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Selecting Economic Immigrants: A Statistical Approach

John McHale[1]

National University of Ireland, Galway

Keith Rogers

Queen's University

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jmchale@nuigalway.ie

krogers@business.queensu.ca

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Abstract

There is growing international interest in a Canadian-style points system for selecting economic immigrants. Although existing points systems are influenced by the human capital literature, the findings have traditionally been incorporated in an ad hoc way. This paper explores a formal method for designing a points system based on a human capital earnings regression for predicting immigrant economic success. The method is implemented for Canada using the IMDB, a longitudinal database that combines information on immigrants' characteristics at arrival with their subsequent income performance as reported on tax returns. We demonstrate the feasibility of the method by developing an illustrative points system. We also explore how the selection system can be improved by incorporating additional information such as country-of-origin characteristics and intended occupations. We discuss what our findings imply for the debate about the relative merits of points- and employment-based systems for selecting economic immigrants.

1. Introduction

There is growing international interest in a Canadian-style points system for selecting economic immigrants.[2] At the same time, there is rising concern in Canada about the income performance of recent cohorts of economic immigrants, as many of those selected through the points system struggle in the labour market (Aydemir and Skuterud, 2005; Picot, Hou, and Coulombe, 2007). In this paper, we explore a new approach to the design and evaluation of a points-based selection system. The basic idea is to select immigrants based on the human capital earnings regression that best predicts the earnings of immigrants. We apply this approach to the design of a points system for Canada using the Longitudinal Immigrant Database (IMDB) to develop the prediction model. The IMDB is one of the few datasets that combines information on the human capital characteristics of immigrants at arrival with income data derived from post-arrival tax filings, and is uniquely suited to developing our design approach.

The design of the existing points system has undoubtedly been influenced by the vast empirical literature relating immigrant characteristics at arrival to their subsequent economic performance. One indication is that the measured human capital—most notably the educational attainment—of immigrants admitted under the points system has increased dramatically (see, e.g., Beach, Green, and Worsick, 2006; Picot and Sweetman, 2005). But the design process has followed what can fairly be called a *clinical* rather than a *statistical* (or actuarial) approach: that is, it has depended on expert judgment rather than an explicit statistically-based design.[3] With

[2] Points systems are also used for skills-based selection in Australia and New Zealand. The United Kingdom is in the process of introducing a permanent system to replace its points-based Highly Skilled Migrant Programme that was first introduced on a pilot basis in 2002 (United Kingdom Home Office, 2006). Ireland has introduced a "Green Card" system with selection is based on skills and salary offers. Points systems have also been under consideration elsewhere. In Germany, a points system went down in a narrow legislative defeat in 2003. A points (or merit-based) system was also part of the comprehensive immigration reform that failed to pass in the U.S. Senate in 2007.

[3] The clinical-actuarial distinction is common in psychology, jurisprudence and medicine. A large literature has developed following Meehl (1954) that compares the predictive success of the two methods. The actuarial method has generally found to be superior where the two methods have access to the same information (see, e.g., Dawes,

the multiple objectives that are weighed in any selection system (economic, humanitarian, family reunification, etc.), it is inevitable that judgment is applied in the system's overall design. However, we think an approach that focuses directly on predicted earnings is both appropriate and feasible for the economic immigrant stream, where the objective is selecting high-earning immigrants who will strengthen the economy and fiscal system for the benefit of the pre-immigration population.

We thus develop a statistical—or optimal-prediction-based-on-historical-data—approach to the design of the system for selecting economic immigrants. The central idea is to use data on the arrival characteristics and subsequent income performance of earlier immigrant cohorts to identify the "best" human capital-based prediction equation. This equation is combined with an explicit threshold for predicted earnings below which applicants are not accepted. The point allocations are then objectively mapped from the parameters of this prediction equation given the chosen threshold.

Although there is growing interest in points systems among industrial countries, there is also a debate about their effectiveness. One view is that the quality of a country's immigrant stream is dominated by the pool of people who desire to move to the country (Jasso and Rosenzweig, 2005). This suggests that fine-tuning the selection system is unlikely to have significant effects. Another view holds that the design of the selection system does have first order effects on immigrant labour market success (see, e.g., Lester and Richardson on the comparison of the Canadian and Australian points systems). The statistical approach allows us

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Faust, and Meehl, 1989). Of course, where an expert (i.e. clinician) has access to information unavailable to someone using the statistical model, it is quite possible that the former will make more accurate predictions. For example, a visa officer interviewing an applicant could make a judgment about the individual's social skills and ambition, information that would not be available to the statistical model. However, the use of this type of information is not what is at issue in the design of a system that is dependent on objectively verifiable information. The design problem relates to how best to weigh the various available pieces of information (educational attainment, fluency in official languages, etc.) In this equal-information setting, it is harder to see an advantage for expert judgment over statistical models that are chosen to best fit the historical data.

to examine the potential for fine-tuning a conventional points system by adjusting allocations to the usual point sources such as education, experience and language skills. Subject to data availability, this approach also allows us to explore systematically the potential contribution of less conventional sources of points suggested by the human-capital literature (country-of-origin, achievement on literacy tests, quality of educational institution, pre-emigration earnings, etc.). By exploring the performance of the best-designed points systems, the statistical approach should help inform whether there is a need for more radical departures from points-based selection, such as strict pre-immigration job offer requirements or probationary periods on temporary work visas before granting permanent immigration status.

In the next section, we review the related literature on immigrant assimilation and the effectiveness of selection systems. In Section 3, we discuss the objectives and principles that should guide a skills-based selection system. We then describe our design methodology in Section 4 and our data in Section 5. Section 6 develops an illustrative points system and discusses various extensions. Section 7 concludes with a discussion of what our results imply about the effectiveness of even the best-designed points system.

2. Related Literature

Following Chiswick (1978), a large literature has developed that explores how human capital characteristics at arrival affect an immigrant's subsequent labour market success. A major theme in this literature is how more recent immigrant cohorts to the United States compare with earlier cohorts in terms of entry earnings and subsequent earnings growth (e.g. Borjas, 1985; Duleep and Regets, 2002). A substantial parallel literature has developed looking at Canadian immigrants. A central focus has been the declining performance of more recent immigrant cohorts relative to native-born workers (Abbott and Beach, 1993; Baker and

Benjamin, 1994; Bloom, Grenier, and Gunderson, 1995; Grant, 1999; Frenette and Morissette, 2003; Green and Worswick, 2004; Aydemir and Skuterud, 2005; Picot, Hou, and Coulombe; 2007). Two important findings have been that immigrants that come at young ages tend to perform better (possibly reflecting the acquisition of Canadian schooling) and that there is a negligible return to foreign experience.[4] A number of recent studies have looked at how less traditional human capital measures are associated with labour market performance: credential acquisition or "sheepskin effects" (Ferrer and Riddel, 2004); source-country educational quality (Sweetman, 2004); and literacy skills (Ferrer, Green, and Riddell, 2004; Alboim, Finnie, and Meng, 2005).

There is also a smaller literature that looks at how alternative immigrant selection systems affect immigrant characteristics and performance. A major question in this literature is whether immigrant quality is affected more by who desires to emigrate to a particular host country or by the selection system that the host country employs. Jasso and Rosenzweig (1995) find a small difference between the performance of U.S. immigrants screened for skills and those who gain admission based on family ties. More recently, Jasso and Rosenzweig (2005) find little difference in the operation of the employment-based U.S. and the skills-based Australian selection systems, leading them to conclude that the immigrant mix is largely driven by the self-selection decisions of the immigrants. Antecol, Cobb-Clark, and Trejo (2001) find that immigrants to Australia and Canada do have more measured human capital than immigrants to the U.S., but conclude that this has more to do with the latter's geographic and historic ties to Mexico than with differences in selection systems.

[4] See Schaafsma and Sweetman (2001). See also Friedberg (2002) for a similar finding of a low return to foreign experience for immigrants to Israel.

For Canada, Beach, Green, and Worswick (2006) have found variations in the Canadian selection system—including variations in the way points are allocated for different measures of human capital—do impact the characteristics of the admitted immigrants. Adyemir (2002) develops and empirically implements a model that allows for both self-selection and host-country selection, and finds that both are important in determining who actually immigrates. In a direct comparison of the Australian and Canadian points-based systems, Lester and Richardson (2004) argue that reforms to the Australian system explain the recent better performance of the Australian economic immigrants (see also Hawthorne, 2005).

It is difficult to sum up these substantial literatures. The immigrant-assimilation literature has certainly demonstrated the usefulness of human capital-based earnings regressions for predicting immigrant success. The selection-system literature shows that when a system selects for given characteristics it does tend to have an immigration flow with those characteristics, but there is less agreement on how much the selection system can affect the labour market success of the admitted immigrants. To the best of our knowledge, there has not been a previous attempt to explore the optimal design of the selection system using human capital-based earnings prediction. With the proposed actuarial approach, we hope to identify the optimal selection in a rigorous and transparent way, to explore the scope for fine-tuning a conventional points system to improve immigrant selection, and to contribute to the debate about the merits of points-based selection.

1.1 3. Designing an Immigrant Selection System: General Considerations

3.1 Objectives

What policy objectives should guide the design of a selection system for economic immigrants? As we are dealing with *economic* immigration, we assume the broad objective is to maximize the social welfare of the existing population.[5] However, identifying the impacts on this population is not an easy task. Immigration has a complicated set of impacts on the labour markets, capital markets and the fiscal system (see, e.g., Borjas, 1995). Even looking at just static impacts requires knowledge of labour demand and supply elasticties as well as details of the fiscal rules. The analysis becomes more complicated once we allow for dynamic effects on economic growth over multiple generations. Precise identification of the optimal policy requires, then, both an agreed social welfare function and a well-specified and empirically implementable dynamic model of the economy.

We adopt a simpler approach, but one we believe is likely to be robust across reasonable social welfare functions and models of the economy. We assume that the existing population gains from admitting immigrants with sufficient human capital to make them successful in the labour market. More concretely, we assume existing residents expect to gain from immigrants with predicted earnings above some threshold level.[6] Skilled immigrants are most likely to improve the income distribution, foster economic growth, provide positive net fiscal contributions, and support human capital transmission to following generations.

While we believe that a selection policy based on predicted labour market success is defensible as an approximation to what would result from more complicated design algorithm, it has the added advantage of consistency with the revealed preferences of policy makers. In a

[5] Of course, concern for source-country populations—including potential immigrants—can be a consideration in the design of immigration policy. While such broader "cosmopolitan" objectives are relevant for the overall design of immigration policy, we make the simplifying assumption that social welfare in the receiving country is the focus of explicitly economically motivated immigration policy.

[6] In a companion paper (McHale and Rogers, 2009), we develop a model that identifies threshold earnings level. In the model, the economy faces a tradeoff between the benefit of additional human capital and the adjustment costs of admitting more immigrants. The threshold earnings level is chosen so as to admit the optimal number of immigrants given this tradeoff. We show that improving the selection system leads a better tradeoff and higher social welfare.

number of OECD countries, policy makers are shifting their selection systems to target workers with valuable skills. Our design approach provides a systematic method for designing a points system to meet this objective.

3.2 Principles

What principles should guide the design of a points system? We argue for four:

(i) *Effectiveness.* The system should be effective in identifying those most likely to be successful in the host-country labour market. This requires the use of all available information with predictive value and the appropriate weighting of the disparate pieces of information.

(ii) *Cost efficiency.* The selection system should be cost efficient to run. This suggests the use of pre-existing datasets on immigrant characteristics and performance to develop predictive models if immigrant success. It also points to limiting costly administrative discretion unless it is proven to improve the quality of selections.

(iii) *Transparency.* The basis for acceptance and rejection should be accessible to applicants. (Potential applicants should also be able assess their chances of success before engaging in a costly and time-consuming application process.) This argues for a linear points system, where applicants receive points for well-defined human capital characteristics that can be added up to achieve a total points score. We will see that this requirement imposes specific constraints on the form of the human capital earnings regression that underlies the selection system.

(iv) *Non-discrimination.* While of course "selection" implies discriminating between applicants, we believe there is wide agreement that discrimination based on characteristics such as race, gender, sexual orientation, or country of origin should not be allowed. In our empirical application, we explore one form of discrimination that may overstep the acceptable limit: the use of objective data on an applicant's country of origin such as its GDP per capita. The rationale for using such information might be that it has predictive value for the quality or transferability of human capital for a particular applicant. While the use of this type of information does not discriminate against individuals because they come from a particular country, it might discriminate against those that come from poorer (or more distant, or more equal) countries in general. Our analysis is not meant as an endorsement of any particular view of allowable discrimination. However, we see no point in exploring the use information that industrialized countries would explicitly reject – e.g. gender – even when it has predictive power for earnings.

4. Optimal Design Methodology

4.1 A Simple Points System

In this section, we summarize the basic steps for identifying the optimal points system. The inputs are a barebones human capital-based earnings regression for making predictions of immigrant labour-market success and a (lifetime) predicted-earnings threshold for deciding who to accept. The outputs are the point allocations per unit of each human capital characteristic.

To illustrate the basic design approach, we assume that an immigrant's earnings depend only on their years of schooling (S_i), years of experience (E_i), and years since migration (t_i). Host-country earnings are given by a log-linear earnings regression:

$$(1) \qquad \ln Y_i = y_{it} = \beta_0 + \beta_S S_i + \beta_E E_i + \beta_t t_i + u_{it} \qquad\qquad u_i \sim n(0, \sigma_u^2)\ .$$

We assume we can use regression analysis to obtain a predictor of log earnings,

$$(2)\qquad \hat{y}_i = \hat{\beta}_0 + \hat{\beta}_S S_i + \hat{\beta}_E E_i + \hat{\beta}_t t_i$$

To obtain the log of expected earnings, we must add $\sigma_{\hat{u}}^2 / 2$ to the expectation of log earnings,[7]

$$(3)\qquad \ln \hat{Y}_i \approx \frac{\sigma_{\hat{u}}^2}{2} + \hat{y}_{it} = \frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_S S_i + \hat{\beta}_E E_i + \hat{\beta}_t t_i .$$

Letting T_i represent the number of years that the immigrant will be in the host labour market and letting δ represent the discount rate, we can use (3) to write the present discounted value of predicted earnings as,[8]

$$(4)\qquad \begin{aligned} \hat{Z}_i &= \int_0^{T_i} e^{-\delta t_i} \hat{Y}_i dt_i \\ &= e^{\frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_S S_i + \hat{\beta}_E E_i} \int_0^{T_i} e^{(\hat{\beta}_t - \delta) t_i} dt_i \\ &= e^{\frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_S S_i + \hat{\beta}_E E_i} \left(\frac{1}{\hat{\beta}_t - \delta} \right) \left(e^{(\hat{\beta}_t - \delta) T_i} - 1 \right) \end{aligned}$$

We assume that the immigrant will work until age $\overline{A}$, so that $T_i = \overline{A} - A_i$, where A_i is age at arrival. Making this substitution and taking logs yields,

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[7] The expectation of log earnings is less than the log of expected earnings; see Goldberger (1968).
[8] Assuming that there is no out-migration of emigrants, δ will reflect the rate at which the policy maker discounts future earnings relative to current earnings. However, assuming a constant conditional probability of exit (or "hazard rate"), δ can also conveniently include a discount due to expected attrition due to out-migration.

$$(5) \qquad \ln \hat{Z}_i = \frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_S S_i + \hat{\beta}_E E_i - \ln\left(\hat{\beta}_t - \delta\right) + \ln\left(e^{\left(\hat{\beta}_t - \delta\right)\left(\bar{A} - A_i\right)} - 1\right)$$

We next assume that the policy maker sets a threshold, $\hat{Z}^{th}$, for predicted lifetime earnings. Any applicant with predicted earnings at or above this level is accepted; the others are rejected. Setting the value for lifetime expected earnings equal to the threshold in (5), and collecting all terms not indexed by *i* to the right-hand side, it is convenient to rewrite the equation as,

$$(6) \qquad \ln \hat{Z}^{th} - \frac{\sigma_{\hat{u}}^2}{2} - \hat{\beta}_0 - \ln\left(\hat{\beta}_t - \delta\right) = \hat{\beta}_S S_i + \hat{\beta}_E E_i + \ln\left(e^{\left(\hat{\beta}_t - \delta\right)\left(\bar{A} - A_i\right)} - 1\right)$$

To obtain the points allocations, we arbitrarily set the points allocation to 100 for someone with predicted earnings that is exactly equal to the threshold. This is done by dividing each side of (6) by the right-hand side of (6) and multiplying through by 100.

$$(7) \qquad \frac{100\tilde{\beta}}{\tilde{\beta}} = \left(\frac{100\hat{\beta}_S}{\tilde{\beta}}\right) S_i + \left(\frac{100\hat{\beta}_E}{\tilde{\beta}}\right) E_i + \left(\frac{100 \ln\left(e^{\left(\hat{\beta}_t - \delta\right)\left(\bar{A} - A_i\right)} - 1\right)}{\tilde{\beta}}\right),$$

$$\text{where} \qquad \tilde{\beta} = \ln \hat{Z}^{th} - \frac{\sigma_{\hat{u}}^2}{2} - \hat{\beta}_0 + \ln\left(\hat{\beta}_t - \delta\right).$$

The respective points allocations for schooling and experience are given by the relevant terms in parentheses in equation (6). The last term in the equation determines the non-linear point allocations given for age-at-arrival. Based on these allocations, any applicant that scores 100 points or above meets the threshold predicted earnings level and is accepted.

4.2 Statistical Complication I: Selection

An obvious concern with our design approach is that the immigrant earnings generation process might not be stable over time. One reason to worry about instability is that past immigrants are obviously a selected sample, and the nature of that selection may change over time. Indeed, there are two form of selection to worry about: selection based on the polices used by the receiving country government; and self-selection into immigration to the particular destination country.

We have tried to minimize the instability in two ways. First, we have limited our sample to immigrants who enter as principal applicants in the skilled worker stream to deal with government-driven selection. Since these individuals have been selected through the points system, they have been selected based on *observed* human capital characteristics. With selection on observables, even the fact that our historic sample is in an obvious way a "selected sample" should not lead to a bias that is sensitive to the (potentially changing) design of the selection process.

Second, although the composition of the immigrant pool has certainly been changing over time (most obviously in the country-of-origin distribution of the admitted immigrants), we can capture the changing distribution with cohort dummies. We can then use the regression model that applies to the most recent available cohort for projecting forward (or even take account of trends in the cohort effects).[9]

4.3 Statistical Complication II: Disentangling Age-Cohort-Year Effects

[9] Using just cohort dummies assumes that the coefficients on the human capital characteristics are stable over time. This assumption can be relaxed using cohort-human capital variable interactions.

The separation of years-since-migration, cohort and macro effects has been a major focus of the empirical literature on immigrant earnings. Since our data from the IMBD is for immigrants only, we could not utilize the common identification practice of assuming that marco effects are equal for immigrants and natives. We explored the method originated independently by Hall (1971) and Mason et al. (1973) of including a full set of both cohort and time dummies (in addition to the year-since-migration variable), and imposing the identification constraint that either two of the cohort dummies or two of the time dummies have equal coefficients. As described by Glenn (2005), the results can be highly sensitive to the chosen identification constraint.   Some experimentation with alternative conditions showed this to be the case with our data.   Lacking a priori grounds for choosing a restriction, we decided against this approach. Instead, we include a years-since-migration variable, a set of cohort dummies, and macroeconomic variables to control for time effects. The chosen macro variables are the national unemployment rate and the log of average real earnings for full time, full year workers.

The complete specification we use for our empirical applications (including a general specification for the human capital variables and both cohort and macro effects) is detailed in the appendix. However, the basic logic for developing the points system from the estimated human capital earnings regression exactly parallels the simplified example outlined above.

5. Data[10]

The actuarial approach to designing a points system depends on the availability of historical data on both the characteristics of immigrants at arrival and their subsequent performance in the labour market. Canada's IMDB is an ideal source of both types of data. The

[10] The information in this section draws heavily on publicly available documentation of the IMDB provided by Citizenship and Immigration Canada (CIC) and Statistics Canada as well as Abbott (2003) and personal communication with CIC employees.

IMDB is an administrative database containing information on immigrants to Canada since 1980. It combines static information from an immigrant's arrival records with income data from tax filings.[11] It is worth noting that this is not a sample of immigrants, but rather the population of immigrants with at least one personal income tax filing. The database is updated annually as new immigrant cohorts arrive and new tax data becomes available. Tax return data is only recorded for the fifteen years after the first tax filing, so that we have at most 15 annual income observations on each immigrant.

The static (or "tombstone") component of the IMDB contains data on characteristics at arrival: demographic data (sex, age, country of birth); skill measures (English / French language ability, native language, years of schooling, educational attainment); intended settlement in Canada (province and city, industry and occupation); family status; and admission details (immigrant category, applicability of points system, allocation of sufficient points for admission, principal applicant flag). The dynamic data consists of up to 15 years of income data by income type (e.g. employment earnings, investment income, rental income, etc.)

Our interest in this data is principally on the economic immigrants as opposed to those admitted under the family class or refugees. We are further interested in separating the impact of earnings from returns to capital, and so we exclude immigrants from the investor and entrepreneur classes and use wage and salary earnings as our dependent variable. The selection criteria then are: principal applicants between the ages of 18 and 64 who enter in IMCAT category 7 (skilled workers principal applicant abroad no special program) or IMCAT category 8 (skilled workers principal applicant in Canada or with special program). For this group our

[11] Public access to the IMDB is strictly constrained given the sensitive nature of the underlying tax and personal information. Consequently, we did not have direct access to the data. We are extremely grateful to Citizenship and Immigration Canada and Statistics Canada for generously agreeing to work with us to implement the required data runs.

dependent variable is the log of total earned income, which is the sum of all reported earnings on the individual's tax records.

The IMDB does have some limitations. First, a number of immigrants to Canada have never filed a tax return and therefore do not appear in the sample. Second, immigrants can be temporarily or permanently absent from the country through return-migration, on-migration to a third country, or death. This results in an unbalanced panel sample. Third, the IMDB does not contain reason-codes for individuals not filing a tax return, so that we cannot be sure why an individual has disappeared from the sample.

We have supplemented the IMBD data with aggregate variables for both country-of-destination and country-of origin. Two aggregate Canadian variables were added to control for macroeconomic effects: the national unemployment rate (CANSIM Table 282-0002) and the log of average real annual earnings for full-time, full-year workers (CANSIM Table 202-0101). Three aggregate country-of-origin variables were included to control for conditions in the source country that might affect the unobserved human capital of immigrants. Since higher cost to emigrate should tend to increase the selection based on unobservable human capital and migration costs rise with distance, we included log of distance from Canada (taken from Andrew Rose's bilateral trade database[12]). Based on Borjas (1987) we hypothesized that when source-country inequality is high, there is a reduced incentive for highly skilled individuals to emigrate. To capture the unobservable component, we included the 1980-2004 average of the Gini coefficient[13] (World Bank, World Development Indicators). Finally, an immigrant's human capital is likely better suited to the Canadian economy and the educational institutions are likely to be of higher quality if that immigrant comes from a developed country. To capture this, we

[12] Available at http://faculty.haas.berkeley.edu/arose/.
[13] The Gini coefficient is only available in household survey years. These years vary from country to country.

included, the log of real GDP per capita adjusted for purchasing power parity (World Bank, World Development Indicators). The summary statistics for all variables used in the regressions are shown in Table 1.

6. Empirical Implementation

6.1 Base Regression

To determine the feasibility of the proposed design approach, we first demonstrate the development of a simple points system that is linear in experience, language ability and educational attainment, and non-linear in age-at-arrival. The base regression from which this illustrative points system is derived is shown in Table 2. We record two specifications: the first with and the second without an age-at-arrival variable.[14] We also record two estimation methods for each specification: ordinary least squares (with standard errors that are robust to individual immigrant-level clustering), and random effects to explicitly take account of serial correlation in individual earnings over time.[15]

The dependent variable is the log of real annual earnings expressed in constant 2005 dollars. We impose the additional restriction that annual earnings are greater than $1,000. We do not include earnings observations for the year of arrival, since the length of time will typically

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[14] Recall that age-at-arrival still matters for points even if an age-at-arrival variable is not included in the regression. The reason is that age-at-arrival determines potential years in the Canadian labour market. Although age-at-arrival is likely to affect an immigrant's capacity to adapt to the Canadian labour market, we are concerned about our ability to separately identify the age-at-arrival and experience effects. This stems from our relatively crude measure of experience: Age-at-Arrival – Years of Schooling – 5. Controlling for age-at-arrival, the experience effect is then identified by variation in years of schooling (holding educational attainment constant), which we think is a weak basis for identification. Thus, we concentrate on the results without the age-at-arrival variable in developing the illustrative points system.

[15] We use random effects rather than fixed effects for two reasons. First, under fixed effects, the coefficients on all linear time-invariant explanatory variables cannot be estimated. In our regressions, most of the central variables of interest take this form. And second, given that our interest is in predicting earnings, we are not concerned about correlation between the explanatory variables and the error term (a problem that fixed effects can help fix). Provided that these correlations are stable over time—e.g. high educational attainment has a stable correlation with unobserved natural abilities that positively affect earnings—it is advantageous for earnings predictions to be able to use observed human capital characteristics as indicators of unobserved abilities. Thus we do not present our estimated coefficients as estimates of the returns to human capital, but rather as associations in the historic data.

be less than a full year and will vary across immigrants. Experience is defined as Age-at-Arrival – Years of Schooling – 5. Language enters as a pair of dummy variables: an English dummy that takes the value 1 if English is the immigrant's native language; and a French dummy that takes the value 1 if French is the native language. Educational attainment enters as a set of seven dummy variables (with Primary the excluded category): Secondary, Some Post-Secondary, Trade Certificate, Diploma, Bachelors, Masters, and PhD. We also include a full set of cohort year dummies for the years 1981 to 2003 (with 1980 chosen as the excluded cohort).[16] We include two variables to control for macro/time effects: the national unemployment rate to control for business cycle effects and trend movements in the underlying structural rate of unemployment; and the log of real annual earnings for full-time, full-year workers to control for secular trends in economy-wide earnings.

The estimated human capital equation appears to perform well, with results that are broadly consistent with the existing literature. Focusing on Regression (1), we find a small negative effect of foreign experience. The coefficient on the years-since-migration variable shows that immigrant earnings grow at a real rate of roughly 2 percent per-year post-arrival (after controlling for average economy-wide earnings). On language, we find that English is substantially more highly rewarded than French (approximately a 44 percent premium versus a 6 percent premium), no doubt reflecting the fact that a substantial majority of admitted immigrants move to English-speaking Canada. The educational attainment variables broadly show the expected pattern, with the anomaly that Secondary shows slightly lower returns than Primary.[17] Interestingly, immigrants with a trade certificate have roughly equal earnings to those with some post-secondary attainment. The results show substantial earnings premiums are associated with

[16] There is no 2004 cohort since we include earnings observations only on the first full year after year of arrival.
[17] The difference is not statistically significant in our base regression. The coefficient on Secondary becomes positive and statistically significant when we include all streams in the sample.

higher educational attainment. Compared to the base category, the premium for a bachelor's degree is approximately 19 percent higher than that for a diploma; a Master's degree has a premium that is approximately 11 percent higher than that for bachelors; and a PhD has a premium that is approximately 29 percent higher than that for a Masters. The macro variables have the expected signs. Most notably, the coefficient on the economy-wide average earnings variable is quantitatively large, with a 1 percent increase in economy-wide earnings associated with a 2.2 percent increase in immigrant earnings.[18]

Figure 1 displays the cohort effects (with the excluded cohort, 1980, equal to zero). The pattern of deteriorating cohort earnings holding human capital constant is consistent with previous findings—but the extent of the deterioration is dramatic.

Overall, the regression explains just over 14 percent of the variation in log earnings. While this is broadly in line with the vast literature on human capital-based earnings regressions, it is an undeniably low number, suggesting that immigrant earnings performance is dominated by idiosyncratic factors. This in turn suggests fundamental limits to the points-based selection approach. In Section 5.3 we explore how the predictive power of the regression might be improved by adding additional observables. First, however, we show how a simple quasi-linear points system can be developed based on an illustrative regression.

6.2 An Illustrative Points System

The points system that is implied by Regression (1, OLS) is shown below in Table 3. For this illustration, we assume that the discounted lifetime earnings threshold is set at $1,500,000 in

[18] It is worth noting that this was a period of relatively low growth in economy-wide average earnings (just 0.5 percent over 1980 to 2004). Thus even with the high sensitivity to economy-wide earnings, there was still relatively low macro-related trend growth in immigrant earnings (approximately 1.1 percent).

constant 2004 dollars and the discount rate is set at 0.02. As described in Section 3, any applicant with a combination of characteristics that yield 100 points or more will be accepted (since 100 points or more means that lifetime predicted earnings are at least $1,500,000).

The underlying regression is somewhat more complicated than the simple example in Section 3, as it includes both cohort and macro effects in addition to measures of human capital at arrival (see the appendix). Assuming that the most recent available estimated cohort effect (i.e. for 2003) provides the best indicator of future cohort effects, we add this to the regression constant to determine the constant for prediction equation for log earnings that underlies the points system. For the macro effects, we set the log of average earnings at its 2005 level ($47,800) and assume trend growth in earnings equal to the Bank of Canada's estimate for the underlying productivity growth rate (1.5 percent, Bank of Canada, 2006). We also assume that the unemployment rate is constant at its 2005 level (6.8 percent).

There are a number of notable features of the resulting point allocations. First, rather than being a source of points, experience at arrival actually attracts a small points penalty. Second, points for English exceed points for French by a factor of more than six. Third, while the highest point allocations are granted to those with higher educational attainment, the holders of trade certificates also receive substantial points (comparable to someone with some post-secondary education). And fourth, and perhaps most surprisingly, age-at-arrival has a dramatic impact on points. In our illustrative system, it is practically impossible for someone older than their mid-forties to meet the points threshold; on the other hand, it is hard for someone younger than their mid-twenties not to meet the threshold. The strong influence of age follows from the aggregation of lifetime earnings over potential years in the Canadian labour market (64 – Age-at-Arrival). However, the relative impact of the age-at-arrival variable can be attenuated by using a higher discount rate (matched by an appropriately lowered threshold), which effectively reduces the weight given to later years worked in Canada.

It is useful to examine a couple of examples to get a better feel for when someone succeeds or fails to make the threshold in this illustrative system. For our first example, we take a 37-year-old native English speaker with a Master's degree and 12 years of experience.[19] The projected lifetime earnings of this individual is $1,700,082. Using equation (A.4) from the appendix (which is an extended version of equation (4) in Section 4), this projection can usefully be decomposed into the product of initial earnings of $38,529 (the term before the parentheses) and a factor (44.124) we refer to as the "adjusted potential years." The adjusted potential years reflects the potential years in Canada adjusted by the coefficient on the years since migration variable, the discount rate, and the product of the coefficient on the log of average annual earnings variable and the assumed growth rate for these earnings.

The points allocations for this applicant are -1.1 for experience, 32.7 for language, 47.8 for educational attainment and 30.0 for age, for a total of 109.4 points. This applicant has more than 100 points and would, therefore, be accepted.

For our second example, we take a 25-year-old native French speaker with a trade certificate and 5 years of experience. Initial projected earnings are $17,985 and adjusted potential years are 81.02, for total projected earnings of $1,487,065. This individual falls just below the projected earnings cutoff. Consistent with the earnings shortfall there is also a points shortfall: -0.5 for experience, 4.7 for language, 18.1 for educational attainment and 75.5 for age, for a total of 97.8. An applicant with this profile would be rejected. However, if this individual was just one year younger with correspondingly one year less experience they would score 101.4 points (with projected lifetime earnings of $1,527,402) and would be accepted.

[19] We assume they apply in 2005.

Even though this points system is just meant as an illustration, it is interesting to compare it with Canada's existing points allocation. The clearest picture comes from comparing the relative points given for various pairs of characteristics rather than the absolute allocations of points. Most strikingly, under the present grid, 25 out of a maximum of 100 points are available for experience, while our findings suggest that no – or even slightly negative points – should be allocated for experience. For education, the same points (25) are allocated for a PhD as for a Masters degree, which is not far above the points given for a two-year university degree (20). In contrast, our findings identify a much steeper educational attainment-points gradient. On age, the current grid calls for the maximum of age-related points to be given for applicants between 21 and 49 (10), with two-points per year penalties for each year above or below this range. Our findings identify both a larger relative weighting on age in general, and monotonically falling points with the actual age at arrival. Because it is not limited to variables that are available in the IMDB, the current points system has the advantage of access to certain information not available to us. This information includes the presence of arranged employment, spouse's educational attainment, years of post-secondary study in Canada, and family relationships in Canada. However, these data could be collected in an expanded IMDB. We return to the benefits of expanding the range of individual data that is collected in the concluding comments below.

6.3 Extended Regressions

Taking the IMDB as given, we next explore how enriching the informational base for which points are given can lead to a better performing immigrant pool. We explore the addition of three types of information: non-linear terms for the foreign experience and years-since-migration variables; country-of-origin information; and intended-occupation dummies. To ensure valid comparisons, we limit our sample to observations for which all three forms of additional information are available. This causes the number of observations to drop from 313,631 to 258,175, and the number of immigrants to drop from 50,160 to 43,218.

The results are recorded in Table 4. The first regression is our base regression (without the age-at-arrival variable) estimated on the restricted sample. The results are very similar to those for the unrestricted sample. The next three regressions separately add the non-linear terms, the country-of-origin variables and the intended-occupation dummies to the base regression. The final regression adds all three forms of additional information simultaneously.

Regression (2) shows the effects of adding squared terms for experience and years since migration. The negative coefficient on experience squared shows that the proportionate earnings penalty on foreign experience rises, *cet. par*., with the extent of foreign experience. The coefficient on years since migration squared is also negative, indicating the growth rate of earnings tends to decline, *cet. par*., with years in Canada. Indeed, earnings peak after just over 19 years. Overall, however, adding these squared terms adds minimally to the explanatory power of the regression, with the R^2 rising slightly from 0.1501 to 0.1541. Of course, adding two quadratic terms to the regression does not exhaust the potential for non-linearities. In particular, it would be worthwhile to explore the additional explanatory power that comes from adding additional polynomial terms and interaction effects.

Regression (3) shows the effects of adding three country-of-origin variables: the log of real GDP per capita (adjusted for purchasing power parity); the log of distance from Canada, and the Gini coefficient (as a measure of source-country inequality). We hypothesized that the coefficient on the GDP per capita variable would be positive. Our results support this hypothesis, with a 100 percent increase in source country GDP per capita resulting in a roughly 10 percent increase in earnings. We next hypothesized that an increase in the distance of the source-country from Canada would be positively associated with immigrant earnings. This hypothesis also receives support, with a 100 percent increase in distance leading to approximately an 11 percent increase in earnings. Finally, we hypothesized that an increase in source-country inequality will tend to reduce immigrant earnings. Once again, the hypothesis receives support, with a 10 point increase in the Gini coefficient being associated with an approximately 0.8 percent decrease in immigrant earnings. All told, the addition of the three country-of-origin variables only marginally increases the explanatory power of the regression, with the R^2 rising from 0.1501 to 0.1631.

Regression (4) shows the effects of introducing dummies for intended occupation. A dummy variable is introduced for each 2-digit National Occupation Classification (NOC) code with a number of additional classifications introduced by CIC. The introduction of the occupational dummies does lead to a more substantial improvement in the fit of the regression, with the R^2 rising from 0.1501 to 0.1936. It is worth emphasizing that this way of introducing occupation-specific information is quite different from the occupation-shortage approach that is, for example, an important aspect of the Australian points system. Under the latter approach, extra points are granted if there is deemed to be a shortage in the particular occupation. In contrast, our approach looks backwards to the earnings success of past immigrants destined for particular occupations. This has the disadvantage of looking at past rather than present conditions in given occupations, but it has the advantage of focusing on how immigrants have actually done when destined for those occupations rather than economically dubious measures of shortage.[20] For example, there may be real shortages in certain health-related professions, but immigrants may face challenges in utilizing their human capital in those occupations because of difficulties getting their credentials recognized. Our approach has the merit of recognizing the

[20] Often it seems that the term “shortage” is used where there is upward pressure on wages.

de facto challenges in given occupations; although one could reasonably question the fairness of punishing future applicants because of poor credential recognition in the past.

Table 5 records the occupation effects (measured in log points), which are ordered by size of effect. The omitted category is the CIC category of "new worker" (NOCD9914). A small number of the CIC categories did not contain any observations in our sample and are not listed in the table. The first column of the table records the share of our sample destined for the occupation. Clearly, some of the shares are quite small, so that the estimated effects should be treated with some caution. However, the pattern of effects looks largely plausible, with immigrants intending to enter senior management earning the largest premium over new workers, while those intending to be homemakers earning the lowest. By far the largest category is NOCD21 "professional occupations in natural and applied sciences," with almost a quarter of the sample. Workers intending to enter this occupational category earn a premium over new workers of approximately 50 percent.

Regression (5) finally adds all three forms of information in a single regression. Overall, the fit of the regression increases by more than one-third. But the percentage of variation in log earnings explained is still low at just over 20 percent. While we obviously have not exhausted the types of information that could be used in the underlying prediction regression, the evident difficulty of predicting who will succeed economically based on observed human capital characteristics at arrival leads one to ask if there is a better way to select economic immigrants. We take up this question in the concluding section.

7. Concluding Comments

Is there a better way to select economic immigrants? The limited predictive power of the models we have explored certainly motivates a search for alternatives. A leading contender is

U.S.-style employer-driven selection. Employers are obviously motivated to work hard to identify talented individuals. They can also utilize a richer informational base: Where did they get their education? How well do they speak the language? How likely is it that their recommenders value their reputations for honest evaluations? Put simply, employers are well-placed to be "experts" when it comes to predicting who will be successful on the job. While granting that employers often have information that cannot easily be integrated into a points system, it is important to recognize that there is a vast literature on the superiority of actuarial/statistical-based over clinical/expert-based judgment across a range of settings (see Grove et al., 2000, for a meta-analysis). This edge is often present even when the clinician has information that is not available for the statistical analysis (Grove and Meehl, 1996). The typical, and for many surprising, superiority of the actuarial approach stems from a combination of its edge in solving the complex problem of appropriately weighting disparate pieces of information and its avoidance of biases that afflict subjective judgment.[21]

We believe that employer assessments have a critical role to play in an effective selection system. But the most effective feasible selection system is likely to be one that integrates the informational value of employer assessments into statistical-based predictions. The evidence from other areas suggests that this should be done, not by allowing employers to selectively override the points system, but by turning the employer information into a source of points. This could be done, for example, by giving points based on the existence of job offers (Canada), salary offers (Ireland), or prior home-country salaries (United Kingdom).

The Australian experience also suggests that better selections can be made by improving the informational quality of the type of variables that are currently used: better language ability

[21] See Ayres (2007, Chapter 5) for an accessible recent discussion.

testing through formal language tests; or better measures of educational attainment by making use of objective rankings of educational institutions. Since the statistical method looks backwards to determine the optimal weights to place on the various pieces of predictive information, it is important to begin collecting the more fine-grained information as soon as possible. For the IMBD, this means adding new variables to the "tombstone data" part of the database. This additional data could be collected on a random sample of admitted immigrants until it has proven its value for prediction.

Applying the design approach developed in this paper requires data on both immigrant characteristics at arrival and post-arrival income performance. Is there a U.S. dataset that could be used in the design of a U.S. points—or "merit-based"—system? Most promisingly, the New Immigrant Survey (NIS) provides panel data on immigrant characteristics and their income performance over time. Although the time dimension is currently short, the NIS is well suited to our design approach. Indeed, the NIS has variables not available in the IMDB, such as earnings in the last home-country employment, which should have substantial predictive value for post-immigration income performance.

Appendix

This appendix develops the actual specification we use for estimating the immigrant earnings regression and identifying the point allocations. Building on the simplified example in the text, the complete specification of the immigrant earnings equation is,

$$\text{(A.1)} \quad \ln Y_{ijk} = y_{ijk} = \beta_0 + \beta_H H_i + \beta_t t_i + C_j + X_k + u_{ijk} \qquad u_{ijk} \sim n(0, \sigma_u^2) .$$

Y_{ijk} is the earnings of immigrant *i*, from cohort *j*, in year *k*. H_i is a vector of human capital characteristics of immigrant *i* at arrival. We allow this vector to contain purely individual characteristics (educational attainment, pre-immigration experience, language skills, intended occupation, etc.) and characteristics of the immigrant's country-of-origin that predict the "quality" of the immigrant (real GDP per capita, income inequality, physical distance, etc). The next three terms capture years-since-migration (t_i), cohort (C_j), and time/macro (X_k) effects.

As with our simplified example, we obtain the predictor of log earnings using regression analysis:

$$\text{(A.2)} \quad \hat{y}_{ijk} = \hat{\beta}_0 + \hat{\beta}_H H_i + \beta_t t_i + \hat{C}_j + \hat{X}_k .$$

We make the standard adjustment to obtain an expression for the *log of expected earnings*,

$$\text{(A.3)} \quad \ln \hat{Y}_{ijk} = \frac{\sigma_{\hat{u}}^2}{2} + \hat{y}_{ijk} = \hat{\beta}_0 + \hat{\beta}_H H_i + \hat{\beta}_t t_i + \hat{C}_j + \hat{X}_k .$$

It is convenient at this stage to be explicit about the macro variables we use in our specification. These variables are the national unemployment rate (UR_k) and the log average real earnings for full-year, full-time workers ($\ln \overline{Y}_k$).

$$\text{(A.3')} \quad \ln \hat{Y}_{ijk} = \frac{\sigma_{\hat{u}}^2}{2} + \hat{y}_{ijk} = \hat{\beta}_0 + \hat{\beta}_H H_i + \hat{\beta}_t t_i + \hat{C}_j + \hat{\beta}_{UR} UR_k + \hat{\beta}_{\overline{Y}} \ln \overline{Y}_k \ .$$

This equation is used to predict the present discounted value of the earnings of a newly admitted immigrant. Of course, to make this prediction we must make specific predictions of the cohort effect and the evolution of the macro variables. Our approach here is to take the most recently available estimated cohort effect ($\hat{C}^*$) and the most recently available unemployment rate (UR^*), and to assume they are constant for the lifetime of the immigrant in the labour market.[22] Furthermore, we assume that average real earnings grows at the same rate, g, as forecasted labour productivity. Taking the current year as year 0, predicted average real earnings k (= t_i) years into the future is then: $\ln \overline{Y}_k = \ln \overline{Y}_0 + g t_i$.

The present discounted value of predicted earnings for an immigrant i arriving in year 0 is then:

[22] The latter is an appropriate assumption assuming the unemployment rate follows a random walk.

$$\hat{Z}_i = \int_0^{T_i} e^{-\delta t_i} \hat{Y}_{ijk} dt_i$$

$$(A.4) \quad = e^{\frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_H H_i + \hat{C}^* + \hat{\beta}_{UR} UR^* + \hat{\beta}_{\overline{Y}} \ln \overline{Y}_0} \int_0^{T_i} e^{\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}} g - \delta\right) t_i} dt_i$$

$$= e^{\frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_H H_i + \hat{C}^* + \hat{\beta}_{UR} UR^* + \hat{\beta}_{\overline{Y}} \ln \overline{Y}_0} \left(\frac{1}{\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}} g - \delta\right)} \right) \left(e^{\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}} g - \delta\right) T_i} - 1 \right).$$

Assuming as in the simplified example that the immigrant will work until age $\overline{A}$, so that $T_i = \overline{A} - A_i$, where A_i is age are arrival, we can write our extended present discounted value equation in logs as:

(A.5)

$$\ln \hat{Z}_i = \frac{\sigma_{\hat{u}}^2}{2} + \hat{\beta}_0 + \hat{\beta}_H H_i + \hat{C}^* + \hat{\beta}_{UR} UR^* + \hat{\beta}_{\overline{Y}} \ln \overline{Y}_0 - \ln\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}} g - \delta\right) + \ln\left(e^{(\hat{\beta}_t + \tilde{\beta}_{\overline{Y}} g - \delta)(\overline{A} - A_i)} \right).$$

We next set predicted lifetime earnings equal to the chosen threshold and collect all non-immigrant specific variables (i.e. all variables not indexed by *i*) to the right-hand side of A.5:

(A.6)

$$\ln \hat{Z}^{th} - \frac{\sigma_{\hat{u}}^2}{2} - \hat{\beta}_0 - \hat{C}^* - \hat{\beta}_{UR} UR^* - \hat{\beta}_{\overline{Y}} \ln \overline{Y}_0 + \ln\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}} g - \delta\right) = \beta_H H_i + \ln\left(e^{(\hat{\beta}_t + \tilde{\beta}_{\overline{Y}} g - \delta)(\overline{A} - A_i)} - 1 \right).$$

To finally obtain the point allocations, we arbitrarily set the right-hand side equal to 100 (so that anyone scoring 100 or above has predicted earnings equal to or greater than the threshold). We do this by dividing both sides of A.6 by the right-hand side of A.6 and then multiplying though by 100.

$$\frac{100\tilde{\beta}}{\tilde{\beta}} = \left(\frac{100\hat{\beta}_H}{\tilde{\beta}}\right)H_i + \left(\frac{100\ln\left(e^{(\hat{\beta}_t+\hat{\beta}_{\overline{Y}}g-\delta)(\overline{A}-A_i)}-1\right)}{\tilde{\beta}}\right),$$

(A.7)

where $$\tilde{\beta} = \ln\hat{Z}^{th} - \frac{\sigma_{\hat{u}}^2}{2} - \hat{\beta}_0 - \hat{C}^* - \hat{\beta}_{UR}UR^* - \hat{\beta}_{\overline{Y}}\ln\overline{Y}_0 + \ln\left(\hat{\beta}_t + \hat{\beta}_{\overline{Y}}g - \delta\right).$$

This equation completely specifies the points system. The first term in parentheses is a vector that gives the point allocations for each element of the vector of human capital characteristics. The second term in parentheses gives the non-linear adjustment for age at arrival.

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Table 1 - Summary Statistics

	Obs.	Median	Mean	S.D
Individual Variables				
Log Annual Earnings (constant 2005 Dollars)	314,892	10.44	10.29	0.95
Landing Year	314,892	1991	1991	6.49
Tax Year	314,892	1998	1996	5.97
Age at Landing	314,892	32	33	7.14
Years Since Migration	314,892	5	6	3.80
Years of Schooling	313,631	15	14	3.83
Experience	313,631	12	14	7.70
English Language (mother tounge)	314,892	0	0.21	0.41
French Language (mother tounge)	314,892	0	0.05	0.21
Primary	314,892	0	0.09	0.28
Secondary	314,892	0	0.14	0.34
Some Post-Secondary	314,892	0	0.07	0.26
Trade Certificate	314,892	0	0.14	0.34
Diploma	314,892	0	0.11	0.31
Bachelors	314,892	0	0.32	0.47
Masters	314,892	0	0.10	0.29
PhD	314,892	0	0.04	0.19
Macro Variables				
Unemployment Rate	314,892	0.078	0.086	0.01
Log Average Annual Earnings (constant dollars)	314,892	10.75	10.73	0.04
Country-of-Origin Variables				
Log GDP-Per-Capita	284,866	8.36	8.62	1.01
Log Distance (from Canada)	299,074	8.66	8.52	0.36
Gini	279,736	39.33	39.77	7.30

Sample includes Skilled Workers, Principal Applicants (IMCAT categories 7 & 8) with earnings > $1,000

Table 2 - Basic Log Earnings Regressions
Skilled Workers, Principal Applicants

Dependent Variable = Log Annual Earnings

	(1)		(2)	
	OLS	Random Effects	OLS	Random Effects
Age at Landing	. . .	. . .	0.0201 *	0.0170 *
			(0.0020)	(0.0021)
Years Since Migration	0.0202 *	0.0142 *	0.0202 *	0.0142 *
	(0.0009)	(0.0006)	(0.0009)	(0.0006)
Experience	-0.0013 **	-0.0023 *	-0.0203 *	-0.0184 *
	(0.0005)	(0.0005)	(0.0019)	(0.0021)
English Language	0.4366 *	0.5268 *	0.4292 *	0.5197 *
	(0.0094)	(0.0105)	(0.0094)	(0.0105)
French Language	0.0621 *	0.1403 *	0.0655 *	0.1422 *
	(0.0165)	(0.0174)	(0.0164)	(0.0174)
Secondary	-0.0026	0.0009	-0.0837	-0.0666 *
	(0.0154)	(0.0120)	(0.0172)	(0.0216)
Some Post-Secondary	0.2331 *	0.2150 *	0.0858 *	0.0910 *
	(0.0189)	(0.0223)	(0.0236)	(0.0270)
Trade Certificate	0.2421 *	0.2212 *	0.1319 *	0.1276 *
	(0.0161)	(0.0202)	(0.0192)	(0.0232)
Diploma	0.3315 *	0.3161 *	0.1862 *	0.1940 *
	(0.0170)	(0.0208)	(0.0219)	(0.0257)
Bachelors	0.5291 *	0.5037 *	0.3463 *	0.3515 *
	(0.0154)	(0.0188)	(0.0232)	(0.0266)
Masters	0.6383 *	0.5846 *	0.4188 *	0.4020 *
	(0.0182)	(0.0209)	(0.0279)	(0.0380)
PhD	0.9294 *	0.8862 *	0.6602 *	0.6606 *
	(0.0218)	(0.0259)	(0.0340)	(0.0380)
Unemployment Rate	-3.3675 *	-3.8351 *	-3.3743 *	-3.8357 *
	(0.1500)	(0.1067)	(0.1500)	(0.1067)
Log Average Annual Earnings	2.2447 *	2.6093 *	2.2454 *	2.6095 *
	(0.1129)	(0.0832)	(0.1129)	(0.0832)
Constant	-13.7058 *	-17.6144 *	-13.9653 *	-17.8306 *
	(1.2046)	(.8896)	(1.2048)	(0.8900)
Cohort Year Dummies	Yes	Yes	Yes	Yes
R Squared	0.1410	0.1386	0.1423	0.1400
Within	. . .	0.0607	. . .	0.0607
Between	. . .	0.1352	. . .	0.1362
Root Mean Square Error	0.8770	. . .	0.0876	. . .
Observations	313,631	313,631	313,631	313,631
Individuals	50,610	50,610	50,610	50,610

Standard errors are in parentheses; OLS standard errors are robust to individual-level clustering.
* = signficance at 1% level; ** = significance at 5% level.
Sample includes Skilled Workers, Principal Applicants (IMCAT categories 7 & 8) with annual earnings > $1,000

Table 3 - Illustrative Points System

Points threshold = 100; Points allocations based on Regression 1 (OLS), Table 2

Experience (per year)	-0.1		
Language			
English	32.7		
French	4.7		
Eduational Attainment			
Secondary	-0.2		
Some Post-Second	17.5		
Trade Certificate	18.1		
Diploma	24.8		
Bachelors	39.6		
Masters	47.4		
PhD	69.6		
Age at Landing		Age at Landing (Continued)	
63	-252.4	40	16.8
62	-199.2	39	21.3
61	-167.5	38	25.7
60	-144.7	37	30.0
59	-126.7	36	34.2
58	-111.7	35	38.3
57	-98.9	34	42.3
56	-87.5	33	46.2
55	-77.4	32	50.1
54	-68.2	31	53.9
53	-59.7	30	57.6
52	-51.8	29	61.3
51	-44.5	28	64.9
50	-37.5	27	68.5
49	-31.0	26	72.0
48	-24.8	25	75.5
47	-18.9	24	78.9
46	-13.2	23	82.3
45	-7.8	22	85.7
44	-2.5	21	89.0
43	2.6	20	92.3
42	7.5	19	95.6
41	12.2	18	98.8

Calculated Beta-Tilda 0.0133451

Assumptions:

1. Lifetime earnings threshold (constant 2004 dollars) 1,500,000
2. Assumed trend growth in average annual earnings 1.50%
3. Average Earnings in 2003 (full year, full time) 48,700
4. Unemployment rate in 2003 6.8%
5. Discount rate (δ) 0.02

Table 4 - Extended OLS Regressions: Skilled Workers, Principal Applicants

Non-linearities, Country of Origin, Intended Occupations

Dependent Variable = Log Annual Earnings

	(1)	(2)	(3)	(4)	(5)
Years Since Migration	0.0183 *	0.0763 *	0.0190 *	0.0191 *	0.0784 *
	(0.0010)	(0.0020)	(0.0010)	(0.0010)	(0.0019)
Years Since Migration Squared	. . .	-0.0040 *	. . .	. . .	-0.0041 *
		(0.0001)			(0.0001)
Experience	-0.0018 *	0.0044 *	-0.0013 *	-0.0042 *	-0.0006 *
	(0.0006)	(0.0016)	(0.0010)	(0.0005)	(0.0016)
Experience Squared	. . .	-0.0002 *	. . .	. . .	-0.0001 *
		(0.0000)			(0.0000)
English Language	0.4774 *	0.4805 *	0.4242 *	0.4418 *	0.4166 *
	(0.0106)	(0.0106)	(0.0118)	(0.0101)	(0.0112)
French Language	0.0525 *	0.0587 *	-0.0654 *	0.0987 *	0.0222
	(0.0177)	(0.0178)	(0.0185)	(0.0173)	(0.0181)
Secondary	-0.0009	-0.0066	-0.0275	0.0212	-0.0067
	(0.0181)	(0.0181)	(0.0174)	(0.0171)	(0.0170)
Some Post-Secondary	0.2700 *	0.2637 *	0.2378 *	0.2081 *	0.1863 *
	(0.0218)	(0.0218)	(0.0213)	(0.0210)	(0.0209)
Trade Certificate	0.2523 *	0.2437 *	0.1855 *	0.1623 *	0.1184 *
	(0.0188)	(0.0187)	(0.0182)	(0.0178)	(0.0175)
Diploma	0.3610 *	0.3532 *	0.3051 *	0.2433 *	0.2101 *
	(0.0197)	(0.0198)	(0.0192)	(0.0195)	(0.0194)
Bachelors	0.5395 *	0.5326 *	0.5029 *	0.3526 *	0.3376 *
	(0.0179)	(0.0180)	(0.0174)	(0.0186)	(0.0185)
Masters	0.6469 *	0.6418 *	0.6298 *	0.4394 *	0.4412 *
	(0.0206)	(0..0206)	(0.0201)	(0.0126)	(0.0215)
PhD	0.9345 *	0.9295 *	0.9067 *	0.7185 *	0.7142 *
	(0.0239)	(0..0239)	(0.0233)	(0.0258)	(0.0255)
Unemployment Rate	-3.0114 *	-2.7417 *	-3.0245 *	-3.0247 *	-2.7636 *
	(0.1677)	(0.1673)	(0.1667)	(0.1648)	(0.1641)
Log Average Annual Earnings	2.4380 *	2.3702 *	2.3806 *	2.4184 *	2.3143 *
	(0.1238)	(0.1231)	(0.1236)	(0.1221)	(0.1213)
Log GDP Per Capita	. . .	. . .	0.0971 *	. . .	0.0782 *
			(0.0048)		(0.0047)
Log Distance	. . .	. . .	0.1103 *	. . .	0.1018 *
			(0.0146)		(0.0141)
Gini	. . .	. . .	-0.0083 *	. . .	-0.0062 *
			(0.0005)		(0.0005)
Cohort Dummies	Yes	Yes	Yes	Yes	Yes
Occupational Dummies	No	No	No	Yes	Yes
R Squared	0.1501	0.1541	0.1631	0.1936	0.2040
Root MSE	0.8768	0.8748	0.8708	0.8542	0.8487
Observations	258,175	258,175	258,175	258,175	258,175
Immigrants	43,218	43,218	43,218	43,218	43,218

Standard errors are in parentheses; OLS standard errors are robust to individual-level clustering.

* = signficance at 1% level; ** = significance at 5% level.

Sample includes Skilled Workers, Principal Applicants (IMCAT categories 7 & 8) with annual earnings > $1,000

Table 5 - Estimates of Occupation Effects

Based on Regression (4), Table 4

	Share	Cofficient	Stand. Error
Omitted Occupational Category, NOCD9914, New worker (CIC)	6.04%	0	. . . .
NOCD			
00 Senior management occupations	0.37%	1.2364	0.0814
02 Middle and other management occupations	0.26%	0.9628	0.077
09 Middle and other management occupations	0.46%	0.6797	0.0712
08 Middle and other management occupations	0.08%	0.6221	0.1628
01 Middle and other management occupations	1.18%	0.5535	0.0405
92 Processing, manufacturing and utilities supervisors and skilled oper.	0.23%	0.5198	0.0719
21 Professional occupations in natural and applied sciences	23.52%	0.4911	0.0176
9990 Software pilot (CIC)	0.00%	0.4769	0.3114
72 Trades and skilled transport and equipment operators	5.88%	0.4525	0.0198
07 Middle and other management occupations	0.37%	0.4368	0.0575
11 Professional occupations in business and finance	4.26%	0.4165	0.0222
22 Technical occupations related to natural and applied sciences	7.02%	0.3833	0.0195
31 Professional occupations in health	3.17%	0.3356	0.0252
95 Processing and manufacturing machine operators and assemblers	0.86%	0.3339	0.0369
65 Other Services Manager	0.04%	0.3279	0.1421
73 Trades and skilled transport and equipment operators	6.05%	0.3125	0.0197
04 Middle and other management occupations	0.01%	0.301	0.3023
03 Middle and other management occupations	0.10%	0.2935	0.1773
05 Middle and other management occupations	0.24%	0.2922	0.0912
06 Middle and other management occupations	2.16%	0.2388	0.031
41 Prof. occs in social science, education, gov. services and religion	4.55%	0.2372	0.0228
96 Labourers in processing, manufacturing and utilities	0.63%	0.2006	0.0435
32 Techical and skilled occupations in health	1.36%	0.1786	0.0294
74 Intermediate occs in trans., equip. operation, install. and main.	0.68%	0.1782	0.0458
76 Trades helpers, construction labourers and related occupations	0.73%	0.165	0.0375
94 Processing and manufacturing machine operators and assemblers	1.73%	0.1443	0.0277
9999 Open employment authorization (CIC)	0.02%	0.1302	0.1906
82 Skilled occupations in primary industry	0.34%	0.129	0.0684
62 Skilled sales and service occupations	5.94%	0.0824	0.0194
12 Skilled administrative and business occupations	7.06%	0.0813	0.0188
84 Intermediate occupations in primary industry	0.82%	0.0721	0.0355
34 Assisting occupations in support of health services	0.28%	0.048	0.0669
14 Clerical occupations	2.46%	0.0444	0.0244
52 Technical and skilled occupations in art, culture, and recreation	1.12%	0.0094	0.0342
64 Intermediate sales and services occupations	4.29%	-0.0068	0.2141
42 Paraprofessional occs in law, social services, education and religion	0.50%	-0.0219	0.0425
9911 Student (CIC)	1.31%	-0.0722	0.0335
51 Professional occupations in art and culture	1.47%	-0.1043	0.0326
66 Elemental sales and service occupations	2.02%	-0.1756	0.0249
9992 Retired (CIC)	0.04%	-0.3035	0.1829
9980 Other non-worker (CIC)	0.07%	-0.3679	0.1242
9970 Homemaker (CIC)	0.26%	-0.4477	0.07

Occupations are ordered by size of occupation effect.
Occupational codes were supplied by CIC; they include aggregated NOC codes plus special CIC categories.
Occupational categories without observations in our sample are not listed.

Figure 1 - Estimated Cohort Year Effects (1980 = 0), 1980 - 2003