
Prose Ability		0.0589***	0.0588***	0.0589***	0.00336	0.0143
		(0.00805)	(0.00804)	(0.00804)	(0.0203)	(0.0211)
Potential Exp*Education			-0.000197	-0.000212	-0.000506**	-0.000544**
			(0.000228)	(0.000228)	(0.000247)	(0.000247)
Potential Exp*Foreign				-0.00364*	-0.000883	-0.00526**
				(0.00191)	(0.00214)	(0.00246)
Potential Exp*Prose Score					0.00215***	0.00196***
					(0.000720)	(0.000727)
Prose Score*Foreign						-0.0261
						(0.0226)
Education*Foreign						-0.0197**
						(0.00779)
N	4124	4124	4124	4124	4124	4124
R2	0.0412	0.0545	0.0547	0.0558	0.0582	0.0604

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

5.4.1 Statistical Discrimination and Employer Learning over Immigrant Status for Male Employment Outcomes

Table 23 looks at the employment outcomes for male immigrants, interestingly in column (5) we can see that immigrants seem to have a significantly higher rate of employment, they are estimated to have a 14.1 percent higher employment rate upon labour market entry. It is possible that employment rates for male migrants are likely higher compared to natives, with the same potential experience, education and ability, because of the selection mechanisms used by the NZ Government in choosing migrants, self-selection. Some migrants are required to have already secured a job before being granted entry into the country, this would push up the initial immigrant employment rate. The interaction between experience and immigrant status enters with a negative sign (-0.00347), this result does not fit with our statistical discrimination hypothesis as it implies that when male migrants first enter the labour force, they have a relatively higher employment rate that decreases (converges) with that of New Zealand Pakeha over time.

This result more aligns with a preference hypothesis, as immigrants spend longer in the country, their employment preferences (decision to work) merge with that of natives. However, employer learning is confirmed with the Experience*Ability variable estimated to have a significant positive coefficient.[33] The immigrant group is further fragmented such that we compare the Foreign born Europeans to New Zealand born Pakeha, as was established earlier in section 4.4.2, Table A.14 of Appendix A shows the foreign born Europeans are again found to face no statistical discrimination or gap in employment. These immigrants have very similar cultural and educational backgrounds, in comparison to New Zealand Pakeha, which provides a more informative signal about productivity for New Zealand employers.

Table 24 presents the regression analysis comparing the employment outcomes of male foreign born Asian and Pasifika to New Zealand born Pakeha. It appears that the employment rate gap is completely explained by the difference in ability between the two groups as adding in the ability measure renders the foreign born intercept to be insignificant in column (2).

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[33] As in section 7.1, the employment outcome regressions are also conducted using YSM as the measure of experience for immigrants, but these results are no different to what is found with just potential experience for all immigrants and can be seen in Table A.12, Appendix A.

However, we can find the presence of employer learning in column (6) with an interaction between experience and ability entering positively with significance. Such result indicates that employers do learn about the ability of both these groups over time but there is no significant statistical discrimination present. Column (6) also presents similar evidence to what we have found in Table 23, male Asian and Pasifika immigrants are estimated to have 38 percent higher employment rates upon labour market entry than natives and the potential experience interaction with immigrant status is found to be negative (-0.00526). We can again conclude that self selection and immigrant preferences are behind these results with no statistical discrimination present.

5.4.2 Statistical Discrimination and Employer Learning over Immigrant Status for Female Employment Outcomes

Turning our attention to the female immigrants bears some interesting results, we can see in Table 25 below that female immigrants, as a group, have lower employment rates. Column (5) estimates female immigrants to face employment rates 13.4 percent smaller in comparison to the New Zealand born Pakeha upon entry into the labour force. No evidence of statistical discrimination is found, this suggests that it is female immigrant preferences driving the lower employment rates found. It could be the case that females prefer looking after their children upon migration into a new country rather than partaking in employment. Employer learning is found with the interaction between potential experience and ability estimated to be positive (0.00156).[34]

Finally, we look to investigate the employment status effects for constituent migrant groups, female migrants from European descent have no significant employment gap and are not found to be discriminated against, as can be seen in Table A.15 of Appendix A. Similar to the male migrants from European background, New Zealand employers have no trouble in reading the productivity from this groups credentials. Homogenous culture and educational infrastructure can be attributed to this result. Table 26 shows the results for foreign born Asian and Pasifika female immigrants in comparison with New Zealand born female Pakeha.

[34] As in section 7.1, the employment outcome regressions are also conducted using YSM as the measure of experience for immigrants, but these results are no different to what we find using only potential experience and can be seen in Table A.13, Appendix A.

We can see in column (6) that there is no significant labour force entry employment gap or statistical discrimination for this group but employer learning does exist.

The results for immigrant employment outcomes suggest that preferences play quite a large role in the decision to work, as male immigrants tend to either have greater or significantly indifferent employment rates and female immigrants tend to choose less employment. No significant statistical discrimination can be confirmed against male or female immigrants in terms of employment outcomes. We found that male immigrants seem to be self selected migrants and enter the country with secured employment, whilst females may be choosing to establish their home lives before entering the labour force.

Table 25: Female Employment Outcomes for NZ Born Pakeha vs. ALL Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.196***	-0.160***	-0.163***	-0.102**	-0.126***	-0.254**
	(0.0174)	(0.0179)	(0.0179)	(0.0400)	(0.0416)	(0.108)
Potential Exp	0.0217***	0.0204***	0.0326***	0.0329***	0.0355***	0.0351***
	(0.00241)	(0.00240)	(0.00525)	(0.00525)	(0.00531)	(0.00535)
Potential Exp Squared	-0.000405***	-0.000375***	-0.000463***	-0.000464***	-0.000460***	-0.000458***
	(0.0000457)	(0.0000456)	(0.0000563)	(0.0000562)	(0.0000563)	(0.0000564)
Education	0.0235***	0.0145***	0.0286***	0.0279***	0.0336***	0.0314***
	(0.00215)	(0.00234)	(0.00590)	(0.00590)	(0.00634)	(0.00658)
Prose Ability		0.0649***	0.0652***	0.0660***	0.0252	0.0254
		(0.00767)	(0.00765)	(0.00763)	(0.0190)	(0.0198)
Potential Exp*Education			-0.000574***	-0.000562***	-0.000787***	-0.000775***
			(0.000217)	(0.000217)	(0.000236)	(0.000238)
Potential Exp*Foreign				-0.00252*	-0.00169	-0.000760
				(0.00150)	(0.00156)	(0.00171)
Potential Exp*Prose Score					0.00156**	0.00154**
					(0.000668)	(0.000672)
Prose Score*Foreign						-0.000279
						(0.0180)
Educ*Foreign						0.00760
						(0.00590)
N	4438	4438	4438	4438	4438	4438
R2	0.0742	0.0904	0.0920	0.0927	0.0941	0.0946

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

Table 26: Female Employment Outcomes for New Zealand Born Pakeha vs. Foreign Born Asian and Pasifika

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.187***	-0.113***	-0.117***	-0.00686	-0.0734	-0.107
	(0.0203)	(0.0224)	(0.0225)	(0.0444)	(0.0503)	(0.143)
Potential Exp	0.0201***	0.0188***	0.0267***	0.0290***	0.0318***	0.0316***
	(0.00243)	(0.00243)	(0.00545)	(0.00549)	(0.00554)	(0.00556)
Potential Exp Squared	-0.000383***	-0.000352***	-0.000409***	-0.000433***	-0.000419***	-0.00042***
	(0.0000464)	(0.0000464)	(0.0000580)	(0.0000580)	(0.0000581)	(0.0000583)
Education	0.0217***	0.0133***	0.0224***	0.0226***	0.0297***	0.0289***
	(0.00227)	(0.00247)	(0.00625)	(0.00626)	(0.00671)	(0.00681)
Prose Ability		0.0622***	0.0621***	0.0620***	0.00803	0.0131
		(0.00807)	(0.00806)	(0.00806)	(0.0202)	(0.0212)
Potential Exp*Education			-0.000371	-0.000407*	-0.000686***	-0.000671***
			(0.000228)	(0.000229)	(0.000246)	(0.000248)
Potential Exp*Foreign				-0.00514***	-0.00252	-0.00266
				(0.00180)	(0.00204)	(0.00234)
Potential Exp*Prose Score					0.00210***	0.00201***
					(0.000718)	(0.000729)
Prose Score*Foreign						-0.0133
						(0.0226)
Educ*Foreign						0.00202
						(0.00753)
N	4197	4197	4197	4197	4197	4197
R2	0.0632	0.0774	0.0781	0.0803	0.0826	0.0827

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis. The regression model also includes a constant.

6. Conclusion

New Zealand employers, similarly to what has been found in international literature, have been found to remunerate seemingly equal workers of different groups unequally. The idea of statistical discrimination used against certain employee groups has been adopted to explain unequal pay among equally able workers in labour economics for more than thirty years. From the standpoint of classical microeconomic theory, there could be justification behind such firm behaviour. The world we live in is rampant with imperfect information. It is rational for employers to use limited information to maximise their profit. An economy with statistical discrimination could therefore be considered more efficient than one where employers completely neglect all available information. However, discriminating against minority groups can lead them to poor labour market outcomes. This thesis investigated whether firms use education, gender, ethnicity and immigration status to statistically judge worker ability in New Zealand within a simple employer learning model, given that worker productivity is difficult to observe. We apply the analysis within both wage and employment status regressions in order to avoid sample selection bias. Moreover, evidence on employer learning has also been examined. This implies that a firm will learn to adjust their initially formed productivity beliefs, as better information about a worker becomes available in the market.

In terms of education signalling in wages, employers are not found to statistically discriminate against New Zealand born Pakeha male workers. However, employer learning and statistical discrimination over education level is found for New Zealand born Pakeha females when examining wages. When considering employment status, significant statistical discrimination was found for both male and female New Zealand born Pakeha with employer learning also confirmed for the latter. It is clear that employers place more emphasis on education credentials in the recruiting process compared with wage setting.

Considering gender signalling, we find that New Zealand born Pakeha females face wages 22.5 percent smaller wages than their equivalent male counterparts when entering the labour force, with employer learning also present. Although, no evidence of statistical wage discrimination over gender can be confirmed. The gender signalling hypothesis is confirmed in the employment status model. While females tend to have lower employment rates in general, we find that they do increase with worker experience such that evidence of statistical discrimination is present.

Aside from gender and education signalling, statistical grouping of Maori workers was also investigated. Within a wage setting context, male Maori wages are found to be indifferent to that of New Zealand born Pakeha males when accounting for the ability, education and experience levels of these groups. Again, this points to the conclusion that employers apply less signalling with New Zealand born males, whether of Maori or Pakeha ethnicity. Female Maori are shown to suffer statistical wage discrimination on the basis of their ethnicity with employer learning present. It could be the case that female productivity signals are more noisy than males, forcing employers to use statistical discrimination to distinguish workers. Turning our attention to ethnic signalling in employment status, male Maori, as with wages, do not face any statistical discrimination. Female Maori face a 24.5 percent lower likelihood of employment, upon labour market entry, compared with equivalent New Zealand born, with statistical discrimination and employer learning also confirmed.

Lastly, immigrant signalling is explored. As an entire group, there is no evidence of wage signalling found for males or females. However, a model using YSM for immigrant experience finds that foreign males may have greater initial wages, in comparison to natives, when first entering the labour force due to self selection. Asian and Pasifika male immigrants do not face any statistical discrimination in wages but, for females, signalling evidence is found and females are estimated to earn 21.3 percent smaller wages than natives. Employer learning is also confirmed for this group. When looking at employment status, male immigrants, as an entirety, and the Asian and Pasifika group in particular, are found to have greater levels of employment upon labour market entry. These rates are estimated to converge with the New Zealand born over the experience profile suggesting that immigrants may have chosen to move to New Zealand with a job already secured as opposed to natives just entering the labour force. Female immigrants, as an entire group, tend to have lower employment rates than natives but face no signalling, implying that upon entry into New Zealand, females choose to establish their home life before entering the work force. Employer learning is found for foreign born Asian and Pasifika females.

Overall, evidence of statistical discrimination by education levels has been found in the wages of females and when examining the employment status of both male and female New Zealand born Pakeha. New Zealand born Pakeha also face statistical discrimination over gender when analysing employment status, while supporting evidence of statistical discrimination is presented for female Maori both in wages and employment status. The models for males lack evidential support in terms of education and ethnic group signalling, in wages, and ethnic group signalling in employment outcomes. Also, no significant statistical discrimination has been identified within either the wages or employment status for any of the immigrant groups in each gender except for in the wages of female Asian and Pasifika immigrants. Significant statistical discrimination and employer learning is found for this group.

We must remember that when employer learning and statistical discrimination exists in the labour market, any policy reform should be evaluated within this context. However, simply enforcing a discrimination law to eliminate unequal pay is risky. If workers are in fact different in their abilities, the discrimination law may actually produce a negative effect in the market. Rational firms may respond to this kind of restriction by hiring fewer disadvantaged workers, which may further reduce a minority group's incentive for making further skill investments. Rather, policymakers should turn the focus to advocacy of policies that encourage lower productivity workers to make themselves more valuable.

One shortcoming of this study is that it assumes individuals' experience profiles to be independent of education and prose ability scores. The ALL survey aimed to measure workplace demonstrated ability, so it is reasonable to consider that our standardised prose ability measure of productivity may be correlated with experience. A more general approach, one that accounts for the effects of on-the-job training, can be taken in the future research. The present thesis was unable to accurately measure an on-the-job training variable due to limitations with the ALL data. Economic theory generally suggests that on-the-job training is often given to more educated and able individuals and accounting for this may remove bias from other estimates. As a whole, any bias caused from a relation between our ability and experience variables would affect each of our observable groups equivalently, hence looking at the signs for our variable tests is still valid. Accurate measurement of worker actual experience is another limitation of this work. The ALL survey data did not contain any information ascertaining to the actual level of worker experience, instead our models used both potential experience and tenure. The main issue surrounding potential experience as a measure is the inability to capture female experience.

In terms of future research, there are a number of areas which could be addressed. Firstly, it could be interesting to examine a model with the relaxation of the symmetric employer learning assumption. This involves testing whether incumbent employers have greater information about their workers' productivity in comparison to outside firms. Another avenue, would be to compare differences for workers with high and low levels of education to see whether employers treat these groups differently. Further research into grouping immigrants by language skills and testing whether those that speak languages more similar to English are treated like natives, could be fruitful. Lastly, adopting this same methodology to other countries would allow for broader findings in terms of immigrant, ethnic and gender signalling as well as international comparisons.

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Appendices

Appendix A. Tables

Table A.1 Mean Years of Education for Employed Immigrants and New Zealand Born

	Female	Male	Total
NZ born	13.56	13.64	13.60
Forborn	14.99	14.84	14.92
Total	14.28	14.24	23.65

Table A.2 Mean Hourly Wages ($/h) for Employed Immigrants and New Zealand Born

	Female	Male	Total
NZ born	22.17	26.62	24.40
Forborn	21.27	24.53	22.90
Total	21.72	25.58	23.65

Table A.2 Mean Hourly Wages ($/h) for Employed Maori and New Zealand Born Pakeha

	Female	Male	Total
NZ Born Pakeha	22.49	27.10	24.80
Maori	19.00	20.52	19.76
Total	20.75	23.81	22.28

Table A.3 The Effects of Standardised Prose Score, Schooling and Tenure on Male NZ Pakeha Wages

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.0279***	0.0274***	0.0276***	0.0275***	0.0280***
	(0.00649)	(0.00635)	(0.00667)	(0.00669)	(0.00671)
Potential Experience Squared	-0.000427***	-0.000406***	-0.000409***	-0.000408***	-0.000417***
	(0.000127)	(0.000124)	(0.000130)	(0.000130)	(0.000131)
Tenure	0.00531	0.00274	0.00367	0.00433	0.00481
	(0.00660)	(0.00658)	(0.0112)	(0.0115)	(0.0115)
Tenure Squared	-0.000109	-0.0000410	-0.0000422	-0.0000397	-0.0000344
	(0.000194)	(0.000193)	(0.000193)	(0.000193)	(0.000193)
Education	0.0711***	0.0548***	0.0554***	0.0560***	0.0539***
	(0.00625)	(0.00670)	(0.00823)	(0.00842)	(0.00872)
Standardised Prose Score		0.127***	0.127***	0.123***	0.0458
		(0.0204)	(0.0204)	(0.0259)	(0.0714)
Education*Tenure			-0.0000674	-0.000126	-0.000177
			(0.000658)	(0.000701)	(0.000702)
Prose Score*Tenure				0.000439	0.000567
				(0.00209)	(0.00207)
Prose Score*Education					0.00596
					(0.00552)
Constant	1.679***	1.883***	1.872***	1.866***	1.882***
	(0.122)	(0.123)	(0.150)	(0.150)	(0.151)
N	1247	1247	1247	1247	1247
R^2	0.114	0.138	0.139	0.139	0.139

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.4 The Effects of Prose Score, Schooling and Tenure on Male NZ Pakeha Wages

	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.0279***	0.0274***	0.0233	0.0254*	0.0219
	(0.00649)	(0.00635)	(0.0148)	(0.0145)	(0.0148)
Potential Experience Squared	-0.000427***	-0.000406***	-0.000380**	-0.000373**	-0.000348**
	(0.000127)	(0.000124)	(0.000166)	(0.000167)	(0.000168)
Tenure	0.00531	0.00274	0.00472	0.00450	0.00612
	(0.00660)	(0.00658)	(0.0113)	(0.0116)	(0.0116)
Tenure Squared	-0.000109	-0.0000410	-0.0000470	-0.0000474	-0.0000467
	(0.000194)	(0.000193)	(0.000194)	(0.000194)	(0.000193)
Education	0.0711***	0.0548***	0.0509***	0.0563***	0.0497***
	(0.00625)	(0.00670)	(0.0155)	(0.0159)	(0.0165)
Standardised Prose Score		0.127***	0.127***	0.0850*	-0.0582
		(0.0204)	(0.0203)	(0.0502)	(0.101)
Potential Experience*Education			0.000209	0.00000763	0.000169
			(0.000617)	(0.000627)	(0.000633)
Tenure*Education			-0.000139	-0.000120	-0.000250
			(0.000659)	(0.000704)	(0.000707)
Potential Experience*Prose Ability				0.00167	0.00256
				(0.00181)	(0.00189)
Tenure*Prose Ability				-0.000291	-0.000483
				(0.00216)	(0.00214)
Education*Prose Ability					0.00961
					(0.00603)
Constant	1.679***	1.883***	1.951***	1.888***	1.984***
	(0.122)	(0.123)	(0.275)	(0.271)	(0.280)
N	1247	1247	1247	1247	1247
R2	0.114	0.138	0.139	0.139	0.140

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.5 The Effects of Prose Score, Schooling and Tenure on Female NZ Pakeha Wages					
	(1)	(2)	(3)	(4)	(5)
Potential Experience	0.00506	0.00358	0.00830	0.00980	0.00965
	(0.00687)	(0.00692)	(0.0145)	(0.0148)	(0.0146)
Potential Experience Squared	-0.000130	-0.0000888	-0.000144	-0.000122	-0.000121
	(0.000132)	(0.000133)	(0.000154)	(0.000152)	(0.000151)
Tenure	0.0212***	0.0197***	0.0317**	0.0376***	0.0376***
	(0.00634)	(0.00637)	(0.0131)	(0.0134)	(0.0134)
Tenure Squared	-0.000365*	-0.000338*	-0.000344*	-0.000355*	-0.000354*
	(0.000206)	(0.000205)	(0.000202)	(0.000201)	(0.000202)
Education	0.0707***	0.0625***	0.0721***	0.0827***	0.0819***
	(0.00658)	(0.00680)	(0.0190)	(0.0199)	(0.0194)
Standardised Prose Score		0.0758***	0.0749***	-0.0290	-0.0521
		(0.0233)	(0.0234)	(0.0577)	(0.140)
Potential Experience*Education			-0.000142	-0.000381	-0.000378
			(0.000663)	(0.000726)	(0.000722)
Tenure*Education			-0.000867	-0.00147	-0.00147
			(0.000886)	(0.000934)	(0.000933)
Potential Experience*Prose Ability				0.00215	0.00230
				(0.00208)	(0.00219)
Tenure*Prose Ability				0.00658**	0.00651**
				(0.00315)	(0.00320)
Education*Prose Ability					0.00150
					(0.00860)
Constant	1.780***	1.880***	1.717***	1.618***	1.630***
	(0.125)	(0.130)	(0.314)	(0.320)	(0.311)
N	1397	1397	1397	1397	1397
R2	0.101	0.107	0.108	0.112	0.112

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.6 The Effects of Potential Experience, Tenure and Ethnic Group on Male Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Maori	-0.103**	-0.0376	-0.0371	-0.125*	-0.130*	-0.00934
	(0.0496)	(0.0501)	(0.0499)	(0.0684)	(0.0693)	(0.270)
Potential Experience	0.0254***	0.0242***	0.0247***	0.0249***	0.0249***	0.0248***
	(0.00590)	(0.00578)	(0.00608)	(0.00606)	(0.00607)	(0.00608)
Potential Experience Squared	-0.000390***	-0.000355***	-0.000365***	-0.000370***	-0.000369***	-0.00037***
	(0.000117)	(0.000115)	(0.000120)	(0.000120)	(0.000120)	(0.000120)
Tenure	0.00822	0.00546	0.00909	0.00548	0.00677	0.00710
	(0.00610)	(0.00607)	(0.0106)	(0.0107)	(0.0109)	(0.0109)
Tenure Squared	-0.000156	-0.0000864	-0.0000924	-0.0000756	-0.0000709	-0.0000723
	(0.000178)	(0.000177)	(0.000179)	(0.000177)	(0.000176)	(0.000176)
Education	0.0680***	0.0521***	0.0547***	0.0531***	0.0542***	0.0553***
	(0.00579)	(0.00611)	(0.00772)	(0.00772)	(0.00789)	(0.00808)
Standardised Prose Score		0.128***	0.128***	0.128***	0.120***	0.114***
		(0.0194)	(0.0194)	(0.0194)	(0.0257)	(0.0249)
Education*Tenure			-0.000263	-0.0000917	-0.000207	-0.000229
			(0.000607)	(0.000615)	(0.000649)	(0.000648)
Prose Score*Tenure				0.0126**	0.0131**	0.0130**
				(0.00508)	(0.00530)	(0.00536)
Prose Score*Tenure					0.000890	0.00103
					(0.00206)	(0.00203)
Maori*Prose Score						0.0325
						(0.0764)
Maori*Education						-0.00864
						(0.0189)
Constant	1.734***	1.943***	1.901***	1.932***	1.919***	1.905***
	(0.110)	(0.111)	(0.139)	(0.139)	(0.139)	(0.142)
N	1502	1502	1502	1502	1502	1502
R2	0.114	0.139	0.139	0.141	0.141	0.141

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.7 The Effects of Standardised Numeracy Score, Schooling and Ethnic Group on Male Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Potential Experience	-0.109**	-0.00192	-0.00218	0.0194	0.00789	0.0916
	(0.0504)	(0.0503)	(0.0503)	(0.122)	(0.126)	(0.325)
Potential Experience Squared	0.0279***	0.0257***	0.0194	0.0199	0.0208	0.0211
	(0.00582)	(0.00563)	(0.0134)	(0.0135)	(0.0132)	(0.0133)
Maori	-0.000418***	-0.000364***	-0.000320**	-0.000324**	-0.000323**	-0.000324**
	(0.000117)	(0.000113)	(0.000150)	(0.000151)	(0.000151)	(0.000152)
Education	0.0695***	0.0482***	0.0406***	0.0412***	0.0431***	0.0441***
	(0.00559)	(0.00580)	(0.0136)	(0.0135)	(0.0136)	(0.0138)
Standardised Numeracy Score		0.154***	0.155***	0.155***	0.140***	0.137***
		(0.0185)	(0.0186)	(0.0185)	(0.0439)	(0.0447)
Education*Experience			0.000306	0.000286	0.000210	0.000193
			(0.000557)	(0.000556)	(0.000558)	(0.000559)
Maori*Experience				-0.000929	-0.000458	-0.000636
				(0.00505)	(0.00513)	(0.00526)
Numeracy Score*Poten Exp					0.000567	0.000622
					(0.00168)	(0.00169)
Numeracy Score*Maori						0.0158
						(0.0814)
Maori*Education						-0.00579
						(0.0196)
Constant	1.721***	1.986***	2.113***	2.102***	2.079***	2.065***
	(0.109)	(0.106)	(0.241)	(0.240)	(0.234)	(0.238)
N	1502	1502	1502	1502	1502	1502
R2	0.112	0.151	0.151	0.151	0.151	0.151

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.8 The Effects of Standardised Numeracy Score, Schooling and Ethnic Group on Female Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Potential Experience	-0.0749*	0.00408	0.00342	-0.237**	-0.285***	0.674***
	(0.0443)	(0.0424)	(0.0424)	(0.108)	(0.104)	(0.249)
Potential Experience Squared	0.0137**	0.0121**	0.0203	0.0151	0.0194	0.0193
	(0.00617)	(0.00612)	(0.0124)	(0.0127)	(0.0130)	(0.0130)
Maori	-0.000225*	-0.000168	-0.000220	-0.000188	-0.000164	-0.000148
	(0.000120)	(0.000119)	(0.000135)	(0.000136)	(0.000136)	(0.000134)
Education	0.0707***	0.0554***	0.0655***	0.0609***	0.0714***	0.0788***
	(0.00569)	(0.00593)	(0.0157)	(0.0160)	(0.0174)	(0.0174)
Standardised Numeracy Score		0.126***	0.126***	0.126***	0.0536	0.0276
		(0.0205)	(0.0204)	(0.0204)	(0.0553)	(0.0526)
Education*Experience			-0.000413	-0.000226	-0.000631	-0.000682
			(0.000565)	(0.000577)	(0.000638)	(0.000633)
Maori*Experience				0.00988**	0.0118***	0.0107**
				(0.00408)	(0.00398)	(0.00418)
Numeracy Score*Poten Exp					0.00291	0.00304
					(0.00203)	(0.00198)
Numeracy Score*Maori						0.219***
						(0.0738)
Maori*Education						-0.0635***
						(0.0174)
Constant	1.748***	1.945***	1.776***	1.885***	1.758***	1.664***
	(0.110)	(0.112)	(0.258)	(0.265)	(0.278)	(0.280)
N	1670	1670	1670	1670	1670	1670
R2	0.0871	0.109	0.109	0.112	0.113	0.121

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.9 The Effects of Standardised Prose Score and Schooling on Male Wages of NZ Born Pakeha vs. European Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	0.0535	0.0432	0.0434	0.0448	0.0489	0.0909
	(0.0496)	(0.0490)	(0.0490)	(0.121)	(0.120)	(0.134)
Potential Experience	0.0269***	0.0258***	0.0204	0.0204	0.0223	0.0225
	(0.00593)	(0.00582)	(0.0140)	(0.0141)	(0.0138)	(0.0138)
Potential Experience Squared	-0.000399***	-0.000369***	-0.000331**	-0.000331**	-0.000324**	-0.000326**
	(0.000117)	(0.000115)	(0.000153)	(0.000154)	(0.000155)	(0.000155)
Education	0.0691***	0.0535***	0.0470***	0.0470***	0.0521***	0.0521***
	(0.00562)	(0.00605)	(0.0145)	(0.0146)	(0.0150)	(0.0150)
Prose Ability		0.128***	0.128***	0.128***	0.0868*	0.0903*
		(0.0194)	(0.0194)	(0.0194)	(0.0483)	(0.0485)
Potential Exp*Education			0.000256	0.000257	0.0000746	0.0000689
			(0.000577)	(0.000582)	(0.000595)	(0.000595)
Potential Exp*Foreign				-0.0000552	-0.000254	-0.000941
				(0.00410)	(0.00409)	(0.00429)
Potential Exp*Ability					0.00152	0.00151
					(0.00171)	(0.00172)
Ability*Foreign						-0.0547
						(0.0657)
Constant	1.742***	1.930***	2.042***	2.042***	1.983***	1.981***
	(0.111)	(0.112)	(0.258)	(0.259)	(0.256)	(0.256)
N	1368	1368	1368	1368	1368	1368
R2	0.113	0.137	0.138	0.138	0.138	0.138

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.10 The Effects of Human Capital on Female Wages for NZ Born Pakeha vs. Foreign Born Europeans

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	0.0306	0.0297	0.0284	0.0703	0.0709	0.0386
	(0.0584)	(0.0579)	(0.0581)	(0.0778)	(0.0775)	(0.110)
Potential Experience	0.00486	0.00336	0.00499	0.00485	0.00479	0.00470
	(0.00643)	(0.00648)	(0.00665)	(0.00665)	(0.00662)	(0.00663)
Potential Experience Squared	-0.000127	-0.0000859	-0.000118	-0.000115	-0.000114	-0.000113
	(0.000124)	(0.000125)	(0.000128)	(0.000128)	(0.000128)	(0.000128)
Tenure	0.0205***	0.0192***	0.0294**	0.0300**	0.0380***	0.0381***
	(0.00611)	(0.00612)	(0.0122)	(0.0123)	(0.0124)	(0.0124)
Tenure Squared	-0.000357*	-0.000335*	-0.000345*	-0.000355*	-0.000364*	-0.000364*
	(0.000202)	(0.000200)	(0.000197)	(0.000198)	(0.000198)	(0.000198)
Education	0.0698***	0.0614***	0.0666***	0.0666***	0.0725***	0.0723***
	(0.00607)	(0.00621)	(0.00862)	(0.00863)	(0.00870)	(0.00871)
Prose Ability		0.0807***	0.0799***	0.0792***	0.0205	0.0187
		(0.0224)	(0.0224)	(0.0225)	(0.0298)	(0.0300)
Tenure*Education			-0.000727	-0.000723	-0.00151*	-0.00151*
			(0.000811)	(0.000809)	(0.000833)	(0.000832)
Tenure*Foreign				-0.00515	-0.00422	-0.00319
				(0.00595)	(0.00587)	(0.00638)
Tenure*Ability					0.00790***	0.00785***
					(0.00293)	(0.00294)
Ability*Foreign						0.0468
						(0.0873)
Constant	1.800***	1.898***	1.809***	1.809***	1.747***	1.752***
	(0.116)	(0.119)	(0.151)	(0.151)	(0.152)	(0.152)
N	1511	1511	1511	1511	1511	1511
R2	0.107	0.115	0.115	0.115	0.119	0.119

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.11 The Effects of Experience on Female Wages of NZ Born Pakeha and YSM for ALL Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.0820**	-0.0227	-0.0209	-0.108	-0.116	0.266
	(0.0353)	(0.0355)	(0.0355)	(0.0709)	(0.0723)	(0.187)
Potential Experience	0.0108**	0.00912*	0.0119	0.0111	0.0124	0.0163*
	(0.00476)	(0.00465)	(0.00958)	(0.00960)	(0.00981)	(0.00976)
Potential Experience Squared	-0.000153	-0.000125	-0.000138	-0.000125	-0.000127	-0.000151
	(0.0000938)	(0.0000916)	(0.000102)	(0.000102)	(0.000102)	(0.000102)
Education	0.0712***	0.0563***	0.0599***	0.0615***	0.0639***	0.0778***
	(0.00539)	(0.00550)	(0.0122)	(0.0124)	(0.0129)	(0.0137)
Prose Ability		0.120***	0.120***	0.117***	0.0998**	0.0349
		(0.0179)	(0.0179)	(0.0179)	(0.0404)	(0.0449)
Potential Exp*Education			-0.000152	-0.000244	-0.000349	-0.000546
			(0.000434)	(0.000441)	(0.000469)	(0.000465)
Potential Exp*Foreign				0.00393	0.00417	0.00303
				(0.00257)	(0.00260)	(0.00262)
Potential Exp*Ability					0.000751	0.00197
					(0.00146)	(0.00145)
Ability*Foreign						0.101***
						(0.0365)
Education*Foreign						-0.0259**
						(0.0112)
Constant	1.757***	1.939***	1.880***	1.902***	1.873***	1.684***
	(0.101)	(0.100)	(0.207)	(0.207)	(0.211)	(0.221)
N	1883	1883	1883	1883	1883	1883
R2	0.0933	0.113	0.113	0.114	0.114	0.118

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.12 The Effects of Potential Experience and YSM on Male Employment Outcomes of NZ Born Pakeha and for All Immigrants					
	(1)	(2)	(3)	(4)	(5)
Foreign Born	0.0558***	0.0951***	0.0946***	0.140***	0.449***
	(0.0174)	(0.0176)	(0.0177)	(0.0308)	(0.0989)
Potential Exp	0.0159***	0.0150***	0.0141***	0.0167***	0.0195***
	(0.00214)	(0.00212)	(0.00443)	(0.00456)	(0.00465)
Potential Exp Squared	-0.000308***	-0.000288***	-0.000283***	-0.000294***	-0.000301***
	(0.0000418)	(0.0000415)	(0.0000477)	(0.0000483)	(0.0000485)
Education	0.0167***	0.00752***	0.00644	0.00928	0.0172***
	(0.00213)	(0.00231)	(0.00527)	(0.00568)	(0.00608)
Prose Ability		0.0630***	0.0629***	0.0367**	0.0350*
		(0.00737)	(0.00737)	(0.0160)	(0.0187)
Potential Exp*Education			0.0000458	-0.0000695	-0.000217
			(0.000196)	(0.000214)	(0.000218)
Potential Exp*Foreign				-0.00244**	-0.00367***
				(0.00123)	(0.00127)
Potential Exp*Ability				0.00115*	0.00124**
				(0.000593)	(0.000626)
Ability*Foreign					0.00526
					(0.0176)
Education*Foreign					-0.0198***
					(0.00602)
Constant	0.412***	0.533***	0.551***	0.493***	0.371***
	(0.0424)	(0.0435)	(0.0908)	(0.0945)	(0.101)
N	4244	4244	4244	4244	4244
R2	0.0307	0.0482	0.0482	0.0505	0.0538

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.13 The Effects of Potential Experience and YSM on Female Employment Outcomes of NZ Born Pakeha and for All Immigrants						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.156***	-0.121***	-0.121***	-0.0852**	-0.106***	-0.249***
	(0.0185)	(0.0188)	(0.0190)	(0.0335)	(0.0346)	(0.0949)
Potential Exp	0.0173***	0.0163***	0.0172***	0.0179***	0.0212***	0.0201***
	(0.00221)	(0.00219)	(0.00422)	(0.00423)	(0.00438)	(0.00442)
Potential Exp Squared	-0.000315***	-0.000295***	-0.00030***	-0.0003***	-0.000310***	-0.000308***
	(0.0000426)	(0.0000422)	(0.0000471)	(0.0000473)	(0.0000471)	(0.0000471)
Education	0.0243***	0.0148***	0.0160***	0.0157***	0.0218***	0.0180***
	(0.00210)	(0.00231)	(0.00510)	(0.00510)	(0.00563)	(0.00593)
Prose Ability		0.0662***	0.0662***	0.0674***	0.0268	0.0185
		(0.00765)	(0.00765)	(0.00767)	(0.0175)	(0.0196)
Potential Exp*Education			-0.0000506	-0.0000327	-0.000288	-0.000241
			(0.000184)	(0.000185)	(0.000208)	(0.000211)
Potential Exp*Foreign				-0.00165	-0.00106	-0.000491
				(0.00130)	(0.00133)	(0.00135)
Potential Exp*Ability					0.00168***	0.00184***
					(0.000632)	(0.000659)
Ability*Foreign						0.0128
						(0.0191)
Education*Foreign						0.00938*
						(0.00570)
Constant	0.281***	0.407***	0.387***	0.375***	0.297***	0.360***
	(0.0425)	(0.0440)	(0.0877)	(0.0880)	(0.0926)	(0.0968)
N	4438	4438	4438	4438	4438	4438
R2	0.0705	0.0875	0.0875	0.0879	0.0897	0.0911

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.14 Male Employment Outcomes for New Zealand Born Pakeha vs. Foreign Born Europeans

	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	0.0722***	0.0713***	0.0725***	0.0741	0.0756	0.0785
	(0.0254)	(0.0249)	(0.0248)	(0.0718)	(0.0724)	(0.0819)
Potential Experience	0.0223***	0.0211***	0.0302***	0.0302***	0.0328***	0.0328***
	(0.00257)	(0.00256)	(0.00573)	(0.00573)	(0.00580)	(0.00580)
Potential Experience Squared	-0.000415***	-0.000384***	-0.00044***	-0.000447***	-0.000436***	-0.000437***
	(0.0000489)	(0.0000489)	(0.0000595)	(0.0000596)	(0.0000597)	(0.0000598)
Education	0.0203***	0.0114***	0.0224***	0.0224***	0.0291***	0.0291***
	(0.00232)	(0.00246)	(0.00676)	(0.00676)	(0.00723)	(0.00723)
Prose Ability		0.0674***	0.0673***	0.0673***	0.0171	0.0172
		(0.00837)	(0.00836)	(0.00837)	(0.0222)	(0.0222)
Potential Exp*Education			-0.000440*	-0.000440*	-0.000691***	-0.000691***
			(0.000247)	(0.000247)	(0.000265)	(0.000265)
Potential Exp*Foreign				-0.0000615	-0.000184	-0.000230
				(0.00263)	(0.00264)	(0.00271)
Potential Exp*Ability					0.00186**	0.00186**
					(0.000772)	(0.000772)
Ability*Foreign						-0.00452
						(0.0356)
Constant	0.287***	0.399***	0.213*	0.213*	0.137	0.137
	(0.0485)	(0.0492)	(0.118)	(0.118)	(0.121)	(0.121)
N	3717	3717	3717	3717	3717	3717
r2	0.0446	0.0618	0.0628	0.0628	0.0646	0.0646

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Table A.15 Female Employment Outcomes for New Zealand Born Pakeha vs. Foreign Born Pakeha						
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born	-0.109***	-0.117***	-0.117***	-0.0312	-0.0268	-0.00544
	(0.0346)	(0.0346)	(0.0345)	(0.0880)	(0.0882)	(0.105)
Potential Experience	0.0223***	0.0211***	0.0302***	0.0297***	0.0322***	0.0323***
	(0.00259)	(0.00258)	(0.00566)	(0.00568)	(0.00573)	(0.00574)
Potential Experience Squared	-0.000418***	-0.000388***	-0.00045***	-0.00045***	-0.000434***	-0.000435***
	(0.0000493)	(0.0000492)	(0.0000598)	(0.0000600)	(0.0000602)	(0.0000602)
Education	0.0206***	0.0120***	0.0228***	0.0220***	0.0285***	0.0286***
	(0.00231)	(0.00247)	(0.00649)	(0.00653)	(0.00699)	(0.00700)
Prose Ability		0.0662***	0.0662***	0.0664***	0.0171	0.0175
		(0.00850)	(0.00849)	(0.00849)	(0.0223)	(0.0224)
Potential Exp*Education			-0.000436*	-0.000411*	-0.000657**	-0.000658**
			(0.000240)	(0.000241)	(0.000259)	(0.000259)
Potential Exp*Foreign				-0.00311	-0.00335	-0.00373
				(0.00311)	(0.00312)	(0.00327)
Potential Exp*Ability					0.00183**	0.00183**
					(0.000778)	(0.000778)
Ability*Foreign						-0.0234
						(0.0546)
Constant	0.284***	0.393***	0.209*	0.219*	0.146	0.144
	(0.0487)	(0.0497)	(0.115)	(0.115)	(0.118)	(0.118)
N	3742	3742	3742	3742	3742	3742
r2	0.0445	0.0604	0.0613	0.0617	0.0634	0.0634

Notes: Stars represent level of significance with one star representing the ten percent level, five percent level showed with two stars and three stars for the one percent level of statistical significance. Also robust standard errors are showed in parenthesis

Appendix B. Figures

Figure B.1 Relationship between Standardised Numerical Ability and Education by Ethnic Group

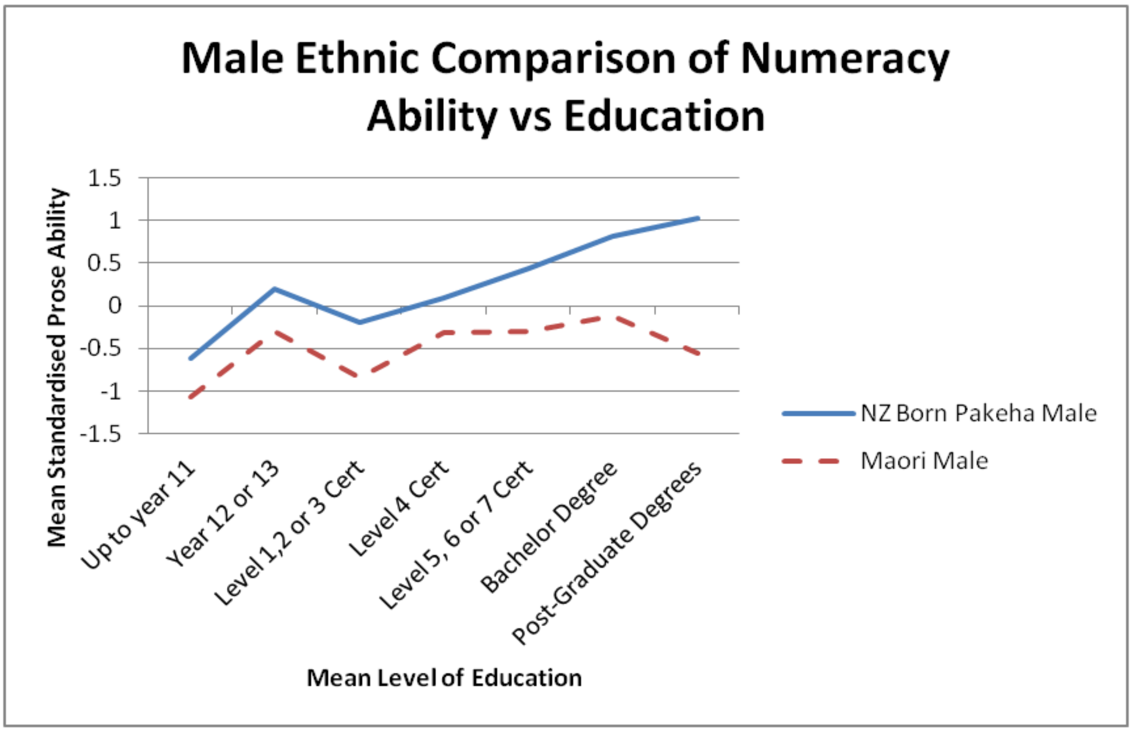

Figure B.2 Relationship between Standardised Numerical Ability and Education by Ethnic Group