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EMPLOYER LEARNING AND STATISTICAL DISCRIMINATION IN THE CANADIAN LABOUR MARKET

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Graduate Studies and Research
In Partial Fulfillment of the Requirements
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ABSTRACT

Statistical discrimination is frequently applied to illustrate different economic opportunities among equally able individuals. We use statistics from 1994, the second wave of the Survey of Labour and Income Dynamics, to analyze the income received from paid work jobs as the measure of an individual's economic opportunity. At the same time, Heckman's two-stage procedure is performed to account for possible bias that arises from estimating with only a pool of paid workers. We are interested in testing the following hypotheses: whether employers statistically discriminate among potential workers on the basis of education and immigration status if they have limited information about those workers and whether they learn to revise their judgments as new information is obtained.

The results confirm the employer learning and statistical discrimination based on years of schooling hypotheses for the Canadian labour market. The labour market returns to initially unobservable characteristic increases with time spend in the labour market. In addition, wage becomes less related to education that employers initially use to infer an individual's productivity. On the other hand, immigration status is not very informative about the productivity of a worker and the results do not support the hypothesis of statistical discrimination on the basis of immigration status. This paper points out the challenges faced by traditional labour market policies in a world of statistical discrimination and employer learning.

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DEDICATION

This thesis is dedicated with love and gratitude to my parents and my brother for their constant support and encouragement for going through my tough periods with me. It also demonstrates my dedication to my grandparents and uncle who always give me their faraway love and blessing.

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CHAPTER 1

INTRODUCTION

As human beings, it is often the case that we must make many and sometimes significant decisions on the basis of limited information. Examples might range from whether or not to purchase a used car, to get on an airplane, to become involved in a relationship, or to invest in financial markets. The scenarios described above are not uncommon. They demonstrate the problem of uncertainty and asymmetric market information in reality. Market agents realize this, but they nevertheless make judgements with every piece of available information. Further, learning new information will induce agents to re-evaluate initial assessments.

Statistical discrimination results from individuals' rational reactions to imperfect information. When presented with incomplete information, people attach estimates on the basis of statistical evidence. In labour economics, the true productivity of job applicants is not directly observable. As a result, given that the process of information acquisition on productivity can incur substantial costs, managers may categorize applicants according to the typical characteristics of the type (such as gender or ethnic group) to which applicants belong. In other words, group averages are applied to individuals. Unfortunately, however, statistical information may be misleading when an individual is an exception to the type.

Yet employers *can* learn or update their beliefs in various ways. During the hiring process, they are able to learn about potential employees' backgrounds and characteristics through documents including school reports, criminal reports, resumes, and also through job interviews. Once a worker is hired, information about his or her performance can be generated and collected in the form of job surveillance. Learning is therefore an essential process in order for employers to gather and improve their knowledge of their workers.

The relationship between education and wage is often explained within the traditional human capital model. The model suggests two implications. First, that attending school enables individuals to acquire knowledge, which in turn makes them more able and/or more productive. Therefore, the second implication is that better-educated people receive higher wages. However, an alternative called the "signaling model" has been proposed in information economics. This model suggests that education alone is not a mechanism for productivity enhancing but rather only provides information that signals ability. That is, if it is believed that more years of schooling indicates increased motivation (or other positive attributes) and that motivation affects job performance, then cost-minimizing firms have incentive to statistically discriminate among workers on the basis of education because it can signal worker productivity and is information usually free for employers to use. Nevertheless, once new information becomes available in the market, the impact of education on pay decision should decrease.

Canada is well-known for its open immigration policy. Immigration not only plays an important role in the Canadian economy, but also creates a lot of policy debate. According to studies done by Immigration Canada (2003), 229,091 immigrants entered Canada in 2002. Without doubt, the impact on society when immigrants start to participate in the labour force is one of the most interesting policy questions. Over the past two decades, there have been many studies regarding immigrants' earning opportunities in Canada. Many empirical results show that since 1970 recent immigrants are mostly from Third World countries and appear to suffer high levels of economic penalties upon entry (Chiswick and Miller 2000; De Silva 1992). 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.

This paper is motivated primarily by the study on testing statistical discrimination and employer learning done by Altonji and Pierret (1998, 2001). The argument for conducting the test was to point out that, contrary to many previous empirical studies, employees might *not* be the source of causing earning inequality. The researchers first suggest that initial wages are indeed determined by early signals such as education. As learning by employers 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 Canada? This is what we aim to find out. This paper intends to analyze the role of employees' education in firms' pay decisions. Furthermore, we would also like to investigate whether immigration status is used as a cheap informational source to determine wage, since most immigrants are from the less developing countries and employers may lack the knowledge necessary to evaluate their abilities.

The two main objectives of this study are:

- To identify the effects of education on wages. With a rich data set, this study tries to answer the questions: Do employers statistically discriminate on the basis of education in Canada? Also, can we find any evidence regarding employer learning in Canada?

- To test whether employers statistically discriminate among workers on the basis of immigration status.

This paper utilizes a Canadian data set: the second wave of Survey of Labour and Income Dynamics (SLID) – 1994 Public Use Micro Data Report, which provides both person specific and job information. We exclude self-employed individuals because we for the purposes of this study are interested only in market opportunities of paid workers. Since paid workers are not a random sample of the overall population, sample selection bias is a potential problem. An attempt has been made in this study to correct this bias.

The results support the hypotheses for employer learning and statistical discrimination based on years of schooling in Canada. The labour market returns to initially unobservable characteristic increases with time spend in the labour market. In addition, wage becomes less related to education that employers initially use to infer an individual's productivity. On the other hand, immigration status is not very informative about the productivity of a worker and the results do not support the hypothesis of statistical discrimination on the basis of immigration status.

The organization of this thesis is as follows. Chapter 2 describes the literature on statistical theory of discrimination and related empirical results in different countries. Chapter 3 presents the theoretical background on testing statistical discrimination and employer learning. The standard Mincerian wage function is applied here. Chapter 4 discusses the data source, variable groupings, and estimation technique. Chapter 5 addresses the regression results and the contribution that each factor makes. A summary of the findings and some possible directions for future research will be presented in the final chapter.

CHAPTER 2

LITERATURE REVIEW

Although there exists a significant amount of research regarding why wage differences exist among equally productive individuals in the competitive labour market, no single theory claims to explain these differences thoroughly. According to the personal prejudice model (Becker 1971), employers have prejudicial opinions against certain groups of people. A result of these opinions is discriminatory treatments of equally able workers. However, Becker argued that, once the product market competition is at work, non-discriminating employers will drive discriminating employers out of the marketplace since firms that discriminate will need to forego profits in order to satisfy their prejudicial desires. While prejudice is one possible explanation for these differing treatments, our study here builds on the employer ignorance. This chapter discusses the idea of statistical discrimination and reviews the literature on the dynamic pattern of returns relative to education and experience within an employer learning model.

2.1 Statistical Theory of Discrimination

Economists have proposed several types of labour market discrimination, which vary according to the sources of discrimination. One of the types that arose in the early 1970s is based on the statistical theory. This theory argues that scanty information about career performance or attributes on job applications may lead rational employers to predict applicants' abilities by attaching values to some non-relevant factors, such as gender and ethnic group. There are basically two strands in the statistical discrimination literature. Derived by Arrow (1973), the first strand suggests that incorrect stereotyping of ability may cause employers' beliefs to be self-fulfilled. The most common example stemming from this strand is that individuals from certain groups will tend to have weak incentives to obtain human capital investments if they expect that employers think they are less qualified than other applicants. Therefore, these employees remain low in productivity, which reinforces employers' prior beliefs. The second strand in the statistical discrimination literature is addressed by Phelps (1972). The idea is that the accuracy of the information of productivity differs across groups, which in turn causes wage differentials even if the average natural ability is the same for all groups.

2.2 The Quality of Productivity Information Perceived by Employers

- *Phelps (1972)*

In his empirical paper, Phelps (1972) suggests that with a test score, an employer is able to measure an applicant's productivity. Additionally, he brings up the importance of "skin color" in employers' pay decisions. In other words, both the test score of an individual and the physical characteristics of the racial groups that s/he belongs to are observed by employers and are used to assess the performance.

Two cases are considered by Phelps (1972). In the first case, blacks are said to be less productive than whites on average. Then, one might expect to find blacks be offered lower wages even if blacks and whites have the same test score. Described by Phelps (1972), the wage curve relating to the test score for blacks should lie below and parallel to that for whites as shown in Figure 2.1.

In the second case, the reliability of the test scores is allowed to vary between racial groups. Phelps (1972) argued that less reliable test score for blacks would lead to a situation where high-ability blacks could earn less than high-ability whites. This is because less accurate information about blacks causes employers to assess higher measurement error when estimating productivity.

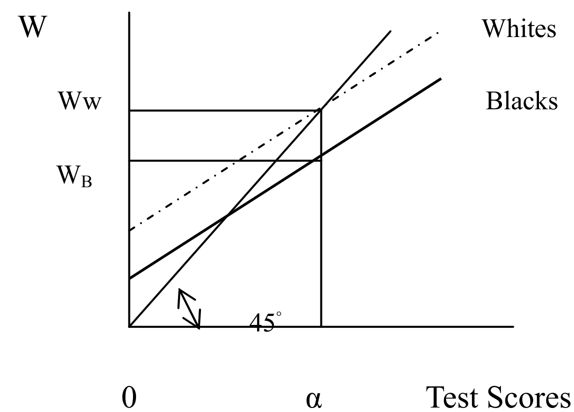

Figure 2.1: Wage curve with Test score and Race. Based on Phelps (1972, Figure 1).

- *Aigner and Cain (1977)*

Aigner and Cain (1977) take a slightly different approach from that of Phelps's statistical discrimination model. In their opinion, Phelps's model does not convincingly describe statistical discrimination because it assumes a difference in average productivity between whites and blacks in the first case. Theoretically, the labour market discrimination is defined as different pay for equally productive workers. Moreover, both groups with the same average test scores receive the same average wages, as at Point A in figure 2.2.

Instead, their assumptions are as follows:

1. Workers' pre-labour market investments and endowments are given.

2. The test scores of black people (or of women) have more variability.

3. And more importantly, employers are risk-averse.

Assumption 3. states that rational employers will attempt to maximize the expected actual performance discount the risk, while assumption 2. simply implies that the risk factors for blacks or women are larger than those for whites or men.

As indicated in Figure 2.2, the slope is flatter for blacks because the test scores of blacks are not heavily weighted compared to those of whites. Therefore, for equally productive whites and blacks, having a larger risk value ascribes the lower wage for black.

In general, Aigner and Cain's results confirm that minority group workers with the same test scores as those of dominant group workers are on average rewarded with unequal wages or earnings. However, they also mention that their empirical results should be read with caution because the analysis deals only with statistical discrimination within a competitive market.

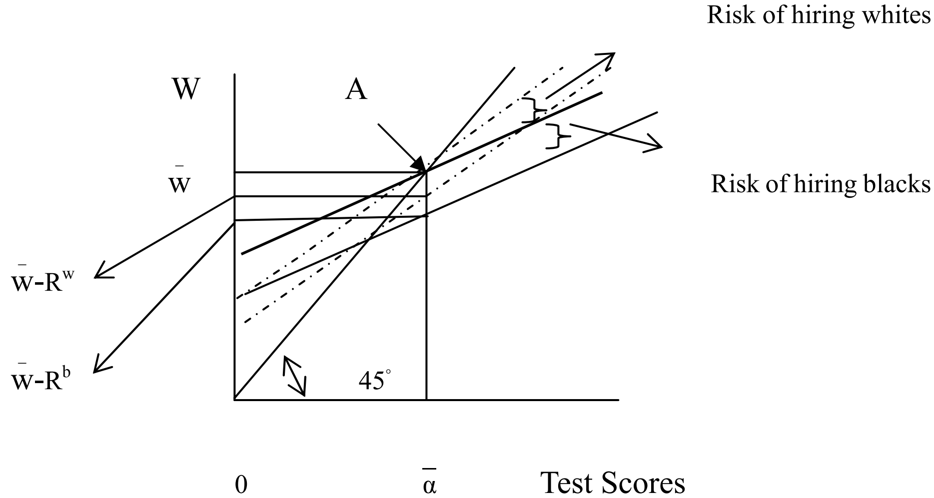

Figure 2.2: Wage curve with Test score and Race with risk discounted. Based on Aigner and Cain (1977, Figure 2).

- *Lundberg and Startz (1983)*

While Aigner and Cain (1977) take the worker's pre-labour market investments and endowments as exogenous, the study conducted by Lundberg and Startz (1983) emphasizes the presence of statistical discrimination will affect individuals' human capital investment decisions. According to their study, the competitive labour market includes the following agents:

1. Profit-maximizing firms: can identify each worker as either white or black and pay a wage equal to the expected value of the worker's marginal product.
2. Utility-maximizing individuals: take the known wage schedules into consideration while making the human capital investments.

They assume that a worker's productivity can be determined by his or her innate and acquired characteristics. The worker has a perfect knowledge of his or her own characteristics and will acquire human capital until the marginal cost equals the marginal benefit of doing so.

In a situation where the information quality for whites is higher than that for blacks, the Lundberg and Startz model again shows that members of the latter group will receive lower reward for their investments in skills prior to labour market entry because employers have more difficulty observing their capabilities. Thereby, this would diminish future blacks' incentives to acquire human capital.

- Feltovich and Papageorgiou (2004)

Unlike the aforementioned studies, Feltovich and Papageorgiou (2004) actually develop simple experiments that study statistical discrimination by examining the decision-making problems faced by employers.

Two experiments were carried out at two universities comprising 36 participants in total. Each experiment consisted of 9 rounds. Participants in each round were presented with 2 buckets. Each bucket contained 50 cards and each card represented one individual. That is, individuals who share some observable characteristics were identified as one group and were put together into one bucket. The participants were allowed to draw 4 cards with subsequent replacement from the 2 buckets. A number representing the true marginal productivity of the worker was printed on the card. Intuitively, the average productivity of a particular group was just the mean of the numbers in a bucket. However, drawing cards also incurred costs. It was the most costly to draw all 4 cards from one bucket. Therefore, a participant's profit was just the sum of numbers on the four cards drawn minus the total cost.

There were three distributions of cards: High, Medium, and Low. For the first six rounds, Bucket One contained a High distribution and Bucket Two contained a Low distribution. Most importantly, both buckets contained Median distribution in rounds 7 to 9. Therefore, the researchers' main hypotheses were:

1. The behavior of participants would tend to move gradually toward the optimal behavior.
2. The results of the first six rounds should have an incorrect impact on participants' beliefs for the last three rounds. That is, better experience with Bucket One would provide participants incentives to continually choose Bucket One more often than Bucket Two, even when there is no longer a distribution difference between them.

Since participants did not know the actual distributions, the results confirm that they learned over time. The main findings are as follows:

1. The results are significantly consistent with the first hypothesis. In other words, when workers' observable characteristics are informative of their productivity, the demands of more able workers will increase (Bucket One).
2. However, there is only weak evidence supporting hypothesis 2. When workers' observable characteristics are not informative; the demands of both types of workers are approximately the same.

2.3 The Dynamic Patterns of Returns to Education and Experience within the Employer Learning Model

With regard to the literature on testing the employer learning phenomenon, the most representative work has been done by Farber and Gibbons (1996), as well as by Altonji and

Pierret (1998, 2001). Farber and Gibbons investigate a learning model using level of earnings. Altonji and Pierre, on the other hand, study a learning model that employs the logarithm of earnings, and further develop a system to test the statistical discrimination in their model.

2.3.1 United States:

- Farber and Gibbons (1996)

Farber and Gibbons (1996) estimate a wage level equation given that the market is public and that the learning process for all employers occurs at the same rate. The data in their study are derived from the National Longitudinal Survey of Youth (NLSY). They consider two types of variables that affect productivity. The first type of variable (s) is schooling, a variable that both firms and researchers can observe directly. The second type of variable (z) is used as a proxy for workers' unobserved characteristics: AFQT test scores and possession of a library card at age fourteen, a variable that can only be accessed by researchers and is assumed to be *uncorrelated* with schooling.

Firstly, Farber and Gibbons (1996) find that both education and experience have the usual positive relationship with wage. The estimated effect of education on the wage level is approximately 9%. However, there is no significant indication that the impact of education varies with labour market experience. Their interpretation for this result is that employers' future observations, in general, verify the positive relationship between expected productivity and education for new labour market entrants. 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. This is consistent with the prediction of the learning model. The reason is that the initial unobserved information which is correlated with the ability of the workers will have an increasingly positive effect on wage as experience accumulates.

- *Altonji and Pierret (1998, 2001)*

While maintaining the public learning assumption in Farber and Gibbons's (1996) study, Altonji and Pierret (1998, 2001) instead analyze a logarithm wage function to test employer learning and statistical discrimination. A crucial difference is that they allow s and z to be correlated with each other. Using the same NLSY data, s is measured by years of schooling, while the standardized AFQT test score, father's education and the wage of siblings measure z.

From Altonji and Pierret's (1998, 2001) results, employers learn about productivity. The negative coefficient on education interacted with experience at –0.0032 (0.0094) indicates that wages become less dependent on education with experience. Moreover, the coefficients on AFQT and AFQT * experience at –0.0060 (0.0360) and 0.0752 (0.0286) imply that the effect of an individual's unobserved ability will increase as time passes.

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).

On the other hand, they find that the results contradict the hypothesis of fully statistical discrimination on the basis of race because the race gap rises sharply with experience. When the experience interactions of AFQT, father's education, and the sibling wage are introduced, the race gap actually decreases, which provides further evidence regarding employer learning. Therefore, Altonji and Pierret (1998, 2001) conclude that as firms learn about productivity, wage will be determined by unobserved ability rather than by some easily observable characteristics.

2.3.2 Canada

- Heisz and Oreopoulos (2002)

Based on the U.S studies, Heisz and Oreopoulos (2002) investigated the effects of school rank, father's wage, and brother's wage on an MBA graduate's earning and a lawyer's earning separately, combining four data sets (T1 Family File, University Student Information System, Longitudinal Employment Analysis Program Database, and School Ranking Data). In addition, they extended the basic model to explain the firms' job placements and promotion decisions.

For both groups, they find that individuals' wages rise as school rank increases. Also, father's wage and brother's wage, which are correlated with new information about worker productivity, have a positive effect on an MBA graduate's or a lawyer's wage. However, they claim that their finding on the effect of school rank with experience is inconsistent with the employer learning and statistical discrimination model. That is, even though both coefficients on father's wage and brother's wage increase with experience, the school rank continuously has a statistically significant and positive effect on wage with experience.

2.3.3 Germany

- Bauer and Haisken-DeNew (2001)

Using the German Socio-Economic Panel data, Bauer and Haisken-DeNew (2001) tested the hypotheses of employer learning for Germany. Since the data set contains no test score information, they used parental education as the indicator of an individual's innate ability. In fact, they conclude that there seems to be no employer learning evidence in Germany. The interaction between parental education and experience is only marginally significant and has a positive effect on wage at 0.045 (1.80), which behaves as the prior expectation. However, the most troublesome result is that the estimated coefficient on education interacted with experience is also positive and statistically significant at 0.095 (4.11).

2.3.4 Ghana

- Strobl (2003)

Strobl (2003) applied the employer learning model to study whether education is used as a signaling device for productivity in Ghana. His data source is from the Regional Programme for Enterprise Development (RPED) data for year 1998 for Ghana. He also points out the importance of distinguishing between different hiring channels. Two types of hiring channels are considered in the paper. The first type is that workers are hired through employers' or existing employees' relatives or friends, while the second type focuses on the hiring of workers who have no connection to the firm. Intuitively, employers have more information about the job applicants in the first case. In the study, years of schooling is treated as the easily observable variable and the maximum years of parents' schooling is used as the proxy for ability.

In general, the results for both hiring channels are similar to each other. The results reveal that education has a positive and significant role in explaining wages. On the other hand, the estimated coefficient on the interaction term of education and experience is statistically insignificant positive for the first type of hiring channel while it is statistically insignificant negative for workers who have no direct contact with firms. Furthermore, the interaction terms of parents' schooling and experience are shown to be positive, although not statistically significant. Hence, Strobl (2003) concludes that employers in Ghana do not learn workers' productivity over time and education is not used as a signal device in Ghana.

2.4 Summary

Theoretically, all studies suggest that members in a group with a noisier productivity indicator would receive lower wages even if two groups of people have the same average level of ability. Feltovich and Papageorgiou's (2004) experiments further indicate that the demands of workers from both groups are approximately the same when the productivity indicators are not very informative.

Table 2.1: Summary of Literature on the Employer Learning Model

Returns to Variable	***FG (1996)***	***AP (1998,2001)***	***HP (2002)***	***BH (2001)***	***Strobl (2002)***
Easily observable (S)	(+)*	(+)*	(+)*	(+)*	(+)*
Difficult-to-observe (Z)	(+)*	(-)	(+)*	(-)	(-)
S * Experience	(-)	(-)*	(+)*	(+)*	(+) and (-)
Z * Experience	(+)*	(+)*	(+)*	(+)	(+)

* represents statistically significant results at 95% of confidence interval

Moreover, most empirical studies focusing on employer learning show that hard-to-observe characteristics play more important roles in situations where firms spend more time with employees. Evidence also suggests that employers tend to use easily observable characteristics to predict workers' productivity at the time of hire. We summarize the literature on the employer learning model in Table 2.1.

CHAPTER 3

THEORETICAL FRAMEWORK

This chapter presents the basic theory of wage determination, which has been employed in many empirical studies to explain inequalities or differences in wage levels among individuals. The propositions used to test statistical discrimination and employer learning are examined in the latter section.

3.1 Specification for Wage Equation

To explain whether readily available information serves as an ideal trait for an employer to predict or infer a labour market entrant's productivity when facing information uncertainty, we follow Altonji and Pierret's (1998, 2001) [hereinafter AP] approach. In their study, the model departs from the standard Mincerian wage equation that we will discuss first, followed by the propositions stated by AP.

3.1.1 Human Capital Theory

As proposed by Mincer (1974), human capital theory states the relationship between human capital investments and earnings. For utility-maximizing individuals, investments will be made only when the present value of future benefits equals or exceeds the present value of costs. In Mincer's study, both education and experience are essential factors in the analysis of individuals' lifetime earnings. To obtain the effects of schooling on wages, let

W_p be the wage that one is going to receive with (p) years of education, and (r) be the rate of return of education to earning

A person's wage is equal to W_0 when his or her year of education is zero. If the person acquires one year of education, the wage function becomes

$$W_1 = W_0 (1+r)$$

Similarly, for a second year of education investment, an individual will earn

$$W_2 = W_1 (1+r) = W_0 (1+r)(1+r) = W_0 (1+r)^2$$

Following the same logic, the wages one can earn after (p) years of investment in education are indicated by

$$W_p = W_0 (1+r) (1+r) \dots (1+r) = W_0 (1+r)^p$$

Taking logarithms on both sides and assuming (r) is a small value, the wage function of a person with (p) years of education is given as below:

$$\begin{aligned} \text{Ln } W_p &= \text{Ln}(W_0 (1+r)^{p}) = \text{Ln } W_0 + p \ln (1+r) \\ &= \text{Ln } W_0 + rp \qquad (3.1) \end{aligned}$$

In addition to education, experience is also an important factor that affects an individual's productivity and earning. Mincer (1974) uses age as a proxy for experience and demonstrates 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. The standard age-earning profile is shown in Figure 3.1. The concavity of the earning curve implies that a worker's human capital starts to depreciate after the peak.

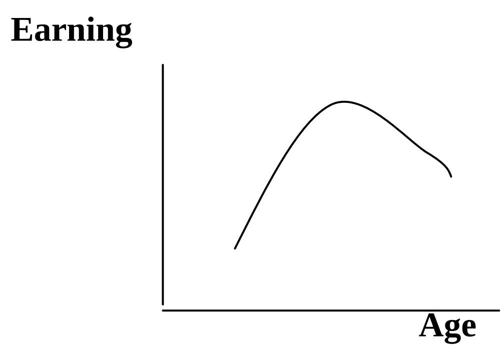

Figure 3.1: Age-Earning Profile

Adding the effects of experience to wage equation (3.1) and introducing a constant term α to present Ln W_0, we have

$$\text{Ln } W = \alpha + rp + \beta_1 t + \beta_2 t^2 \quad (3.2)$$

where t stands for labour market experience.

3.1.2 Employer Learning and Wages

AP simply extend the standard Mincer-type equation (3.2) to investigate the model of employer learning, providing that the labour market is competitive and the learning process for all firms occurs at the same rate. y_t is denoted as the log of labour market productivity, accompanied by t years of work experience, and can be obtained as follows:

$$y_t = rs + \alpha_1 q + \Lambda z + \eta + H(t) \quad (3.3)$$

where

- s are variables that can be directly observed by both the employer and the econometrician, such as years of schooling or race;
- q represents other information that is relevant to an individual's productivity and observable by the employer but not seen by the econometrician;
- z measures a worker's natural ability which can be observed only by the

econometrician, but not by the employer;

- η consists other determinants of productivity and is not directly observed by the employers and the econometrician. In addition, it is scaled to have a unit coefficient; and
- H(t) is the experience profile of a worker (can be first or higher orders of t) and is *crucially* assumed to be independent of s, z, q, or η (it fully captures the effects of on-the-job training).

Since z and η are not readily observable, profit-maximizing firms form conditional expectations $E(z \mid s, q)$ and $E(\eta \mid s, q)$, which are assumed to be linear in q and s. That is,

$$z = E(z \mid s, q) + v = \gamma_1 q + \gamma_2 s + v \tag{3.4}$$

$$\eta = E(\eta \mid s, q) + n = \alpha_2 s + n \tag{3.5}$$

where

$E(v) = E(n) = 0$ and are uncorrelated with s and q.[1]

Combining equations (3.3), (3.4) and (3.5), we have

$$\begin{aligned} y_t &= rs + H(t) + \alpha_1 q + \Lambda(\gamma_1 q + \gamma_2 s + v) + (\alpha_2 s + n) \\ &= (r + \Lambda\gamma_2 + \alpha_2)s + H(t) + (\alpha_1 + \Lambda\gamma_1)\, q + (\Lambda v + n) \end{aligned} \tag{3.6}$$

Therefore, $(\Lambda v + n)$ is defined as the error in the employer's belief about the logarithm of an individual's productivity when s/he begins his/her career. AP further assume $(\Lambda v + n)$ to be independent of q and s. In each period (t) a noise signal of the log productivity becomes available, $\xi_t = y + \varepsilon_t$, where $y = y_t - H(t)$ and ε_t is independent of the other variables in the model. Hence, seeing ξ is equivalent to seeing $d_t = \xi_t - E(y \mid s,q)$ since employers know s and q. Additionally, the vector $D_t = \{d_1, d_2, \ldots, d_t\}$ is introduced, which summarizes

[1] The mean of η does not depend on q in (3.5), since AP define the coefficient vector α_1 on q in (3.3). Moreover, they allow s, z and η to be related to each other.

a worker's performance history. Taken together, all employers' information set consists of q, s and D_t.

AP define μ_t as the difference between $\Lambda v + n$ and $E(\Lambda v + n \mid D_t)$; μ_t is uncorrelated with q, s and D_t and is distributed independent of q, s and D_t. We therefore have

$$\mu_t = (\Lambda v + n) - E(\Lambda v + n \mid D_t) \tag{3.7}$$

Consequently, in a competitive market where all information is common to all employers, the wage of an individual is given by

$$W_t = E(Y_t \mid s, q, D_t) * e^{\zeta t} \tag{3.8}$$

where

W_t is the product of (i) the expected value of productivity Y_t ($Y_t = \exp(y_t)$) and (ii) the error component $\exp(\zeta_t)$ that represents the measurement error and firm-specific factors that are not in the model and are not related to s, z and q.

Equations (3.6), (3.7), and (3.8) imply that

$$\begin{aligned} W_t &= E(Y_t \mid s, q, D_t) * e^{\zeta t} \\ &= e^{(r + \alpha 2 + \Lambda\gamma 2)\, s + (\alpha 1 + \Lambda\gamma 1)\, q}\, e^{H(t)}\, e^{E(\Lambda v + n \mid Dt)}\, E(e^{\mu t})\, e^{\zeta t} \end{aligned} \tag{3.9}$$

Taking logarithms into account, equation (3.9) becomes

$$\begin{aligned} \text{Log}(W_t) = {} & (r + \Lambda\gamma_2 + \alpha_2)s + H(t) + \log(E(e^{\mu t})) + (\Lambda\gamma_1 + \alpha_1)q \\ & + E(\Lambda v + n \mid D_t) + \zeta_t \end{aligned}$$

Let $w_t = \text{Log}(W_t)$ and $H^*(t) = H(t) + \log(E(e^{\mu t}))$, the log wage is equal to

$$w_t = (r + \Lambda\gamma_2 + \alpha_2)s + H^*(t) + (\Lambda\gamma_1 + \alpha_1)q + E(\Lambda v + n \mid D_t) + \zeta_t \tag{3.10}$$

From (3.10), AP point out that wages change with experience because of two effects. The direct effect is due to productivity changes with experience. The indirect effect is captured through E $(\Lambda v + n \mid Dt)$. Employers will adjust wage compensation when they find out the error in initial assessment of employees' productivity.

3.2 Strategy for Testing Employer Learning and Statistical Discrimination

Although information q is not observed and/or not used by econometricians, by definition it is related to information s and z. Hence, AP introduce Φ_{qs} and Φ_{qz} which represent the coefficients of the auxiliary regression of $(\alpha_1 + \Lambda\gamma_1)q$ on s and z:

$$\Phi_{qs} = \delta[(\alpha_1 + \Lambda\gamma_1)q] / \delta s \quad \text{and} \quad \Phi_{qz} = \delta[(\alpha_1 + \Lambda\gamma_1)q] / \delta z$$

In addition, Φ_{st} and Φ_{zt} are the coefficients that are obtained by regressing $E(\Lambda v + n \mid D_t)$ on s and z. These coefficients simply capture the effects of s and z as employers learn about the errors in initial assessment of workers' productivity.

AP consider the following conditional expectation equation when t=0…T where b_{st} and b_{zt} are the coefficients of s and z:

$$E(w_t \mid s, z, t) = b_{st}s + b_{zt}z + H^*(t) \tag{3.11}$$

Since there is no performance history at the beginning of a career, $E(\Lambda v + n \mid D_0) = 0$. And (3.11) is simply

$$E(w_0 \mid s, z, 0) = b_{s0}s + b_{z0}z + H^*(0) \tag{3.12}$$

Based on equation (3.10), the bias least square regression which omits variable q implies that

$$b_{st} = b_{s0} + \Phi_{st} = [(r + \Lambda\gamma_2 + \alpha_2) + \Phi_{qs}] + \Phi_{st} \tag{3.13}$$

$$b_{zt} = b_{z0} + \Phi_{zt} = \Phi_{qz} + \Phi_{zt}$$

Here the coefficients b_{s0} and b_{z0} therefore include part of the effects of q that is used by employers to figure out productivity. In addition, AP use the facts that $\text{cov}(s, E(\Lambda v + n \mid D_t))$

$= 0$ and $\mathrm{cov}(z, E(\Lambda v + n \mid D_t)) = \mathrm{cov}(v, E(\Lambda v + n \mid D_t))$. The coefficient matrix is,

$$\begin{pmatrix} b_{st} \\ b_{zt} \end{pmatrix} = \begin{pmatrix} b_{s0} \\ b_{z0} \end{pmatrix} + 1/\left|\mathrm{var}(s,z)\right| * \begin{pmatrix} \mathrm{var}(z) & -\mathrm{cov}(s,z) \\ -\mathrm{cov}(s,z) & \mathrm{var}(s) \end{pmatrix} \begin{pmatrix} 0 \\ \mathrm{cov}(v, E(\Lambda v + n \mid D_t)) \end{pmatrix} \tag{3.14}$$

Equation (3.14) can also be rewritten as

$$\begin{pmatrix} b_{st} \\ b_{zt} \end{pmatrix} = \begin{pmatrix} b_{s0} \\ b_{z0} \end{pmatrix} + 1/\left|\mathrm{var}(s,z)\right| * \begin{pmatrix} \mathrm{var}(z) & -\mathrm{cov}(s,z) \\ -\mathrm{cov}(s,z) & \mathrm{var}(s) \end{pmatrix} \theta_t \begin{pmatrix} 0 \\ \Lambda \mathrm{var}(v) + \mathrm{cov}(v,n) \end{pmatrix} \tag{3.15}$$

or

$$b_{st} = b_{s0} + \theta_t \Phi_s \tag{3.16}$$

$$b_{zt} = b_{z0} + \theta_t \Phi_z$$

where

Φ_s and Φ_z are the coefficients of regression of $\Lambda v + n$ on s and z

θ_t summerizes how much the employers know about $\Lambda v + n$ at time t and equal to

$$\mathrm{cov}(z, E(\Lambda v + n \mid D_t)) / \mathrm{cov}(z, \Lambda v + n)$$

$$= \mathrm{cov}(v, E(\Lambda v + n \mid D_t)) / \mathrm{cov}(v, \Lambda v + n)$$

In period 0, θ_t is 0 since firms know nothing about $\Lambda v + n$ at this time. When it is 1, firms have learned what $\Lambda v + n$ is and therefore know the productivity y_t. From equation (3.15), we are able to derive

$$\Phi_s = -\mathrm{cov}(s,z) * [\Lambda \mathrm{var}(v) + \mathrm{cov}(v,n) / \left|\mathrm{var}(s,z)\right|] \text{ and}$$

$$\Phi_z = \mathrm{var}(s) * [\Lambda \mathrm{var}(v) + \mathrm{cov}(v,n) / \left|\mathrm{var}(s,z)\right|] \tag{3.17}$$

And it can also be shown that

$$\Phi_s = -\Phi_{zs}\Phi_z \tag{3.18}$$

where

Φ_{zs} is the coefficient of the regression of z on s and is equal to cov(s,z) / var(s).

Using equations (3.17) and (3.18), AP conclude three propositions to test employer learning and the statistical discrimination model.

Proposition 1: *When cov(v, $\Lambda v + n$)>0 and cov(s, z)>0, Φ_s should be negative and Φ_z should be positive. Then, the estimated coefficient on b_{st} (=b_{s0} + $\theta_t\Phi_s$) should be non-increasing in labour market experience. On the other hand, the estimated coefficient on b_{zt} (= b_{z0} + $\theta_t\Phi_z$) is non-decreasing in labour market experience.*

A simple intuition for the decline in b_{st} is stated by AP (page 321):

> As employers learn about the productivity of a worker, an observable variable (s) will get less of the credit for an association with productivity that arises because s is correlated with an initially unobservable variable (z), provided that z is included in the wage equation with a time-dependent coefficient and can claim the credit.

Proposition 2: *If employers have full information about the productivity of new employees or employers do not learn over time, then $\delta b_{st} / \delta t = \delta b_{zt} / \delta t = 0$.*

Proposition 3: *Based on (3.18), one can test $\delta b_{st} / \delta t = - \Phi_{zs} * \delta b_{zt} / \delta t$.*

One can see immediately that equation (3.18) is weighted by $-\Phi_{zs}$. Therefore, the effect of learning on coefficient b_{st} has two components. One comes from the relationship between s and z, which is captured by Φ_{zs}. The other is due to the fact that employers gradually learn about z.

3.3 Statistical Discrimination on the Basis of Schooling

While maintaining the crucial assumptions that the labour market is competitive and that the information is public across all firms in AP's model, the first part of estimation focuses on the role of education in a wage function. That is, education (p) is used as an easily observable characteristic (s).

We add experience and experience square 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. Empirical studies also suggest wage differentials among various occupations and industries. Both occupational and industrial categories are dummy explanatory variables. We include differing marital status, places of residence, and firm sizes as well. All of these variables are denoted by a row vector X.

A total of 5 wage equations will be estimated in this section and the base line of our estimation function is

(a) $\text{Ln } W = \beta_x X + \beta_p p + \upsilon$ (3.19)

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

(b) The second step is adding a z variable into the estimation.

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_z z + \upsilon \quad (3.20)$$

(c) Next, we drop the z variable and take schooling interacted with experience into account (p * t).

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_{pt} (p * t) + \upsilon \tag{3.21}$$

(d) Both the z variable and the interaction term for schooling are added into the wage equation.

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_z z + \beta_{pt} (p * t) + \upsilon \tag{3.22}$$

(e) Finally, we estimate an equation which includes the z variable and all interaction variables.

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_z z + \beta_{pt} (p * t) + \beta_{zt} (z * t) + \upsilon \tag{3.23}$$

Our testable hypotheses are as follows. First, β_{zt} is non-decreasing and β_{pt} is non-increasing. Second, that employers have full information about the new workers' productivity implies $\beta_{pt} = \beta_{zt} = 0$. Third, if an employer statistically discriminates on the basis of education, the negative coefficient of the regression of z on schooling (p) multiplied by β_{zt} should equal to β_{pt}.

3.4 Statistical Discrimination on the Basis of Immigration Status

In order to investigate whether firms statistically discriminate on the basis of immigration status (I), it is treated as a second observable variable (s) in the second part of estimation

In addition to those control variables discussed in the previous section, we also include years since migration and years since migration square as additional explanatory variables into vector X. Moreover, we specifically distinguish the experience into Canadian labour market experience (t_c) and non-Canadian labour market experience (t_{nc}). Therefore, the base estimate equation in this part is:

(a) $$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \upsilon \qquad (3.24)$$

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

(b) z variable is added into the model.

$$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \upsilon \qquad (3.25)$$

(c) z variable is excluded and schooling interacted with labour market experience in Canada is added.

$$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_{pt} (p^* t_c) + \upsilon \qquad (3.26)$$

(d) $$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \beta_{pt} (p * t_c) + \upsilon \qquad (3.27)$$

(e) We add z, its interaction with Canadian experience and the interaction between schooling and Canadian experience, into the equation.

$$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \beta_{pt} (p * t_c) + \beta_{zt} (z * t_c) + \upsilon \qquad (3.28)$$

(f) $(z * t_c)$ is dropped and immigrant * Canadian experience $(I * t_c)$ is added.

$$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \beta_{pt} (p * t_c) + \beta_{It} (I * t_c) + \upsilon \qquad (3.29)$$

(g) Finally, we include z variable * Canadian experience in the model.

$$\text{Ln W} = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \beta_{pt} (p * t_c) + \beta_{It} (I * t_c) + \beta_{zt} (z * t_c) + \upsilon \qquad (3.30)$$

Hypothesis One is that if employers statistically discriminate on the basis of immigration status, adding $(z * t_c)$ into the model should make immigrant intercept (β_I) more negative but make β_{It} less negative. This would suggest that if immigration status is used as a negative signaling device for productivity at the beginning of the career, it should become less important as new information is revealed to employers over time. Hypothesis Two: The product of the negative coefficient of z on p and β_{zt} will equal $\beta_{pt.}$ In addition, the product of the negative coefficient of z on I and β_{zt} will equal $\beta_{It.}$

CHAPTER 4

DATA, VARIABLE GROUPINGS,

AND

ESTIMATION TECHNIQUE

To estimate equations (3.19) through (3.30) and test the propositions as discussed in chapter 3, this study utilizes a data set provided by Statistics Canada. This chapter discusses the detailed data source and variable groupings. The estimation technique will be presented in the final part of the chapter.

4.1 Data Source

In the analysis, we employ the second wave of the Survey of Labour and Income Dynamics (SLID) – 1994 Public Use Micro Data Report, which provides files containing both person-specific and job-specific information. The SLID sample basically covers the population of the ten Canadian provinces, with the exception of residents in institutions, those living on Indian Reserves, and Armed Forces personnel living within barracks. The sample contains 29,632 observations.

This study considers only the male sample aged between sixteen and sixty-nine years. Our wage sample is restricted to individuals who reported positive annual wages and salaries and positive working weeks and hours, and whose main occupation is paid work.

That is, self-employed people are not included in the wage equation. Further restriction involves valid work history information; we eliminated individuals with no applicable years of work experience. Individuals who do not have valid data for mother's education and did not clearly state whether they were native-born or immigrants in 1994 were also excluded here. Ultimately, there are a total of 6251 males in the sample and a total of 4470 males are used in the wage equation.

4.2 Data Description

SLID is an attractive data set for this study. Firstly, it contains rich information on personal characteristics as well as labour market activity throughout the reference year. Secondly, to obtain income information for the year 1994, the income interviews conducted by Statistics Canada were deferred until May 1995 so that interviewers could speak with individuals when income tax information for 1994 was recent and fresh. Lastly, when analyzing the wage equation, instead of relying on potential labour market experience (calculated as Age-schooling-6), SLID records each respondent's work experiences (both part-time and full-time) since s/she first started to work full-time (called FYFTE: Full-year Full-time Equivalent).

It must be noted that the SLID survey does contain several drawbacks. The survey may have ignored any work experience prior to individuals' beginning full-time work. Also, we would like to have access to a more accurate proxy for innate ability such as the IQ test scores used by Farber and Gibbons (1996) and AP, but SLID collects no such information. Finally, the reason we use the 1994 micro data file, rather than the most recent one (2000), is that the latter does not record parental education which is the measure for natural ability in our study.

We will emphasize that, in many empirical studies, parents' education is commonly used as a proxy to measure an individual's ability. Ashenfelter and Zimmerman (1997) and Card (1999) point out that there exists a long tradition of using family background information, such as mother's and father's education, to control for unobserved ability. The implication is that parental education will affect the children's earning performance and productivity. Additionally, by using father's education as an indicator for natural ability, AP are able to identify the employer learning phenomenon in the U.S. labour market.

Much psychological literature indicates that mothers play a bigger role in the development of their children than do the fathers. Lamb (1981) suggests that mothers spend more time interacting with their children; even when they work the same amount of time outside the household as do their partners. In a more recent study, Lamb (1997) explores the interaction between fathers and their developing children. Lamb's results suggest that fathers have at least an indirect impact on the development of their children.

According to Leibowitz (1974), mother's education is significantly related to the child's IQ development, while father's education is not. This indicates that besides genetic factors, time devoted to the child is also an important issue in explaining maternal education/child IQ relationship. Therefore, we chose mother's education as the proxy for individuals' innate ability in this study.

4.3 Variable Groupings

The variable groupings and definitions are given in Table 4.1. A person is defined as a labour market participant if he has positive wage and weeks worked in 1994. The natural log of the hourly wage rate from all jobs is the variable we wish to explain. The explanatory human capital, demographic, and job characteristics variables chosen for this study are Years of Schooling, Labour Market Experience, Marital Status, whether a person is Immigrant, Region of Residence, Occupation Status,[2] Industry, and Firm Size.

While some independent variables can be retrieved directly from the data files, others must be constructed manually. The variables that can be retrieved directly are Hourly Wage rate, Age, and Years of Schooling. The average age in our wage sample is 38 years and the average hourly wage rate is $17.26. Total Years of Schooling are simply the number of years of schooling completed by the person (full-time equivalents) to a maximum of 20. Following AP, those with education levels below 8 years are eliminated from this study in order to reduce the influence of outliers.

The indirect independent variables are discussed below. The work experience (FYFTE) can also be obtained from the SLID data set. People on average have 17.94 years of labour market experience in the wage sample. If further combined with information from the years, in which persons first started working full-time and covering the period of immigration, we are able to identify both experience outside Canada and experience inside Canada. We also include the square of work experience to capture the diminishing returns on experience.

For foreign-born workers, because the information on public use micro data regarding

[2] SLID follows the Pineo-Porter-McRoberts socio-economic classification of occupation.

the number of Years since Migration is reported as an interval, the middle point of the interval was taken. Years since Migration indicates the assimilation effect. The square of Years since Migration is included to indicate the diminishing assimilation effect.

Since the levels of Mother's Education are grouped into categories, year mapping is generated, using the categorical information from the SLID data dictionary. The mean of Mother's Education level is approximately 10 years.

Next, dummy variables are introduced to separate the groups within each independent variable. We chose people with the most common characteristics as our reference group.

Because we are interested in seeing whether people from other countries suffer wage penalty, Non-Immigrants are chosen as the base group. We assign the values 0 to Non-Immigrants and 1 to Immigrants. Table 4.1 shows that there are approximately 8% of men among employed males in 1994 who identified themselves as a member of the immigrant group.

For Marital Status, there are three dummy variables: Married, SepDivWid, (including Separated, Divorced, and Widowed) and Single. The base group is the Single people.

Finally, for Region of Residence variable, 5 dummy variables (Atlantic, Ontario, Quebec, Prairies, and British Columbia) are included. The base group is Ontario. Occupation has 6 dummy variables, where Non-Skilled Worker is the reference group. For firm level controls, we include 14 dummy variables for the Industry and 5 dummy variables for the Firm Sizes. The reference groups are Manufacturing and Fewer than 20 employees in the firm.

Table 4.1 Mean of Variables (Standard Deviation in Parenthesis)

Variable	Mean or %
Wages and Salaries (per year)	$33,957 (18823)
Composite Hourly Wage (w)	$17.26 (7.84)
Age	38.53 (10.98)
Years of Schooling	12.99 (2.84)
* Years since Migration	1.86 (7.15)
* Age of Immigration	1.59 (6.33)
Experience (FYFTE)	17.94 (11.30)
Years of Canadian Work Experience	17.66 (11.16)
* Years of Non-Canadian Work Experience	0.27 (1.95)
Mother's Education	10.05 (2.67)
Reference Group: Single (Marital Status)	
Married	74.32%
Separated, Divorced, and Widowed	6.35%
Reference Group: Non-Immigrant	
Immigrant	8.01%
Reference Group : Ontario (Region of Residence)	25.14%
Atlantic	21.14%
Quebec	20.09%
Prairies	24.85%
British Columbia	8.78%
Reference Group: Non-Skilled Worker (Occupation)	20.14%
Management	12.64%
Professional	15.50%
Supervisor/ Foreman	6.58%

Skilled Worker	22.48%
Semi-Skilled Worker	22.66%
Reference Group: Manufacturing (Industry)	23.88%
Primary	8.86%
Construction	7.96%
Transportation / Storage	7.05%
Communication / Utility	4.61%
Wholesale	6.20%
Retail Trade	9.31%
Finance / Insurance / Real Estate	2.55%
Business	3.11%
Government	10.43%
Educational	6.62%
Health/ Social Service	2.89%
Accommodation	2.82%
Other Services	3.71%
Reference Group: Fewer than 20 (Firm Size)	22.53%
20-99 employees	17.09%
100-499	14.56%
500-999	8.86%
1000 and over	36.96%

* For non-immigrants, the value is zero.

In general, the base group represents Single and Non-Immigrant individuals. In addition, it comprises Non-Skilled workers who work in the Manufacturing Industry and are employed by firms that hire fewer than 20 employees.

4.4 Econometric Specification

4.4.1 Sample Selection Bias

Since it is only for employed males that a market wage rate can be observed, the sample is not randomly selected. The estimated result actually captures only the wage differences among working people rather than the wage rate individuals could earn if they decide to participate in the labour force.

Fortunately, Heckman (1979) proposes a two-stage estimation procedure to correct the sample selectivity bias of the market wage equations. The first step is to estimate a Probit model of labour market participation, then create the selection variable. Secondly, re-estimate the wage equation with the selection variable as an additional regressor. The theoretical concept is as follows: Let K_i be an observed indicator of job market participation for each individual of the population and K^*_i be the difference between market wage and reservation wage. Most importantly, we can only infer the sign of K^*. Therefore, the regression model is:

$$Y_i = \text{Ln } W_i = X_i\beta + \upsilon_i \qquad \text{is observed only when } K_i = 1.$$

where

X_i is a row vector of various observable characteristics that affect the market wage rate and error term υ_i is assumed to be normally distributed ($N[0, \sigma^2_\upsilon]$).

Selection mechanism is:

$$K^*_i = H_i \gamma + u_i$$

where

H_i is a row vector of various observable factors that determine the selection into paid employment and error term u_i is assumed to have standard normal distribution (N[0, 1]).

$$K_i = 1 \text{ if } K^*_i = H_i \gamma + u_i > 0 \quad \text{(participate in labour market)}$$

$$K_i = 0 \text{ if } K^*_i = H_i \gamma + u_i \leq 0 \quad \text{(not participate in labour market)}$$

$$\Pr(K_i = 1) = \Pr(K^*_i > 0) = \Pr(u_i > - H_i \gamma) = 1 - \Pr(u_i \leq - H_i \gamma)$$

$$\Pr(K_i = 0) = \Pr(K^*_i \leq 0) = \Pr(u_i \leq - H_i \gamma)$$

In terms of standard normal cumulative distribution function,

$$\Phi(- H_i \gamma) = \Pr(u_i \leq - H_i \gamma)$$

Since the standard normal distribution has a symmetric density function, it implies that

$$\Pr(K_i = 1) = \Pr(K^*_i > 0) = \Pr(u_i > - H_i \gamma) = 1 - \Pr(u_i \leq - H_i \gamma)$$

$$= \Phi(H_i \gamma)$$

$$\Pr(K_i = 0) = \Pr(K^*_i \leq 0) = \Pr(u_i \leq - H_i \gamma) = 1 - \Phi(H_i \gamma)$$

Suppose that υ_i and u_i have a bivariate normal distribution with zero means and correlation ρ. Then the wage model that applies to the observations in the sample of employed persons can be written as

$$E(Y_i | X_i, K^*_i > 0) = E(Y_i | X_i, u_i > - H_i \gamma)$$

$$= X_i\beta + E(\upsilon_i | u_i > - H_i \gamma)$$

$$= X_i\beta + \rho\sigma_\upsilon\lambda_i(H_i \gamma) = X_i\beta + \beta_\lambda\lambda_i(H_i \gamma)$$

where

β_λ is the regression coefficient of $\lambda_i(H_i \gamma)$;

$\lambda_i(H_i \gamma) = \phi(H_i \gamma)/\Phi(H_i \gamma)$;

$\phi(H_i \gamma)$ is the probability density function of the standard normal distribution; and

$\Phi(H_i \gamma)$ is the cumulative distribution function of the standard normal distribution. So,

$$Y_i \mid X_i, K^*_i > 0 = E(Y_i \mid X_i, K^*_i > 0) + v_i$$

$$= X_i\beta + \beta_\lambda\lambda_i(H_i\,\gamma) + v_i$$

The OLS regression now produces a consistent estimate of β because we include the omitted variable, $\beta_\lambda\lambda_i(H_i\,\gamma)$ in the estimated wage equation.

4.4.2 Labour Market Participation Model

In order to correct the sample selection bias, the concept of the Probit model is discussed below. The dependent variable (K_i) is set to be 0 for non-labour market participants and 1 for labour market participants. This implies that K_i is used to represent the occurrence of an event and can take on only two values. Therefore, instead of using the ordinary least square technique (which requires K_i to be continuous), the binary response model has to be used here. The simplest estimation is to apply the linear probability model. However, the main drawback to this approach is that the fitted probability is not limited to lie between 0 and 1. Therefore, the Probit model (which is designed to be more sophisticated to the characteristics of the binary dependent variable) is used here.

As suggested by Greene (2000), the probability of getting the values 0 and 1 is

$$\text{Prob}(K_i = 1) = F(\gamma' H_i) = \int_{-\infty}^{\gamma' H_i} \phi\,(t)\,dt = \Phi(\gamma' H_i)$$

$$\text{Prob}(K_i = 0) = 1\text{-}\ F(\gamma' H_i) = 1\text{-}\Phi(\gamma' H_i)$$

where

H is row vector of observable variables, γ is the vector of coefficients which has to be estimated, F is a monotonically increasing function which takes a real value that falls within 0 and 1, Φ(.) is the cumulative distribution function of the standard normal distribution, and $\phi(.)$ is the standard normal density. So the probability model is

$$E\,[K_i \mid H_i] = 0[1- F(\gamma' H_i)] + 1[F(\gamma' H_i)] = F(\gamma' H_i)$$

The estimates obtained from the Probit regression can then be used to construct the selection variable which is called the Inverse Mills Ratio (λ_i). We introduce λ_i into wage equations as an additional variable to correct for the bias that may have resulted from exclusion of people with zero or negative income. Thus, our wage functions are defined as following:

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_z z + \beta_{pt} (p * t) + \beta_{zt} (z * t) + \text{Selection variable} + \upsilon \quad (4.1)$$

$$\text{Ln } W = \beta_x X + \beta_p p + \beta_I I + \beta_z z + \beta_{pt} (p * t_c) + \beta_{It} (I * t_c) + \beta_{zt} (z * t_c) + \text{Selection variable} + \upsilon \quad (4.2)$$

4.4.2.1 Marginal Effect

The primary interest is to understand the effect of H_i on the conditional probability. Since $\Phi(\gamma' H_i)$ is not a linear function, the estimated coefficient γ from the Probit model does not represent the marginal effect of the H. The actual marginal effect in the probability model is calculated by

$$\frac{\partial E\,[K \mid H]}{\partial H} = \left\{\frac{d\Phi(\gamma' H)}{d(\gamma' H)}\right\}\gamma = \phi(\gamma' H)\,\gamma \quad (4.3)$$

This marginal effect is simply the product of the estimated coefficient and the standard normal density function. Because $\Phi(.)$ is the strictly increasing cumulative distribution function, the effect of H on $E[K \mid H]$ depends on the sign of γ. That is, the probability of participating in the labour market will increase if the value of γ is positive.

CHAPTER 5

EMPIRICAL RESULTS AND INTERPRETATIONS

This study investigates the employer learning phenomenon and statistical discrimination in the Canadian labour market. In general, there are two main parallel estimations of wage equations. One is specific to test statistical discrimination on the basis of education (equation 4.1) and the other is specific to test statistical discrimination on the basis of immigration status (equation 4.2).

The first section in this chapter discusses the results of labour market participation decision, which are used to calculate the sample selection correction variable. The second section examines the standard controlled variables, which include Experience, Marital Status, Region of Residence, Occupation, Industry and Firm Size. In addition, we control Year since Migration and its square in the immigration equation. Finally, we present the findings on employer learning and whether firms use education to predict the productivity of new workers. The results related to immigration status will be presented at the end.

5.1 Empirical Results of Labour Market Participation Equation

The regression results of the probability for participating in paid job labour market are displayed in Table 5.1. The labour market participation equation corresponding to statistical discrimination on the basis of education is presented under specification A while the equation for immigration status is presented under specification B. The marginal effect, which is calculated by using (4.3), indicates the effect on the probability of participating in the labour market with respect to a change in the explanatory variable. The probability densities at the mean for specification A and specification B are 0.2857 and 0.2854 respectively.

Table 5.1 Marginal Effects of Probit Model of Labour Market Participation Decision (t-statistics are presented in parentheses)

Dependent variable: Participant = 1, otherwise = 0 (6251 observations)

Variable Name:	**Specification A**	**Specification B**
Years of Schooling	0.0106 (5.83)	0.0107 (5.85)
Immigrant		-0.0646 (-1.09)
Experience	0.0085 (3.61)	0.0083 (3.46)
Experience Square	-0.0001 (-1.20)	-0.0001 (-1.06)
Age	-0.0018 (-0.40)	-0.0017 (-0.38)
Age Square	-0.0001 (-2.91)	-0.0001 (-2.89)
Years since Migration		0.0078 (1.55)
Years since Migration Square		-0.0002 (-1.90)
Married	0.0570 (3.29)	0.0567 (3.27)
Separated /Divorced/ Widowed	0.0099 (0.39)	0.0100 (0.40)
Atlantic	0.0606 (3.91)	0.0583 (3.72)
Quebec	0.0405 (2.59)	0.0383 (2.42)
Prairies	-0.0095 (-0.66)	-0.0095 (-0.68)
British Columbia	-0.0032 (-0.16)	-0.0033 (-0.17)
Family Size	-0.0179 (-4.16)	-0.0179 (-4.14)
Non-Labour Income /100	-0.0006 (-11.01)	-0.0006 (-11.06)
Constant	0.2860 (3.50)	0.2847 (3.47)
S. E. of Regression	0.4045	0.4044
Log Likelihood	-3165.03	-3162.1
P. D. F at mean	0.2857	0.2854

- **Specifications A and B correspond to equation 4.1 and 4.2 respectively.**

Education is one of the fundamental factors in determining market activities. As noted in many empirical studies in economics, individuals with higher education levels are more likely to engage in the labour market. The results in this study tell a consistent story. The estimates reported in Table 5.1 indicate that the signs of Years of Schooling are positive and as well as are statistically significant in both specifications. That is, education has a positive impact on an individual's labour market participation probability.

Regarding the estimated response probabilities from Experience and Experience Square, the respective signs are statistically significant positive and statistically insignificant negative in both models. Typically, more working experience provides an individual with more incentives to enter the labour market. On the other hand, the negative coefficient on Experience Square supports the hypothesis that the marginal propensity of participating in the job market diminishes with experience.

Age and Age Square are also important determinants relating to labour market participation. In this study, we observe negative estimated coefficients on both variables, though these are not statistically significant for Age coefficients. The results can be interpreted as that while individuals might have the same levels of personal characteristic, being older is estimated to reduce the probability of paid work participation. This is probably an indication of different health status between young and old people.

Many empirical studies have found that immigrant males are more likely to become self-employed in the labour market, as compared to non-immigrants. The result for Immigrant males in specification B in Table 5.1 displays a negative effect on the probability of being a paid worker, relative to the base group (non-immigrants). It decreases the probability of paid job market participation by about 6.46%. However, the corresponding t value is not statistically significant at the 95% confidence interval.

Year since Migration and Year since Migration Square simply capture the change in the probability of participation in the paid work labour market as individuals are resident in Canada. The signs of these coefficients in the estimated model are positive and negative respectively in the last column in Table 5.1. They suggest that the foreign-born immigrants' lengths of stay in Canada increase the probability of entering the labour market because immigrants gradually obtain information about the Canadian market, albeit in a decreasing rate.

Marital Status also has some significance in explaining the probabilities in both specifications. Being married increases the probability of paid job employment by 5.7%, as compared to that for single individuals. On the other hand, the estimated coefficients on Separated, Divorced, and Widowed groups appear to be statistically insignificant positive which implies that the probability for individuals from those groups to participate in the job market is approximately only 1% higher than it is for single men.

Ontario is the base group for the Region of Residence variable. In general, our results indicate that residing in Atlantic and Quebec increases the probability of becoming paid workers by approximately 6% and 4% respectively. The effects are statistically significant. In contrast, individuals who live in Prairies and British Columbia are estimated to be less likely to participate in the paid job market, though the t-values are statistically insignificant.

Family Size is shown to be negatively related to labour market participation and is statistically significant at the 95% confidence interval. An individual who is a member of a large family appears to have a lower incentive to participate in the paid work labour market.

The estimated marginal effect indicates that he is 1.79% less likely to engage in paid work employment.

The last factor that we wish to explain is Non-Labour Income. Consistent with empirical prediction, the Non-Labour Income demonstrates a statistically significant and negative effect on the probability of labour market participation. As each additional thousand dollars of Non-Labour Income becomes available, the probability of being a paid worker for an individual is shown to decrease by 0.6%. The effect is very modest; therefore, we conclude it is not economically very significant.

5.2 The Earnings Function

Using 1994 Survey of Labour and Income Dynamics micro data files, we estimated a total of 5 equations to test for statistical discrimination based on the years of education. The base equation does not include the interaction terms between Years of Schooling (p), Experience (t), and Mother's Education as explanatory variables. The final specification, presented in Table 5.2a, includes interactions between p and t as well as between mother's education and t. Results for alternative specifications with different levels of interaction terms are reported in appendix Table A1. Estimates for testing statistical discrimination on the basis of immigration status with all interaction terms are presented in Table 5.3a.

To determine the statistical significance of the estimated coefficients, we employ the 5% level against a two-tailed test. In general, we see immediately that the signs of our controlled variables yield no surprises. All equations use Heckman's model to correct the sample selection bias.[3] However, the sample selection bias is found to be statistically

[3] Please see appendix Table A3 and Table A4 for regression results not correcting for Sample Selection Bias.

insignificant in Table 5.2a and Table 5.3a since sample selection correction variable (lambda) does not appear to be significantly different from zero in all equations.

5.2.1 Results for the Education-Based Statistical Discrimination Equation

The estimates on Experience are positive and statistically significant and their squares are statistically significant negative related to the wage for all equations. These empirical results are consistent with the concavity of the experience earning profile as discussed in chapter 3, which suggests that individuals' wages increase with labour market experience at a decreasing rate and reach the highest return at approximately 29 years of experience ($\partial \ln W / \partial t = 0.0252 - 0.00088t = 0$).

The literature in labour economics often suggests that married male workers have higher earnings than their unmarried counterparts. Statistics Canada (1996) concurs that Single paid workers are shown to averagely receive lower wages and salaries than do married or separated workers. The estimated coefficients on Married and Separated/Divorced/Widowed confirm this hypothesis.

The coefficients on Region of Residence are consistent with the study conducted by Statistics Canada (2000). All estimated coefficients are statistically significant since t values are well above 1.96 in absolute value. To interpret the estimates on the dummy variable coefficients, we have to remember that the results measure the percentage difference in wage relative to base group. For example, a male individual who resided in British Columbia is estimated to earn about 7% more than one who lived in Ontario, holding levels of other variables fixed.

Table 5.2a: OLS Results of Standard Controlled Variables for Earning Function; Dependent variable: Logarithm of wage rate, t-values are in parentheses

Explanatory Variables:	(5)
Experience	0.0252 (7.64)
Experience Square/100	-0.0444 (-10.61)
Marital Status: Single (Reference Group)	
Married	0.1367 (8.89)
Separated/Divorced/ Widowed	0.0684 (2.81)
Region of Residence: Ontario (Reference Group)	
Atlantic	-0.1640 (-10.96)
Quebec	-0.0337 (-2.23)
Prairies	-0.0892 (-6.23)
British Columbia	0.0702 (3.58)
Occupation: Unskilled Worker (Reference Group)	
Management	0.3220 (16.58)
Professional	0.2582 (12.93)
Supervisor/ Foreman	0.2116 (9.28)
Skilled Worker	0.1987 (12.49)
Semi-Skilled Worker	0.0681 (4.37)
Industry: Manufacturing (Reference Group)	
Primary	0.0779 (3.85)
Construction	0.0830 (3.89)
Transportation / Storage	-0.0061 (-0.28)
Communication / Utility	0.0825 (3.22)
Wholesale	-0.0747 (-3.30)
Retail Trade	-0.2352 (-11.93)
Finance / Insurance / Real Estate	-0.0174 (-0.53)
Business	-0.0410 (-1.32)
Government	0.0163 (0.86)
Educational	0.0334 (1.35)
Health/ Social Services	-0.0502 (-1.61)
Accommodation	-0.3524 (-11.06)
Other Services	-0.2188 (-7.69)
Firm size: Fewer than 20 (Reference Group)	
20-99 employees	0.1147 (7.09)
100-499	0.1575 (9.03)
500-999	0.1840 (9.03)
1000 and over	0.2654(18.09)
Lambda	0.0326 (1.02)

The benchmark Occupation chosen in this study is Unskilled Workers. Individuals are measured to have lower pay if they are members of this group. On average, people in Managerial and Professional occupations show a statistically significant advantage in nominal hourly wage rate compared to those in the base group.

Almost all industry coefficients are statistically significant, except for those on Transportation/Storage, Finance/Insurance/Real Estate, Business, Government, Educational Services, and Health/Social services. In sum, male individuals in Primary and Construction are subject to earning higher incomes relative to individuals in the Manufacturing industry.

The dummy variables for Firm Size are very statistically significant and positive. As Walter and Todd (1999) suggest, workers who work in larger firms are paid higher wages. The base group is firms that employ fewer than 20 employees. Male workers employed in firms of 20-99,100-499, 500-999, and 1000 and over employees earn 12%, 16%, 18%, and 27% more respectively, when other workers' characteristics are held the same.

5.2.2 Results for the Immigration Status-Based Statistical Discrimination Equation

A total of 7 estimate equations have been estimated in this section, where total experience is divided into Canadian and non-Canadian Experience. Only the result for specification with interactions between Canadian Experience and Years of Schooling, Mother's Education, and Immigration status is presented in Table 5.3a. Results for other combinations of interaction terms are presented in the appendix Table A2.

The positive and negative coefficients on Experience and Experience Square again confirm the experience wage profile. More Canadian Experience brings more wage earning. However, it is interesting to see that Experience outside Canada is statistically insignificant in explaining the wage for all equations. As stated by Hum and Simpson (1999), this implies that only experience obtained in the Canadian labour market plays a role in wage differentials.

Although Year since Migration and its square follow the inverted-U shape as many empirical results suggest, these estimates are not very statistically significant.

The estimated coefficients on Married and Separated/Divorced/Widowed once again behave as predicted in past literature. Male workers will earn lower wages in the labour market if they are Single. Married groups on average have about a 14% and Separated/Divorced/Widowed groups on average have about a 7% wage premiums over those who are not married. Both coefficients are statistically significant.

For Region of Residence, all coefficients are statistically significant negative, except for that for British Columbia. Male paid workers who reside in Atlantic suffer the most wage disadvantage, which is predicted to be 16% below that of the base group.

As was the results in Table 5.2a, the estimates on Occupation dummies in Table 5.3a are very statistically significant. Individuals in Management still have the best wage opportunities among all occupations. On the other hand, the wage of the Semi-Skilled group is found to be 7% higher than the base group.

Statistics Canada (2004) shows that in 1996 a worker in the primary or communication/utility industry had higher earnings, compared to a worker in the manufacturing industry. Our results are generally consistent with what Statistics Canada suggests. Primary industry workers are predicted to get paid 7.8% higher and Communication/Utility industry workers are predicted to earn 8% more than workers in

Manufacturing.

The coefficients for Firm Size are almost the same as the results in education estimation. The evidence supports the hypothesis that individuals' wage opportunities increase as firm sizes increase. The wage opportunity for firms employing 20-99 workers is 11% more; that for firms employing 1000 or more workers increases to 26% more than the base group. The results are all significantly different from zero and positive.

Table 5.3a: OLS Results of Standard Controlled Variables for Earning Function with Immigration Status Variable; Dependent Variable: Logarithm of wage rate, t-values are in parentheses

Explanatory Variables:	(7)
Experience in Canada	0.0266 (7.83)
Experience in Canada Square/100	-0.0461 (-10.62)
Experience outside Canada	-0.0038 (-0.45)
Experience outside Canada Square/100	0.0204 (0.57)
Year since Migration	0.0031 (0.51)
Year since Migration Square/100	-0.0042 (-0.36)
Marital Status: Single (Reference Group)	
Married	0.1417 (9.20)
Separated/Divorced/ Widowed	0.0732 (3.01)
Region of Residence: Ontario (Reference Group)	
Atlantic	-0.1636 (-10.88)
Quebec	-0.0345 (-2.26)
Prairies	-0.0877 (-6.12)
British Columbia	0.0708 (3.61)
Occupation: Unskilled Worker (Reference Group)	
Management	0.3212 (16.56)
Professional	0.2542 (12.75)
Supervisor/ Foreman	0.2106 (9.24)
Skilled Worker	0.1974 (12.42)
Semi-Skilled Worker	0.0680 (4.37)
Industry: Manufacturing (Reference Group)	
Primary	0.0787 (3.89)
Construction	0.0801 (3.75)
Transportation / Storage	-0.0050 (-0.23)
Communication / Utility	0.0849 (3.32)
Wholesale	-0.0725 (-3.20)
Retail Trade	-0.2358 (-11.97)
Finance / Insurance / Real Estate	-0.0132 (-0.40)
Business	-0.0356 (-1.15)
Government	0.0169 (0.89)
Educational	0.0339 (1.37)
Health/ Social Services	-0.0511 (-1.64)
Accommodation	-0.3498 (-10.99)
Other Services	-0.2161 (-7.61)
Firm Size: Fewer than 20 (Reference Group)	
20-99 employees	0.1140 (7.06)

100-499	0.1581 (9.08)
500-999	0.1844 (9.06)
1000 and over	0.2639 (18.01)
Lambda	0.0368 (1.14)

5.3 Test for Employer Learning and Statistical Discrimination on the Basis of Education

The OLS estimates for Years of Schooling, Mother's Education, and their interactions with Experience (Full-time Full-year Equivalent) are shown in Table 5.2b. Specification (1) presents the equation, which includes Years of Schooling only. Other specifications provide comparable results by controlling different interaction variables.

All of the results in the following table indicate that Years of Schooling has a positive and statistically significant effect on individuals' wages. Looking at the estimated coefficients, other things being fixed (marital status, region and so on), they predict a 3% to 3.6% ($\partial \ln W / \partial p$) associated returns for another year of education. With the Mother's Education in the equation (specification (2)), the partial effect of Years of Schooling drops very slightly from 3.1% to 3%.

Next, we estimate an equation, which include Years of Schooling and its inter action with Experience. In column (3), the coefficient on the interaction term is -0.0178. It implies that for each additional year of job market experience the impact of schooling on wages only drops by 0.02%. This turns out to be neither statistically significantly different from zero nor economically large.

We control both Mother's Education and interaction between Years of Schooling and Experience in specification (4). The estimate for Mother's Education is statistically significant at the 5% level against a two-tailed test and indicates that the wage of an individual increases by approximately 0.6% when mother's years of schooling increases by another year.

In general, our results provide evidence on employer learning in the Canadian labour market. The evidence comes from the interaction between the hard-to-observe variable (measured by Mother's Education) and job market experience.

In column (5), the main effect of Mother's Education is now -0.0045 and becomes statistically insignificant when the interaction variable is added. The estimated coefficient on Mother's Education * Experience is positive and statistically significant at 0.0556 (3.12). On the other hand, the estimated coefficient on Years of Schooling * Experience is negative but only nearly significant at -0.0300 (-1.85). That is, we have $b_{pt} < 0$ and $b_{zt} > 0$ which confirm Propositions 1 and 2 as mentioned in chapter 3.

There is also supportive evidence indicating statistical discrimination on the basis of education. The parameter of interest is on the interaction term Years of Schooling * Experience: the coefficient measures the decline in education value due to the revelation of new information (Mother's Education) with time, provided we allow that Mother's Education is correlated with Years of Schooling. The coefficient on Years of schooling * Experience we obtain from specification (4) and (5) show that the number drops from –0.0175 (-1.11) to –0.0300 (-1.85), when controlling the Experience interacted with Mother's Education.

Table 5.2b: Earning Function (Table 5.2a continued)
Effects of Mother's Education, Years of Schooling, and Interaction Terms
Dependent variable: Logarithm of wage rate, t-values are in parentheses

Model:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Years of Schooling (p)	0.0310 (13.86)	0.0301 (13.27)	0.0344 (9.26)	0.0334 (8.95)	0.0355 (9.38)
Mother's Education		0.0055 (2.64)		0.0054 (2.63)	-0.0045 (-1.18)
Years of Schooling * Experience/100			-0.0178 (-1.13)	-0.0175 (-1.11)	-0.0300 (-1.85)
Mother's Education * Experience/100					0.0556 (3.12)
Constant	1.7155 (44.03)	1.6645 (38.28)	1.6706 (30.01)	1.6204 (27.55)	1.7030 (26.43)
R-Squared	0.5017	0.5025	0.5019	0.5027	0.5038
Adjusted R-Squared	0.4981	0.4988	0.4982	0.4988	0.4998

Now, we can turn to test Proposition 3: $\partial b_{pt} / \partial t = - \Phi_{zp} * \partial b_{zt} / \partial t$. According to AP, the product of the negative of the coefficient of the regression of Mother's Education on Years of schooling (-cov (p,z)/var(p))[4] and the coefficient on Mother's Education interacted with Experience should equal the coefficient on the interaction between Years of Schooling and Experience. The result in Table 5.4 shows that this product is –0.0001. The coefficient on Years of Schooling * Experience is –0.0003 in column (5), Table 5.2b. Performing the coefficient Wald Test, we fail to reject Proposition 3.[5] However, the number is not economically or practically very large.

Based on our results, we conclude that employers appear to make hiring decisions with very limited information. Early easily observable indicators such as education determine initial wages. When learning takes place, the effect of Mother's Education

[4] The regression result is reported in Table A5 in appendix.
[5] Since the estimated equation is a nonlinear equation, we use the chi-square statistic to test proposition 3. $\chi^2_{1, 95\%} = 3.84$.

increases with Experience and, most importantly, the effect of Years of Schooling declines substantially with Experience.

Table 5.4: Wald Test

Test Statistic:	Value	Degree of Freedom	Probability
F-statistic	0.956800	(1, 4434)	0.3280
Chi-square	0.956800	1	0.3280

Null Hypothesis Summary:

Normalized Restriction (=0)	Value	Standard Error
B_{pt} + 0.262413 * b_{zt}	-0.000154	0.000157

5.4 Test for Employer Learning and Statistical Discrimination on the Basis of Immigration Status

Table 5.3b reports the estimated wage equation results, which additionally include a dichotomous variable for immigration status. As was the case in section 5.2b, the results in all specifications provide evidence supporting a positive relationship between Years of Schooling and wages. Over time, wages paid to workers are strongly related to unobservable ability and less related to easily observable variable (column (5)).

After controlling the effects of demographic, occupation, and industry variables, Immigrant enters the coefficient of -0.1034 (-1.54). This implies that a person who belongs to the immigrant group suffers about 10% wage penalty compared to his/her Canadian counterparts. While the t statistics is not statistically significant different from zero at 95% of confidence interval, the estimate is considered to be economically significant.

When Mother's Education is added in columns (2) and (4), the results reveal very slightly increases on the estimated coefficients of Immigrant, which are -0.0915 and -0.0926 respectively (compared to -0.1034).

In column (6), we add the interaction Immigration * Experience in Canada/10 to the equation, its value is 0.0434 (1.33) and the coefficient on Immigrant is now estimated to be -0.0859 (-1.27). While both t statistics in the equation are statistically insignificant at 95% of confidence interval, the coefficient on Immigrant remains economically large. The result suggests that with each additional year of increase in the Canadian labour experience, the wage of an immigrant is estimated to increase by about 0.4% which is practically not a big change.

When introducing the interaction variable of Mother's education and Experience in Canada into column (7), the intercept of Immigrant becomes more negative at -0.1028 (-1.52). On the other hand, the estimated coefficient on Immigrant * Experience in Canada/10 becomes more positive at 0.0453 (1.39). This value increases slightly, as compared to specification (6). But the results are never statistically significant. One possible explanation is that learning about new information enables employers to have larger information set to evaluate their employees' productivity, instead of relying on early signals (education and immigration status). However, we wish to point out that employee learning can also explain these results. That is, the positive coefficient on Immigrant interacted with Canadian labour market experience might partially be due to the fact that as immigrants actually get involved in the Canadian labour market, they obtain more practical knowledge about the local market. Therefore, their wages will increase with increased Canadian experience.

Table 5.3b: Earning Function (Table 5.3a continued)

Effects of Mother's Education, Schooling, Immigration Status, and Interaction Terms

Dependent variable: Logarithm of wage rate, t-values are in parentheses

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Years of Schooling (p)	0.0311 (13.86)	0.0302 (12.30)	0.0360 (9.66)	0.0350 (9.36)	0.0371 (9.75)	0.0351 (9.39)	0.0372 (9.79)
Immigrant (I)	-0.1034 (-1.54)	-0.0915 (-1.36)	-0.1044 (-1.56)	-0.0926 (-1.38)	-0.1097 (-1.63)	-0.0859 (-1.27)	-0.1028 (-1.52)
Mother's Education		0.0051 (2.44)		0.0050 (2.42)	-0.0044 (-1.16)	0.0051 (2.45)	-0.0044 (-1.16)
S* Experience in Canada/100			-0.0263 (-1.62)	-0.0260 (-1.60)	-0.0381 (-2.28)	-0.0268 (-1.65)	-0.0390 (-2.34)
ME* Experience in Canada/100					0.0537 (2.96)		0.0542 (2.99)
I* Experience in Canada/10						0.0434 (1.33)	0.0453 (1.39)
Constant	1.7142 (43.96)	1.6668 (38.27)	1.6492 (29.5)	1.6030 (27.16)	1.6814 (26.01)	1.6017 (27.14)	1.6808 (26.01)
R-Squared	0.5043	0.5049	0.5046	0.5052	0.5062	0.5054	0.5064
Adjusted R-Squared	0.5001	0.5007	0.5003	0.5009	0.5017	0.5009	0.5018

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We now turn to test Proposition 3: $\partial b_{pt} / \partial t = - \Phi_{zp} * \partial b_{zt} / \partial t$ and $\partial b_{It} / \partial t = - \Phi_{zI} * \partial b_{zt} / \partial t$, where s represents the Years of Schooling and I is Immigration status. To get Φ_{zp} and Φ_{zI}, we regress Mother's Education on Years of Schooling and Immigrant.[6] For Years of Schooling, the interaction product is -0.000145 and the coefficient on Years of Schooling * Experience in Canada is -0.000390. For Immigrant, the interaction product is 0.000269 and the coefficient on Immigrant * Experience in Canada is 0.00453. In Table 5.5, the Joint Wald Test with 2 degrees of freedom fails to reject the proposition that the Immigration Status is used for statistical discrimination by employers.[7] Because the product values are relative small, we conclude that the results are economically not significant.

In general, the results only display a weak indication that employers use education along with immigration status to statistically discriminate against job applicants when their future work performances are uncertain. While both intercept and interaction between Immigrant and Canadian Experience appear to be statistically insignificant in the model, the coefficient on Immigrant remains economically large throughout.

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[6] The regression result is reported in Table A6 in appendix.
[7] $\chi2_{2, 95\%} = 5.99$.

Table 5.5: Joint Wald Test

Test Statistic:	Value	Degree of Freedom	Probability
F-statistic	1.922587	(2, 4428)	0.1464
Chi-square	3.845175	2	0.1464

Null Hypothesis Summary:

Normalized Restriction (=0)	Value	Standard Error
$B_{pt} + 0.266958 * b_{zt}$	-0.000246	0.000162
$B_{It} + (-0.496653) * b_{zt}$	0.004257	0.003265

5.5 Summary

In general, our empirical results confirm the hypotheses of previous studies. First, the signs of estimated coefficients on the demographic and labour market variables behave as expected. Using the standard human capital equation, we find strong evidence to support employer learning and statistical discrimination on the basis of education in the Canadian labour market. Years of Schooling act as a signaling device for employers to predict the productivity of potential workers at the beginnings of their careers. The results on Mother's Education interacted with Experience are also consistent with Farber and Gibbons (1996) and Altonji and Pierret's (1998, 2001) results, in which the effects of unobserved ability increase with experience.

On the other hand, the results do not seem to support statistical discrimination on the basis of immigration status. All estimated coefficients are not statistically significant.

CHAPTER 6

SUMMARY AND CONCLUSION

The problems of statistical discrimination have been used to explain unequal pay among equally able workers in labour economics for more than thirty years. From the standpoint of neoclassical theory, it can be characterized as efficient. In a world of imperfect information, it is rational for employers to use limited information to maximize profit. An economy with statistical discrimination is therefore said to be more efficient than one where employers completely neglect available information. This paper investigates whether firms use education and immigration status to infer performance and/or ability in Canada within a simple employer learning model, given imperfect observability of productivity.

Throughout this study, it is assumed that the labour market is competitive and that the information is symmetric across all employers. We employ the 1994 Public Use Micro Data Report of the second wave of Survey of Labour and Income Dynamics (SLID) in the analysis. In addition, the use of Heckman's sample selection correction technique has been applied to estimate the paid workers' wage equations using the standard human capital framework which controls for several worker level and firm-specific variables.

In accordance with Farber and Gibbons (1996), and Altonji and Pierret's (1998, 2001) studies, the results show that readily available information is a key determinant of initial pay decisions in Canada. We find that in the absence of correct information on the actual productivity of new workers, easily observable characteristics such as years of schooling and immigration status are often used by profit-maximizing firms to distinguish workers. Moreover, evidence on employer learning is also found in this paper. This implies that a firm will learn to adjust the initial beliefs, as better information about a worker becomes available in the market.

In the first part of our estimation we analyze a wage equation, which uses years of schooling and mother's education as the indicators of a worker's general and true productivity respectively. Furthermore, both variables interacted with experience are included in the equation to capture the learning process. First of all, years of schooling is shown to have a statistically significant positive effect on initial wages. Secondly, we are able to confirm the hypothesis of statistical discrimination on the basis of education. The impact of mother's education on wage rises with the length of labour market experience. And most importantly, the reward to schooling falls with experience.

To test whether firms use immigration status as a cheap informational source to statistically discriminate among workers, we include immigration status along with years of schooling into the wage equation. The negative immigrant intercept is consistent with many empirical studies, which suggest that the immigration status is negatively related to wages. However, the results are statistically insignificant at the 95% of confidence interval. On the other hand, the result on the positive relationship between immigrant and work experience when the interaction between mother's education and Canadian experience is added implies that employers gradually learn about the productivity of immigrants and adjust their initial assessments. However, we wish to point out that the latter result can also be explained by employee learning. Finally, our findings show that non-Canadian experience has a positive, however not statistically significant effect on wages. In general, our finding provides only a weak indication of statistical discrimination on the basis of immigration status in the Canadian labour market.

This paper assumes that firms rely on some readily available information to make different wage offers, even if workers are equally productive. 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 will actually produce a negative effect in the market. Rational firms may respond to this kind of restriction by hiring less disadvantaged workers or by lowering the hiring standards, which just further reduces a minority group's incentives for making useful skill investments. Rather, policymakers should turn the focus to the workers' side. Advocacy of policies that encourage lower productivity workers to make themselves more valuable to the employers is necessary.

If both the work experiences acquired abroad and work experiences obtained in Canada have the same quality, our empirical results indicate that different values are attached to the qualifications. Therefore, instead of emphasizing the traditional legislation that tries to enforce labour market opportunity equality, policy implementation should focus on helping employers to recognize the values of foreign human capital.

One shortcoming of this study is that it assumes individuals' experience profiles to be independent of education and mother's education. A more general approach, one that accounts for the effects of on-the-job training, can be taken in the future research.

Economic theory generally suggests that on-the-job training is often given to more educated and able individuals. When this happens, it affects the impact of years of schooling and mother's education on individuals' wages.

Another future research area can focus on the relaxation of the assumption that information is symmetric across all employers in the market. While outside employers usually have access only to the public information about potential employees, current employers will generally have increased levels of information about those same workers.

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APPENDIX

Table A1: OLS Results of Standard Controlled Variables for Earning Function

(Dependent variable: Logarithm of wage rate, t-values are in parentheses)

Explanatory Variables:	(1)	(2)	(3)	(4)	(5)
Experience (t)	0.0269 (-15.99)	0.0274 (-16.18)	0.0296 (-10.17)	0.0300 (-10.30)	0.0252 (-7.64)
t Square/100	-0.0452 (-11.37)	-0.0459 (-11.52)	-0.0463 (-11.31)	-0.0470 (-11.45)	-0.0444 (-10.61)
Marital Status: Single (Reference Group)					
Married	0.1392 (9.12)	0.1414 (9.26)	0.1373 (8.95)	0.1395 (9.09)	0.1367 (8.89)
Separated/Divorced/Widowed	0.0726 (2.98)	0.0726 (2.99)	0.0713 (2.93)	0.0714 (2.93)	0.0684 (2.81)
Region of Residence: Ontario (Reference Group)					
Atlantic	-0.1642 (-10.97)	-0.1631 (-10.89)	-0.1639 (-10.94)	-0.1627 (-10.87)	-0.1640 (-10.96)
Quebec	-0.0399 (-2.66)	-0.0341 (-2.26)	-0.0398 (-2.66)	-0.0341 (-2.25)	-0.0337 (-2.23)
Prairies	-0.0883 (-6.17)	-0.0907 (-6.33)	-0.088 (-6.14)	-0.0904 (-6.31)	-0.0892 (-6.23)
British Columbia	0.0739 (3.78)	0.0692 (3.53)	0.0745 (3.81)	0.0698 (3.56)	0.0702 (3.58)
Occupation: Unskilled Worker (Reference Group)					
Management	0.3267 (16.85)	0.3225 (16.59)	0.3264 (16.84)	0.3222 (16.57)	0.3220 (16.58)
Professional	0.2623 (13.16)	0.2586 (12.95)	0.2613 (13.10)	0.2576 (12.89)	0.2582 (12.93)
Supervisor/ Foreman	0.2154 (9.44)	0.2127 (9.32)	0.2147 (9.41)	0.2121 (9.29)	0.2116 (9.28)
Skilled Worker	0.1998 (12.55)	0.1981 (12.44)	0.1993 (12.52)	0.1976 (12.41)	0.1987 (12.49)
Semi-Skilled Worker	0.0685 (4.39)	0.0675 (4.33)	0.0683 (4.38)	0.0674 (4.32)	0.0681 (4.37)
Industry: Manufacturing (Reference Group)					

Primary	0.0785 (3.88)	0.0784 (3.87)	0.0789 (3.90)	0.0787 (3.89)	0.0779 (3.85)
Construction	0.0813 (3.80)	0.0833 (3.90)	0.0812 (3.80)	0.0833 (3.90)	0.083 (3.89)
Transportation / Storage	-0.0037 (-0.17)	-0.0049 (-0.22)	-0.0044 (-0.20)	-0.0056 (-0.26)	-0.0061 (-0.28)
Communication / Utility	0.0829 (3.23)	0.0817 (3.19)	0.0828 (3.23)	0.0816 (3.18)	0.0825 (3.22)
Wholesale	-0.0730 (-3.22)	-0.0736 (-3.24)	-0.0736 (-3.24)	-0.0741 (-3.27)	-0.0747 (-3.30)
Retail Trade	-0.2363 (-11.97)	-0.2366 (-11.99)	-0.2362 (-11.97)	-0.2365 (-11.99)	-0.2352 (-11.93)
Finance / Insurance / Real Estate	-0.0158 (-0.48)	-0.0161 (-0.49)	-0.0163 (-0.49)	-0.0166 (-0.50)	-0.0174 (-0.53)
Business	-0.0404 (-1.31)	-0.0419 (-1.35)	-0.043 (-1.39)	-0.0444 (-1.43)	-0.041 (-1.32)
Government	0.0169 (0.89)	0.0159 (0.84)	0.0167 (0.89)	0.0158 (0.84)	0.0163 (0.86)
Educational	0.0258 (1.05)	0.0283 (1.15)	0.0286 (1.16)	0.0311 (1.26)	0.0334 (1.35)
Health/ Social Services	-0.0479 (-1.53)	-0.0494 (-1.58)	-0.0487 (-1.56)	-0.0502 (-1.61)	-0.0502 (-1.61)
Accommodation	-0.3535 (-11.07)	-0.3545 (-11.11)	-0.3534 (-11.07)	-0.3545 (-11.11)	-0.3524 (-11.06)
Other Services	-0.2183 (-7.67)	-0.22 (-7.73)	-0.2175 (-7.63)	-0.2192 (-7.70)	-0.2188 (-7.69)
Firm Size: Fewer than 20 (Reference group)					
20-99 employees	0.1152 (7.11)	0.1156 (7.14)	0.1146 (7.07)	0.1149 (7.09)	0.1147 (7.09)
100-499	0.1582 (9.09)	0.1574 (9.02)	0.1578 (9.03)	0.157 (8.99)	0.1575 (9.03)
500-999	0.1823 (8.94)	0.1835 (9.00)	0.1816 (8.90)	0.1828 (8.96)	0.184 (9.03)
1000 and over	0.2664 (18.14)	0.2656 (18.10)	0.2658 (18.09)	0.265 (18.05)	0.2654 (18.09)
Lambda	0.0251 (0.79)	0.034 (1.07)	0.0281 (0.88)	0.0369 (1.15)	0.0326 (1.02)

Table A2: OLS Results of Standard Controlled Variables for Earning Function with Immigration Status Variable (Dependent variable: Logarithm of wage rate, t-values are in parentheses)

Explanatory Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience in Canada (t_c)	0.0270 (15.68)	0.0274 (15.86)	0.0310 (10.33)	0.0313 (10.45)	0.0266 (7.84)	0.0314 (10.46)	0.0266 (7.83)
t_c Square/100	-0.0464 (-11.34)	0.0470 (-11.47)	-0.0482 (-11.37)	-0.0488 (-11.49)	-0.0461 (-10.62)	-0.0488 (-11.49)	-0.0461 (-10.62)
Experience outside Canada (t_{nc})	0.0007 (0.09)	0.0007 (0.09)	0.0009 (0.12)	0.0010 (0.13)	0.0014 (0.19)	-0.0041 (-0.48)	-0.0038 (-0.45)
t_{nc} Square/100	0.0069 (0.20)	0.0059 (0.17)	0.0056 (0.16)	0.0045 (0.13)	0.0033 (0.10)	0.0209 (0.58)	0.0204 (0.57)
Year since Migration (ysm)	0.0037 (1.00)	0.0038 (0.90)	0.0035 (0.96)	0.0039 (0.86)	0.0030 (1.06)	0.0030 (0.34)	0.0031 (0.51)
ysm Square/100	-0.0046 (-0.21)	-0.0046 (-0.19)	-0.0043 (-0.17)	-0.0048 (-0.12)	-0.0041 (-0.27)	-0.0041 (-0.21)	-0.0042 (-0.36)
Marital Status: Single (Reference Group)							
Married	0.1445 (9.45)	0.1462 (9.56)	0.1419 (9.23)	0.1437 (9.34)	0.1411 (9.17)	0.1442 (9.38)	0.1417 (9.20)
Separated/ Divorced/ Widowed	0.0765 (3.15)	0.0764 (3.15)	0.0748 (3.08)	0.0747 (3.07)	0.0720 (2.96)	0.0758 (3.12)	0.0732 (3.01)
Region of Residence: Ontario (Reference Group)							
Atlantic	-0.1642 (-10.91)	-0.1629 (-10.83)	-0.1638 (-10.89)	-0.1625 (-10.80)	-0.1637 (-10.88)	-0.1624 (-10.79)	-0.1636 (-10.88)
Quebec	-0.0405 (-2.68)	-0.0349 (-2.28)	-0.0403 (-2.67)	-0.0348 (-2.28)	-0.0344 (-2.26)	-0.0349 (-2.29)	-0.0345 (-2.26)
Prairies	-0.0871 (-6.08)	-0.0893 (-6.23)	-0.0867 (-6.06)	-0.0889 (-6.20)	-0.0877 (-6.12)	-0.889 (-6.20)	-0.0877 (-6.12)
British Columbia	0.0741 (3.79)	0.0698 (3.56)	0.0748 (3.83)	0.0705 (3.60)	0.0712 (3.64)	0.0701 (3.58)	0.0708 (3.61)
Occupation: Unskilled Worker (Reference Group)							
Management	0.3255 (16.81)	0.3216 (16.57)	0.3252 (16.80)	0.3214 (16.56)	0.3212 (16.56)	0.3214 (16.56)	0.3212 (16.56)
Professional	0.2591 (13.02)	0.2557 (12.82)	0.2576 (12.93)	0.2542 (12.73)	0.2547 (12.77)	0.2537 (12.71)	0.2542 (12.75)
Supervisor/ Foreman	0.2143 (9.40)	0.2119 (9.23)	0.2135 (9.37)	0.2112 (9.26)	0.2106 (9.24)	0.2112 (9.26)	0.2106 (9.24)
Skilled Worker	0.1986 (12.50)	0.1971 (12.40)	0.1979 (12.45)	0.1964 (12.35)	0.1975 (12.43)	0.1963 (12.34)	0.1974 (12.42)
Semi-Skilled Worker	0.0686 (4.40)	0.0676 (4.34)	0.0685 (4.40)	0.0676 (4.34)	0.0683 (4.39)	0.0673 (4.33)	0.0680 (4.37)
Industry: Manufacturing (Reference Group)							

Primary	0.0783 (3.87)	0.0783 (3.87)	0.0786 (3.88)	0.0787 (3.89)	0.0782 (3.87)	0.0792 (3.91)	0.0787 (3.89)
Construction	0.0782 (3.66)	0.0803 (3.76)	0.0780 (3.65)	0.0801 (3.75)	0.0798 (3.74)	0.0803 (3.76)	0.0801 (3.75)
Transportation / Storage	-0.0035 (-0.16)	-0.0044 (-0.20)	-0.0045 (-0.21)	-0.0054 (-0.25)	-0.0057 (-0.26)	-0.0048 (-0.22)	-0.0050 (-0.23)
Communication / Utility	0.0841 (3.28)	0.0830 (3.24)	0.0842 (3.29)	0.0832 (3.25)	0.0838 (3.28)	0.0842 (3.29)	0.0849 (3.32)
Wholesale	-0.0720 (-3.17)	-0.0723 (-3.19)	-0.0726 (-3.20)	-0.0730 (-3.22)	-0.0734 (-3.24)	-0.0721 (-3.18)	-0.0725 (-3.20)
Retail Trade	-0.2375 (-12.04)	-0.2376 (-12.06)	-0.2374 (-12.04)	-0.2375 (-12.05)	-0.2364 (-12.00)	-0.2369 (-12.02)	-0.2358 (-11.97)
Finance / Insurance/ Real Estate	-0.0118 (-0.36)	-0.0120 (-0.36)	-0.0126 (-0.38)	-0.0127 (-0.38)	-0.0137 (-0.41)	-0.0122 (-0.37)	-0.0132 (-0.40)
Business	-0.0348 (-1.13)	-0.0363 (-1.18)	-0.0385 (-1.24)	-0.0400 (-1.29)	-0.0362 (-1.17)	-0.0394 (-1.27)	-0.0356 (-1.15)
Government	0.0152 (0.81)	0.0145 (0.77)	0.0153 (0.81)	0.0146 (0.77)	0.0150 (0.79)	0.0164 (0.87)	0.0169 (0.89)
Educational	0.0244 (0.99)	0.0269 (1.09)	0.0288 (1.17)	0.0312 (1.26)	0.0331 (1.34)	0.0320 (1.29)	0.0339 (1.37)
Health/ Social Services	-0.0485 (-1.55)	-0.0499 (-1.60)	-0.0496 (-1.59)	-0.0509 (-1.63)	-0.0507 (-1.63)	-0.0512 (-1.64)	-0.0511 (-1.64)
Accommodation	-0.3503 (-10.99)	-0.3514 (-11.03)	-0.3503 (-10.99)	-0.3514 (-11.03)	-0.3496 (-10.98)	-0.3516 (-11.04)	-0.3498 (-10.99)
Other Services	-0.2159 (-7.59)	-0.2174 (-7.65)	-0.2149 (-7.56)	-0.2165 (-7.61)	-0.2159 (-7.60)	-0.2167 (-7.62)	-0.2161 (-7.61)
Firm size: Fewer than 20 (Reference group)							
20-99 employees	0.1150 (7.11)	0.1153 (7.13)	0.1141 (7.05)	0.1144 (7.08)	0.1141 (7.06)	0.1144 (7.07)	0.1140 (7.06)
100-499	0.1592 (9.13)	0.1585 (9.09)	0.1585 (9.09)	0.1578 (9.06)	0.1583 (9.09)	0.1577 (9.05)	0.1581 (9.08)
500-999	0.1834 (9.01)	0.1844 (9.06)	0.1824 (8.96)	0.1835 (9.01)	0.1848 (9.08)	0.1831 (8.99)	0.1844 (9.06)
1000 and over	0.2647 (18.06)	0.2640 (18.02)	0.2638 (17.99)	0.2632 (17.95)	0.2636 (17.99)	0.2634 (17.96)	0.2639 (18.01)
Lambda	0.0288 (0.90)	0.0320 (1.14)	0.0337 (1.05)	0.0413 (1.28)	0.0372 (1.16)	0.0409 (1.27)	0.0368 (1.14)

Table A3: OLS Results of Standard Controlled Variables for Earning Function; Dependent variable: Logarithm of wage rate, t-values are in parentheses (Do not correct for Sample Selection Bias)

Explanatory variables:	(1)	(2)	(3)	(4)	(5)
Years of Schooling (p)	0.0308 (13.89)	0.0298 (13.24)	0.0339 (9.24)	0.0328 (8.88)	0.0350 (9.33)
Mother's Education (ME)		0.0052 (2.54)		0.0052 (2.52)	-0.0049 (-1.29)
p * t/100			-0.0166 (-1.06)	-0.0161 (-1.02)	-0.0289 (-1.78)
ME * t/100					0.0564 (3.17)
t	0.0267 (16.05)	0.0271 (16.22)	0.0292 (10.16)	0.0295 (10.25)	0.0246 (7.57)
t Square/100	-0.0440 (-12.00)	-0.0442 (-12.06)	-0.0449 (-11.92)	-0.0451 (-11.98)	-0.0427 (-11.12)
Marital Status: Single (Reference Group)					
Married	0.1387 (9.10)	0.1406 (9.22)	0.1369 (8.93)	0.1389 (9.05)	0.1361 (8.86)
Separated/ Divorced/ Widowed	0.0728 (2.99)	0.0729 (3.00)	0.0717 (2.94)	0.0718 (2.95)	0.0687 (2.83)
Region of Residence: Ontario (Reference Group)					
Atlantic	-0.1657 (-11.14)	-0.1650 (-11.11)	-0.1655 (-11.13)	-0.1649 (-11.10)	-0.1659 (-11.17)
Quebec	-0.0412 (-2.76)	-0.0361 (-2.40)	-0.0412 (-2.77)	-0.0362 (-2.41)	-0.0355 (-2.37)
Prairies	-0.0881 (-6.16)	-0.0904 (-6.31)	-0.0878 (-6.13)	-0.0901 (-6.28)	-0.0889 (-6.21)
British Columbia	0.0737 (3.77)	0.0691 (3.52)	0.0742 (3.79)	0.0696 (3.54)	0.0700 (3.57)
Occupation: Unskilled Worker (Reference Group)					
Management	0.3265 (16.84)	0.3224 (16.58)	0.3262 (16.83)	0.3221 (16.57)	0.3220 (16.58)
Professional	0.2621 (13.16)	0.2585 (12.95)	0.2611 (13.09)	0.2576 (12.89)	0.2582 (12.93)
Supervisor/ Foreman	0.2144 (9.41)	0.2115 (9.28)	0.2137 (9.37)	0.2109 (9.25)	0.2105 (9.24)
Skilled Worker	0.1993 (12.53)	0.1975 (12.41)	0.1998 (12.49)	0.1970 (12.38)	0.1982 (12.46)
Semi-Skilled Worker	0.0679 (4.36)	0.0668 (4.29)	0.0677 (4.35)	0.0666 (4.27)	0.0675 (4.33)
Industry: Manufacturing (Reference Group)					
Primary	0.0789 (3.90)	0.0788 (3.90)	0.0792 (3.91)	0.0792 (3.91)	0.0783 (3.87)
Construction	0.0819	0.0841	0.0820	0.0841	0.0837

	(3.84)	(3.94)	(3.84)	(3.94)	(3.93)
Transportation / Storage	-0.0036 (-0.17)	-0.0047 (-0.22)	-0.0043 (-0.20)	-0.0054 (-0.25)	-0.0060 (-0.28)
Communication / Utility	0.0828 (3.23)	0.0817 (3.19)	0.0828 (3.23)	0.0816 (3.18)	0.0825 (3.22)
Wholesale	-0.0734 (-3.24)	-0.0741 (-3.27)	-0.0740 (-3.26)	-0.0746 (-3.29)	-0.0752 (-3.32)
Retail Trade	-0.2368 (-12.00)	-0.2372 (-12.03)	-0.2367 (-12.00)	-0.2372 (-12.03)	-0.2358 (-11.97)
Finance / Insurance / Real Estate	-0.0157 (-0.47)	-0.0159 (-0.48)	-0.0162 (-0.49)	-0.0164 (-0.49)	-0.0173 (-0.52)
Business	-0.0395 (-1.28)	-0.0405 (-1.31)	-0.0418 (-1.35)	-0.0428 (-1.38)	-0.0395 (-1.27)
Government	0.0175 (0.92)	0.0167 (0.89)	0.0174 (0.92)	0.0167 (0.88)	0.0171 (0.91)
Educational	0.0265 (1.08)	0.0292 (1.19)	0.0293 (1.18)	0.0319 (1.29)	0.0341 (1.38)
Health/ Social Services	-0.0467 (-1.50)	-0.0478 (-1.53)	-0.0473 (-1.52)	-0.0484 (-1.55)	-0.0486 (-1.56)
Accommodation	-0.3532 (-11.07)	-0.3541 (-11.10)	-0.3531 (-11.06)	-0.3540 (-11.10)	-0.3520 (-11.04)
Other Services	-0.2174 (-7.64)	-0.2186 (-7.69)	-0.2165 (-7.61)	-0.2178 (-7.65)	-0.2176 (-7.66)
Firm size: Fewer than 20 (Reference group)					
20-99 employees	0.1147 (7.09)	0.1149 (7.10)	0.1140 (7.04)	0.1142 (7.06)	0.1141 (7.05)
100-499	0.1580 (9.05)	0.1571 (9.01)	0.1575 (9.02)	0.1567 (8.98)	0.1573 (9.02)
500-999	0.1817 (8.92)	0.1827 (8.97)	0.1809 (8.87)	0.1819 (8.93)	0.1833 (9.00)
1000 and over	0.2656 (18.13)	0.2646 (18.07)	0.2650 (18.07)	0.2640 (18.01)	0.2645 (18.06)
Constant	1.7284 (48.87)	1.6840 (42.70)	1.6878 (32.39)	1.6451 (30.03)	1.7259 (28.59)
R-Squared	0.5017	0.5024	0.5018	0.5025	0.5036

Table A4: OLS Results of Standard Controlled Variables for Earning Function with Immigration Status Variable; Dependent variable: Logarithm of wage rate, t-values are in parentheses (Do not correct for Sample Selection Bias)

Explanatory variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Years of Schooling (p)	0.0308 (13.88)	0.0299 (13.26)	0.0353 (9.62)	0.0343 (9.27)	0.0365 (9.69)	0.0344 (9.30)	0.0366 (9.72)
Immigrant (I)	-0.1007 (-1.50)	-0.0887 (-1.32)	-0.1013 (-1.51)	-0.0894 (-1.33)	-0.1071 (-1.59)	-0.0827 (-1.23)	-0.1003 (-1.49)
Mother's Education (ME)		0.0048 (2.33)		0.0048 (2.31)	-0.0048 (-1.27)	0.0048 (2.34)	-0.0048 (-1.27)
p * t_c /100			-0.0247 (-1.53)	-0.0240 (-1.49)	-0.0365 (-2.19)	-0.0249 (-1.54)	-0.0375 (-2.25)
ME * t_c /100					0.0546 (3.01)		0.0550 (3.04)
I * t_c /10						0.0438 (1.34)	0.0446 (1.40)
t_c	0.0267 (15.73)	0.0271 (15.88)	0.0304 (10.30)	0.0307 (10.38)	0.0259 (7.75)	0.0307 (10.39)	0.0259 (7.75)
t_c Square/100	-0.0450 (-11.89)	-0.0453 (-11.95)	-0.0465 (-11.90)	-0.0466 (-11.95)	-0.0441 (-11.06)	-0.0467 (-11.96)	-0.0441 (-11.07)
t_{nc}	0.0010 (0.13)	0.0011 (0.14)	0.0013 (0.17)	0.0014 (0.18)	0.0018 (0.24)	-0.0037 (-0.44)	-0.0035 (-0.42)
t_{nc} Square/100	0.0070 (0.21)	0.0060 (0.18)	0.0057 (0.17)	0.0048 (0.14)	0.0035 (0.10)	0.0213 (0.59)	0.0207 (0.58)
Year since Migration (ysm)	0.0035 (1.00)	0.0039 (0.87)	0.0033 (0.93)	0.0037 (0.83)	0.0035 (1.04)	0.0030 (0.30)	0.0029 (0.48)
ysm Square/100	-0.0045 (-0.21)	-0.0043 (-0.14)	-0.0042 (-0.13)	-0.0049 (-0.07)	-0.0046 (-0.23)	-0.0043 (-0.16)	-0.0042 (-0.033)
Marital Status: Single (Reference Group)							
Married	0.1438 (9.42)	0.1454 (9.51)	0.1413 (9.20)	0.1429 (9.30)	0.1404 (9.13)	0.1434 (9.33)	0.1409 (9.16)
Separated/ Divorced/ Widowed	0.0767 (3.16)	0.0766 (3.16)	0.0751 (3.09)	0.0750 (3.09)	0.0723 (2.98)	0.0762 (3.13)	0.0735 (3.02)
Region of Residence: Ontario (Reference Group)							
Atlantic	-0.1656 (-11.06)	-0.1647 (-11.01)	-0.1654 (-11.05)	-0.1645 (-11.00)	-0.1655 (-11.07)	-0.1644 (-10.99)	-0.1654 (-11.06)
Quebec	-0.0416 (-2.77)	-0.0366 (-2.41)	-0.0417 (-2.78)	-0.0367 (-2.42)	-0.0362 (-2.38)	-0.0368 (-2.43)	-0.0362 (-2.39)
Prairies	-0.0868 (-6.07)	-0.0888 (-6.20)	-0.0864 (-6.04)	-0.0884 (-6.17)	-0.0873 (-6.10)	-0.884 (-6.17)	-0.0872 (-6.09)
British Columbia	0.0738 (3.78)	0.0696 (3.55)	0.0745 (3.81)	0.0703 (3.59)	0.0710 (3.63)	0.0698 (3.56)	0.0706 (3.60)
Occupation: Unskilled Worker (Reference Group)							

Management	0.3253 (16.80)	0.3216 (16.56)	0.3250 (16.79)	0.3213 (16.55)	0.3211 (16.56)	0.3213 (16.55)	0.3211 (16.56)
Professional	0.2589 (13.01)	0.2555 (12.81)	0.2574 (12.92)	0.2542 (12.73)	0.2547 (12.77)	0.2537 (12.71)	0.2542 (12.75)
Supervisor/ Foreman	0.2132 (9.37)	0.2107 (9.25)	0.2123 (9.33)	0.2098 (9.21)	0.2094 (9.20)	0.2098 (9.21)	0.2094 (9.20)
Skilled Worker	0.1981 (12.47)	0.1964 (12.36)	0.1973 (12.42)	0.1957 (12.31)	0.1969 (12.40)	0.1956 (12.31)	0.1968 (12.39)
Semi-Skilled Worker	0.0679 (4.36)	0.0668 (4.30)	0.0677 (4.35)	0.0667 (4.29)	0.0674 (4.34)	0.0664 (4.27)	0.0672 (4.33)
Industry: Manufacturing (Reference Group)							
Primary	0.0787 (3.89)	0.0789 (3.90)	0.0792 (3.91)	0.0793 (3.92)	0.0787 (3.90)	0.0798 (3.95)	0.0793 (3.92)
Construction	0.0790 (3.70)	0.0812 (3.80)	0.0790 (3.70)	0.0811 (3.80)	0.0808 (3.79)	0.0814 (3.81)	0.0810 (3.80)
Transportation / Storage	-0.0033 (-0.15)	-0.0042 (-0.19)	-0.0043 (-0.20)	-0.0051 (-0.24)	-0.0054 (-0.25)	-0.0044 (-0.20)	-0.0047 (-0.22)
Communication / Utility	0.0840 (3.28)	0.0830 (3.24)	0.0841 (3.29)	0.0831 (3.25)	0.0838 (3.28)	0.0841 (3.28)	0.0848 (3.32)
Wholesale	-0.0724 (-3.20)	-0.0729 (-3.22)	-0.0731 (-3.23)	-0.0736 (-3.25)	-0.0740 (-3.27)	-0.0726 (-3.21)	-0.0730 (-3.22)
Retail Trade	-0.2380 (-12.07)	-0.2383 (-12.09)	-0.2380 (-12.07)	-0.2382 (-12.09)	-0.2371 (-12.04)	-0.2377 (-12.06)	-0.2365 (-12.01)
Finance/ Insurance/ Real Estate	-0.0117 (-0.35)	-0.0118 (-0.36)	-0.0124 (-0.38)	-0.0125 (-0.38)	-0.0135 (-0.41)	-0.0120 (-0.36)	-0.0130 (-0.39)
Business	-0.0338 (-1.09)	-0.0349 (-1.13)	-0.0370 (-1.20)	-0.0381 (-1.23)	-0.0344 (-1.11)	-0.0376 (-1.21)	-0.0339 (-1.09)
Government	0.0159 (0.84)	0.0154 (0.81)	0.0161 (0.85)	0.0155 (0.82)	0.0158 (0.84)	0.0174 (0.92)	0.0178 (0.94)
Educational	0.0252 (1.03)	0.0278 (1.13)	0.0295 (1.19)	0.0319 (1.26)	0.0338 (1.37)	0.0327 (1.32)	0.0346 (1.40)
Health/ Social services	-0.0471 (-1.51)	-0.0481 (-1.54)	-0.0479 (-1.54)	-0.0488 (-1.57)	-0.0488 (-1.57)	-0.0492 (-1.58)	-0.0492 (-1.58)
Accommodation	-0.3499 (-10.98)	-0.3509 (-11.01)	-0.3499 (-10.98)	-0.3509 (-11.01)	-0.3492 (-10.97)	-0.3511 (-11.02)	-0.3494 (-10.97)
Other Services	-0.2148 (-7.56)	-0.2160 (-7.60)	-0.2137 (-7.52)	-0.2149 (-7.56)	-0.2145 (-7.56)	-0.2152 (-7.57)	-0.2147 (-7.57)
Firm size: Fewer than 20 (Reference group)							
20-99 employees	0.1144 (7.08)	0.1146 (7.10)	0.1135 (7.02)	0.1137 (7.04)	0.1135 (7.03)	0.1136 (7.03)	0.1134 (7.02)
100-499	0.1589 (9.12)	0.1581 (9.08)	0.1582 (9.08)	0.1575 (9.04)	0.1580 (9.08)	0.1573 (9.03)	0.1578 (9.07)
500-999	0.1827 (8.98)	0.1835 (9.02)	0.1816 (8.92)	0.1825 (9.97)	0.1839 (9.04)	0.1821 (8.95)	0.1835 (9.02)
1000 and over	0.2639 (18.04)	0.2630 (17.98)	0.2629 (17.96)	0.2620 (17.90)	0.2626 (17.96)	0.2623 (17.92)	0.2629 (19.97)

Constant	1.7289 (48.79)	1.6875 (42.60)	1.6703 (32.01)	1.6310 (29.73)	1.7078 (28.25)	1.6294 (29.69)	1.7069 (28.23)
R-Squared	0.5042	0.5048	0.5044	0.5050	0.5060	0.5052	0.5063

Table A5: OLS Results of Regressing Mother's Education on Years of Schooling

Dependent Variable: Mother's Education				
Method: Least Squares				
Sample(adjusted): 1 6242 IF PARTICIPATION=1				
Included observations: 4470 after adjusting endpoints				
Variable:	Coefficient	Std. Error	t-Statistic	Prob.
Years of Schooling	0.262413	0.013502	19.43525	0
C	6.637402	0.179513	36.97441	0
R-squared	0.077951	Mean dependent var		10.04564
Adjusted R-squared	0.077745	S.D. dependent var		2.671660
S.E. of regression	2.565706	Akaike info criterion		4.722792
Sum squared resid	29412.16	Schwarz criterion		4.725658
Log likelihood	-10553.4	F-statistic		377.7288
Durbin-Watson stat	0.155232	Prob(F-statistic)		0

Table A6: OLS Results of Regressing Mother's Education on Years of Schooling and Immigrant

Dependent Variable: Mother's Education				
Method: Least Squares				
Sample(adjusted): 1 6242 IF PARTICIPATION=1				
Included observations: 4470 after adjusting endpoints				
Variable:	Coefficient	Std. Error	t-Statistic	Prob.
Years of Schooling	0.266958	0.013547	19.70567	0
Immigrant	-0.496653	0.141857	-3.501094	0.0005
C	6.618143	0.179372	36.89618	0
R-squared	0.080474	Mean dependent var		10.04564
Adjusted R-squared	0.080062	S.D. dependent var		2.67166
S.E. of regression	2.56248	Akaike info criterion		4.720499
Sum squared resid	29331.67	Schwarz criterion		4.724798
Log likelihood	-10547.31	F-statistic		195.4691
Durbin-Watson stat	0.160759	Prob(F-statistic)		0