Labor Market Conditions, Skill Requirements and Education Mismatch*

Fraser Summerfield

This Draft:

October 21, 2013

Abstract

This paper shows that economic downturns lead to overeducation through changes in the type of jobs created: during a downturn job creation favors manual skill jobs. I generate measures of job skill requirements from the Occupational Information Network (O*NET) database, and document a positive relationship between local unemployment rates and manual skill requirements. One reason for this relationship is a connection between the share of manual skill job vacancies and labor market conditions, which I demonstrate in a model of job search with two-sided heterogeneity. Using various measures of overeducation, I provide empirical evidence that skill requirement changes are the mechanism by which labor market conditions affect overeducation. Estimates accounting for the job mobility selection decisions of workers demonstrate that local labor market conditions at the time of job formation contribute to the incidence of overeducation, but that this relationship is eliminated by conditioning on the skill requirements of a job.

The most recent version of this paper is available at http://www.uoguelph.ca/~fsummerf/papers/JMP.pdf

*I would like to thank Louis Christofides, Louise Grogan, Chris McKenna, Chris Minns, Miana Plesca, Chris Robinson, Asha Sadanand and participants at the 2013 CLSRN and EEA meetings for helpful comments. All errors are my own. This paper makes use of data provided through the Statistics Canada Research Data Centre program, however, the content of this paper in no way reflects the opinions of Statistics Canada. I gratefully acknowledge financial support for this research from the Social Sciences and Humanities Research Council.

1 Introduction

Although firms often post explicit requirements for job vacancies, many workers are found in jobs for which they appear mismatched. Examples of this mismatch might include a clerical worker with a bachelor's degree, or a manager who has only high school education. Questions then arise about why these mismatches occur. Instead of any single explanation, it is likely that several factors contribute to the incidence of mismatch. These contributing factors may also differ depending on the direction of the mismatch. This paper focuses on the case where workers are overeducated with respect to their job. I show that labor market conditions at the time of job formation are one contributor to overeducation, and I that this overeducation follows from changes in the skill requirements of employment opportunities in response to local labor market conditions.

Understanding the causes of overeducation is important for the labor markets in North America. The costly implications for workers are well documented in the overeducation literature, following the works of Duncan and Hoffman (1981) and Verdugo and Verdugo (1989). Cross sectional evidence from many authors suggest a robust penalty for each year of education beyond the requirements of a job, with wage losses of 8% per year for the US and Canada. Overeducation is not only costly, but also pervasive. Close to 37 percent of North American workers are overeducated, and that mismatch has been increasing over time (Leuven and Oosterbeek, 2011).[1]

One contribution of this paper is to present evidence that past labor market conditions contribute to the incidence of overeducation. Using Canada's Labor Force Survey (LFS) and the Occupational Information Network (O*NET) database to generate measures of mismatch, I show that mismatch depends on labor market conditions at the time of hire. The observable overeducation measures in this paper further the empirical literature where a link between labor

[1]These results are from a meta-analysis which suggest that approximately 37% of workers in the US and Canada are overeducated and 16% are undereducated. Other reviews of this literature include (McGuinness, 2006; Rubb, 2003; Sloane, 2003; Groot and Maassen van den Brink, 2000).

market conditions and mismatch has been limited to the context of job mobility (Moscarini and Vella, 2008). In addition, the relative importance of labor market conditions at the time of job formation suggest that the theoretical literature relating job search frictions and mismatch (Marimon and Zilibotti, 1999; Moscarini, 2001; Barlevy, 2002) is a suitable framework for modeling the incidence of overeducation.

The primary contribution of this paper is to illustrate that job skill requirements are the channel through which past labor market conditions affect overeducation. Analyzing the O*NET data, I generate measures of cognitive and manual job skill requirements. I document a positive relationship between local unemployment rates and the share of manual skill jobs at the time of job creation in Canadian data, which has not been documented elsewhere to the best of my knowledge.[2] I further show that overeducation depends on manual skill requirements rather than labor market conditions directly. Whereas the literature on overeducation and wages has attributed mismatch to heterogeneity in the characteristics of workers (Sicherman, 1991; Bauer, 2002; Frenette, 2004; Tsai, 2010), I propose that heterogeneity in the characteristics of jobs is also an important contributor to overeducation.

One potential reason for this change in the skill requirements of jobs is an increase in manual skill vacancies. This paper uses a Pissarides (1990) style search model with two sided heterogeneity to show that a decrease in demand can lead to a change in the distribution of vacancies posted by firms. With a fixed population of workers, this change in vacancies subsequently affects job matches and leads to overeducation. This result of the model is also supported by the data. Estimates on various measures of overeducation demonstrate that downturns increase overeducation. Controlling for skill requirements, however, can eliminate this relationship. This finding is quite robust to specification changes, variation in the measure of mismatch, and does not appear to be the result of sample selection bias.

The importance of skill requirements to the incidence of overeducation also helps to explain

[2] I view these changes in job creation as analogous to changes in the demand for the type skill, which have been suggested as an important contributor to mismatch across countries (Desjardins and Rubenson, 2011).

the wage penalty findings from previous studies of overeducation. Because manual skill jobs pay less than cognitive skill jobs, and because manual skill requirements are positively correlated with economic downturns, job characteristics may be one reason for the wage penalty to overeducation. Using Mincer-type regressions I replicate wage penalties found in the literature for overeducated workers and show that skill requirements can explain approximately half of this wage penalty. Because overeducated workers are found in jobs with proportionally more manual skill requirements than otherwise similar workers who are in a better job match, much of the wage penalty may simply be the result of relatively lower returns to manual tasks.

This paper is also related to the literature on the wage impacts of past labor market conditions. Overeducation occurs at the time of job formation, rather than when a worker is observed in the data, and both of these phenomena have been linked to wage penalties.[3] Poor labor market conditions at graduation (Oreopoulos, von Wachter, and Heisz, 2012; Kahn, 2010; Bowlus and Liu, 2003) and during past job spells (Beaudry and DiNardo, 1991; McDonald and Worswick, 1999; Grant, 2003; Devereux and Hart, 2007) have been shown to reduce worker wages, but have not provided evidence of a link to overeducation. Using alternative measures of job match quality, Bowlus (1995) and Hagedorn and Manovskii (2010) point to mismatch as the mechanism by which past labor market conditions correlate with wages. The current analysis provides complementary evidence based on an observable measure of match quality, while demonstrating that the variation in wages across skill requirements may explain some of these prior links between wages and the job match.

The rest of the paper proceeds as follows: Section 2 outlines the Data, Canada's Labour Force Survey (LFS) and the O*NET database from which I draw information on jobs, and discuss various empirical measures of skill requirements and education mismatch. Section 3 outlines a model of job search which allows the share of cognitive and manual job vacancies to

[3]It is possible that some workers attend school while staying employed and upgrade their education, thus becoming overeducated. It is likely that these workers are the minority and therefore are excluded from the analysis.

vary with labor market conditions at the time of hiring. Section 4 outlines the empirical reduced form estimates and illustrates two key findings: Labor market conditions at the time of hire are important to overeducation, and this impact is due to changes in the skill composition of new jobs. In Section 5 I provide estimates based on a methodology which corrects for selection bias as measured by a worker's propensity to switch out of their job. Section 6 relates my findings to the wage penalty literature, and Section 7 concludes.

2 Data

In order to assess the match between a worker and their job, it is necessary to observe certain characteristics of both. This paper combines worker data from the LFS with occupation data from the O*NET, linked through the occupation codes. Details of the O*NET data and linking procedure are available in the Appendix section A.

2.1 The Labour Force Survey

Data on workers are sourced from confidential monthly files of Canada's LFS for the period 1997-2012.[4] During this period the LFS was expanded to include wages and information on the permanency and unionization status of jobs. In order to understand the contribution of human capital and labor market conditions to mismatch, several standard sampling restrictions attempt to remove observations where labor supply decisions might be affected by confounding factors. The remaining sub-sample of employed males age 16-65 excludes unionized, part-time, and self-employed workers, leaving just over 2.7 million observations. Jobs in the LFS during this period are classified according to the 2001 National Occupational Classification System (NOCS-01) occupation codes, providing a substantial level of detail about occupational differences.

Several measures of human capital are constructed from the LFS sample. Binary variables

[4] I am grateful for access to the data provided through the Statistics Canada Research Data Centre program.

for education milestones are created, including Less than High School (LHS), High School (HS), Post-Secondary non-degree (PS), Bachelor's degree (BA) and higher degrees (PG).[5] This approach allows for non-linearity in the impacts of schooling years and is common in the literature on the returns to education in Canada (Boudarbat, Lemieux, and Riddell, 2010).[6] Using information from the yearly measure of schooling, potential experience is also calculated, and those with negative potential experience are excluded from the sample. Additional controls for worker characteristics include dummy variables for marital status, province or state of residence, and year of observation.

Identifiers for the economic region (ER), a Census geographic division for analysis of economic activity, allow for the definition of a local monthly unemployment rate to capture labor market conditions for the LFS sample. I calculate counts of labor force participants and unemployed workers, and generate the unemployment rate for each ER using the final sampling weights. The LFS samples from 72 of the ERs providing a considerable amount of cross-sectional variation in labor market conditions.[7] Figure 5 provides a map of the ERs.

Because a measure of current job tenure (in monthly units) is available for most employed workers, it is possible to calculate the local unemployment rate at the time of hiring for all jobs commencing since January 1987.[8] Using an extended sample of the LFS, I generate local labor market conditions for the years 1987-2012 and link these to worker observations using their monthly job tenure.[9] This allows labor market conditions at the time of hiring, as well as the time of observation, to be related to the match between a worker and their job. In fact,

[5]For the LFS data, PS captures mainly community college graduates, the closest equivalent in the United States being the Associate's Degree. This category represents the majority of canadians with education beyond high school.

[6]The results presented in this paper were also found to be robust to a yearly measure of education and it's quadratic rather than milestone indicators.

[7]Some ER's, such as those in the territories where representative sampling is prohibitive, are excluded from sampling.

[8]An assumption is made that workers do not re-locate outside of their current ER while staying with the current employer. There are few observations in the data for which this may be the case.

[9]This procedure is limited to 1987 because ER indicators underwent a major change in 1987. Additionally, the 2012 ER boundaries in the dataset are not encoded prior to 1987.

this paper shows labor market conditions during job formation to be relatively more important than current conditions.

Sampling of the LFS respondents occurs on a rotating 6-month basis, meaning that every month only 1/6 of the sample are replaced. It is therefore possible to obtain details of worker job histories up to 5 months prior to observation and identify job switchers as well as those who transition in and out of unemployment.[10] In order to address sample selection bias, I exploit the rotational panel feature of the LFS to observe job mobility using a linkage methodology adopted from the Appendix of Brochu and Green (Forthcoming). Primary estimates are based on the pooled sample of worker observations to maximize sample sizes, although the results are robust to using a restricted sample which contains only a single observation per individual.

2.2 Mismatch

Much of the empirical literature on education mismatch has chosen to focus on overeducation. This is because undereducated workers may not be true cases of "mismatch" (Sicherman, 1991), and it is plausible that the mechanisms generating over and undereducation could differ.[11] The current paper also focuses on overeducation, although I develop measures which allow for both directions of mismatch. Three observable mismatch measures are used in this paper, making it among the first to discuss a measure of mismatch for North America which is not based on self-reports of match quality or job satisfaction.[12]

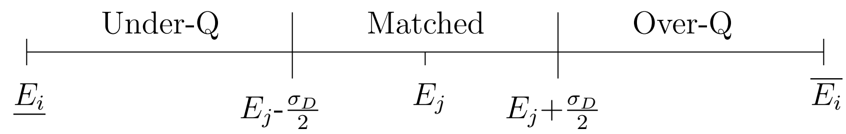
The first measure of observable mismatch is a simple linear distance $D_{ij} = E_j - E_i$, derived

[10] I define job switchers as workers who either switch occupation, or who switch employer, where employer switchers are identified by a job tenure of 1 month, because tenure in the LFS is tied to the employer. Although (Kambourov and Manovskii, 2009b,a) describe a large amount of noise in occupation switching in the American Current Population Survey, this type of problem seems minimal in the LFS. False switchers, those who report an occupation switch followed immediately by a return to the prior occupation, are excluded. A definition requiring both an occupation and an employer switch was also tested, but no substantive differences were found.

[11] It is possible that much of the undereducation is the result of changes in the job requirements over time, where workers have received training on the job to adapt to a changing work environment.

[12] Prior measures of mismatch using Canadian data is limited to subjective questions about how well a worker's education fits within the job requirements. Yuen (2010) uses these measures from the Survey of Labour and Income Dynamics, while Finnie (2001); Boudarbat and Chernoff (2009) use measures from the National Graduates Survey.

Figure 1: The Distance Measure for Assessing Mismatch



by comparing the years of worker reported educational attainment E_i in the LFS data, with the suggested educational requirements for that occupation E_j from the O*NET. Estimates based on this measure are easily interpretable in years of education. The design of D_{ij} allows for both over or undereducation, and is the basis for a second measure.

The second measure is a standard-deviation based binary measure, declaring a worker as overeducated when their excess education as measured by D_{ij} exceeds a certain threshold. Workers within the standard deviation bounds $\alpha\sigma_E$ are considered to be reasonably well matched, while workers above and below are over and undereducated respectively.[13] Based on this measure, with $\alpha = 1$, approximately 25% of the workers in the sample are overeducated and approximately 30% are undereducated. Figure 1 gives a visual representation of this measure.

The third measure of overeducation, which is also binary, is taken from Gottschalk and Hansen (2003). This measure is based on the market return to education, rather than expert categorization. Jobs are classified as "college jobs" if they pay a premium for college education, and overeducated workers are college educated individuals who are found in jobs which do not appear to reward their education.[14] This measure is presented as a robustness check to the O*NET measures, and to illustrate that the results in this paper are not an artifact of particular expert ratings. Although estimates using this measure are smaller, the sign and significance do not change.

[13]Sensitivity on α reveals that results are robust to a range $0.5 < \alpha < 1.5$. In the data, σ_D is equivalent to approximately 1.9 years of education.

[14]I use a threshold wage premium of 10% to define a college job as do the authors, I also attempt a 5% and 20% premium with no changes to the main results.

2.3 Skill Requirements

In addition to generating measure of the education requirements for each occupation, I also generate measures of occupational skill requirements. These requirements are similar to those popularized in the recent literature on offshoring (Autor, Levy, and Murnane, 2003; Firpo, Fortin, and Lemieux, 2011). An important difference between the skill requirement measures generated in this paper and those from the offshoring literature is the choice of O*NET data to use as inputs.[15] In this paper I remain agnostic about which ONET elements would best identify various skills and instead include the entire "ability" category, an approach taken in Peri and Sparber (2009).

Using the 52 "ability" measures from the O*NET database, factor analysis identifies a set of 5 orthogonal skill requirements for each occupation, with mean zero. This approach to identifying occupation specific human capital requirements follows from Poletaev and Robinson (2008), and details of this procedure are in the Appendix section A.1. By examining the factor loadings in Appendix Table 9 it is possible to interpret the skill requirements, following Ingram and Neumann (2006). For example, the leading factor in the LFS data S_{1j} is highly correlated with many cognitive and communication abilities such as "deductive reasoning" and "written expression," while being uncorrelated with abilities such as "finger dexterity". Therefore this factor appears to represent reasoning and communication skill, and could be classified as a cognitive measure. By contrast, S_{2j} correlates positively with manual abilities including aspects of visual perception, "reaction time" and the "speed of limb movement". Similar interpretations are developed for the remaining factors, leading to the skill requirements presented in Table 1. The first and fifth are measures of cognitive skill requirements, while factors 2-4 appear to represent manual skill requirements.[16]

[15]The offshoring literature picks particular elements from the O*NET which may be well suited to illustrate job characteristics which are routine or manual in nature, as these elements relate to the possibility of jobs to be off-shored.

[16]It is also possible to distinguish between factors which report the level of a category of skill from those which further distinguish different subsets of the main categories. Factors 1-3 appear to identify the scale of various

Table 1: Factor Analysis Output

Component	Cog/Man	Requirement Interpretation	Proportion
S_{1j}	COG	Reasoning / Communication	34
S_{2j}	MAN	Sensory / Perception	28
S_{3j}	MAN	Physical Strength	14
S_{4j}	MAN	Coordination vs Strength	9
S_{5j}	COG	Numeracy vs Communication	4

Five skill requirement measures are the leading significant factors from factor analysis on the O*NET database of "abilities". These measures represent recommended job requirements, and are categorized as cognitive or manual. Factors weighted by the population of employed males in a given occupation. Proportion represents the amount of variation in the O*NET abilities explained by a given factor after rotation.

The scale of the skill requirements is set by weighting during the factor analysis procedure, and affects the cardinal interpretation. A single standard deviation in each factor represents a standard deviation of that skill requirement in the distribution of filled vacancies in the Canadian economy. Although this scaling ambiguity diminishes the possibility to make cardinal comparisons between the skill requirements of individual jobs, each skill requirement has an ordinal meaning and the variation in the scale of the skill requirements contains information itself.[17] Because this paper does not make any claims about the magnitudes of any individual job's skill requirements, I avoid further manipulation of the factors.

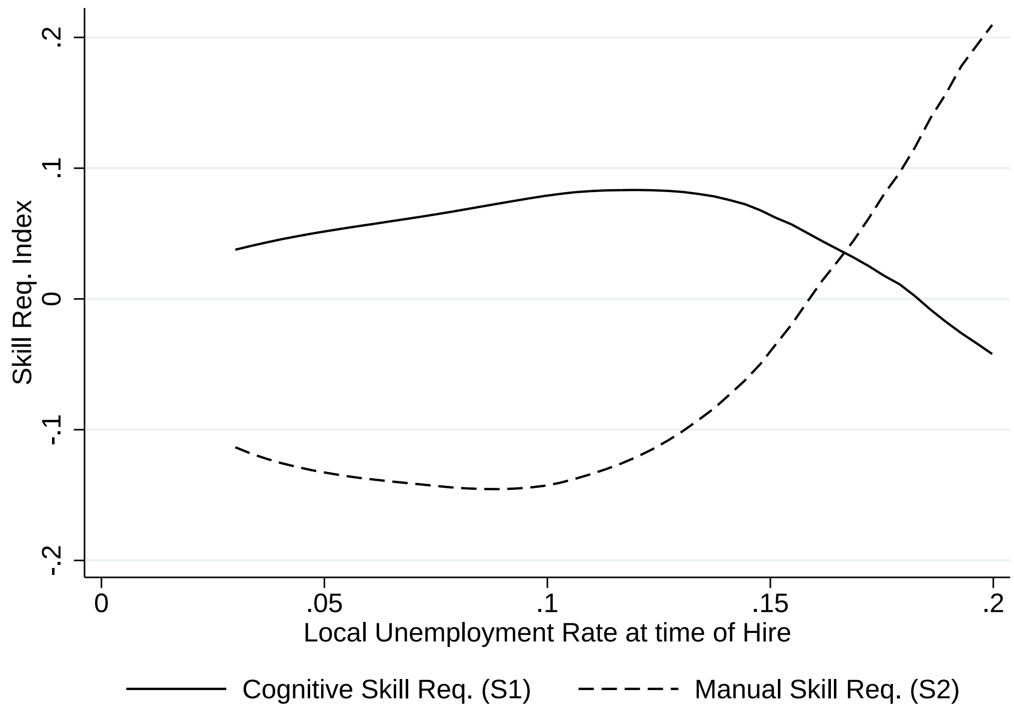
An important aspect of this paper is to document the cyclical properties of specific skill requirements using these measures from the O*NET. Several papers discuss the cyclicality of skill among workers (Chassamboulli, 2011; Barlevy, 2001; Devereux, 2002, 2004) but little is known about the behavior of the firm and the resulting skill requirements of filled job vacancies. Examining the leading two skill requirements in the Canadian labor market, I document a negative correlation between the share of manual skill requirements and the labor market conditions. Figure 2 plots the leading cognitive and manual skill requirements as a function of the local unemployment rates during job formation using a local polynomial smooth.[18] This

skill requirements, while factors 4 and 5 provide some differentiation within these broader skill requirements.

[17]For example, a higher minimum level of one skill requirement than another indicates that the baseline requirement for all jobs in the economy is higher in this first skill.

[18]Because of the confidential nature of the data, this smoothing process minimizes the disclosure risk and

Figure 2: Skill Requirements and Local Unemployment Rates



Plot is a local polynomial smooth (moving average across unemployment rates) of the leading cognitive and manual skill requirements on the Y axis against the local unemployment rates on the X axis. Skill requirements are the output of factor analysis on O*NET data. Each skill requirement is mean zero, and a single standard deviation represents the population standard deviation of that particular skill requirement. Local unemployment rates measured monthly at the ER level, and are trimmed to the range (3%,20%).

plot suggest that when an ER experiences poor labor market conditions, the new jobs which are created have a relatively higher share of manual skill requirements. There are several potential reasons for this relationship including reluctance to fill more crucial positions or invest in research and development when economic conditions are unfavorable.[19] OLS regressions, in Appendix Table 6, on collapsed data at the mean for each ER and month, provide additional evidence of this relationship conditional on the other skill requirements, provincial and time fixed effects. It is evident from this evidence that the type of job formed in a downturn differs from the type of job formed during better economic times.

is encouraged by Statistics Canada. The approach uses a moving average process, incorporating neighboring years.

[19]Note that this does not imply that firms do not hire highly skilled or educated workers during downturns.

3 A Model of Job Search and Mismatch

This section outlines a model of job search that details several important parts of the job matching process. The model shows that market conditions lead to mismatch and overeducation through changes in the type of job; during downturns, which are represented in the model by price decreases, firms respond by posting relatively more manual skill vacancies which require less educated labor. As workers meet with the available jobs, a growing share of highly educated workers meet manual skill vacancies leading to an increasing share of manual skill jobs. The model presented in this section is an extension of Pissarides (1990) with two sided heterogeneity, akin to a set of models with endogenous skill requirements Shimer and Smith (2000); Mortensen and Pissarides (1999); Burdett and Coles (1999). The model is a generalization of Wong (2003); Albrecht and Vroman (2002), in which an equilibrium allows for both over and undereducation.[20] Unlike these models, this paper makes minimal assumptions about the production process and requires only that is increasing in all arguments. Despite this simple production function, the share of cognitive and manual vacancies and the incidence of overeducation are endogenously determined in an equilibrium with search frictions.

3.1 Environment

Consider an economy with two types of workers indexed by their level of education $x \in \{x_L, x_H\}$ and two types of firms indexed by the skill requirement (or task) $y \in \{y_C, y_M\}$. Manual jobs y_M are less productive than cognitive jobs, and the share of these less productive vacancies is given by ϕ. Workers can chose whether or not to accept wage offers arriving from a firm, and firms chose to enter the market and which type of vacancy to post. All workers who are unemployed, regardless of type, meet vacancies of measure v according to the standard meeting function

$$m(u, v) = m(1, \theta)u$$

[20] Although these studies consider other equilibria, the data indicate that over and undereducation are present in the current state of the Canadian labor market.

where $\theta = v/u$ and u denotes the unemployment rate. Only unemployed workers search for jobs, and therefore unemployed workers meeting firms with empty vacancies at a rate of $m(\theta)$, while firms with vacancies meet unemployed workers at a rate of $m(\theta)/\theta$. A filled job dissolves according to an exogenous probability σ, and the interest rate in the economy is given by $r > 0$. Market conditions are given by the market price of final goods p, which is strictly positive.

3.2 Workers

In this economy there are a continuum of risk-neutral and infinitely lived agents of mass 1. The exogenous parameter ψ gives the share of workers that are type x_L. Workers can be either employed or unemployed, where γ determines the share of unemployed who are endowed with a low level of education. Because search is random from a common unemployment pool, $\gamma = \psi$ in equilibrium. In a given period, an unemployed agent receives a present value return of

$$rU(x) = b + m(\theta)\left(\phi \max\{N(x, y_M) - U(x), 0\} + (1-\phi)\max\{N(x, y_C) - U(x), 0\}\right) \tag{1}$$

where b is the unemployment benefit to a worker of either type.[21] The present value return to employment for a worker of x in a job of type y, which depends on the wage $w(x, y)$ is given by

$$rN(x, y) = w(x, y) + \sigma(U(x) - N(x, y)) \tag{2}$$

3.3 Firms

There is also a continuum of firms in the economy, each capable of posting at most one vacancy. When firms chose to enter the market and post a vacancy, that vacancy may either fill with a worker, or remain empty at a cost of $k(y)$, $k(y_C) > k(y_M)$. An empty vacancy of type y therefore gives a firm the present value return of

$$rV(y) = -k(y) + \frac{m(\theta)}{\theta}\left(\gamma \max\{J(x_L, y) - V(y), 0\} + (1-\gamma)\max\{J(x_H, y) - V(y), 0\}\right) \tag{3}$$

[21] There is no loss of generality assuming this benefit is the same for both workers.

and the asset value of a type y vacancy filled by a type x worker is given by

$$rJ(x,y) = pf(x,y) - w(x,y) + \sigma(V(y) - J(x,y)) \tag{4}$$

A filled vacancy produces according to the production function $f(x,y)$ where output is increasing in x and y. This assumption about the production process means that high educated works produce more than low educated workers for a given job y and that cognitive jobs produce more than manual jobs for a given worker of type x. The importance of this general production function is that it permits workers with either high or low education to be productive in a cognitive skill job, a major departure from models such as Albrecht and Vroman (2002) where any (x_L, y_C) partnerships are not productive by assumption. Because undereducated workers are observed in the data, such an assumption may be too strong.[22] Despite the fact that a x_H worker is more productive in a y_M job than a x_L worker, such a worker may be considered overeducated because they would be more productive and earn a higher wage in a y_C job.

3.4 Wage Determination

Wages are determined by Nash bargaining, where the parameter β represents the worker's share of the total surplus in the economy. Each meeting pair therefore solves

$$w(x,y) = argmax\big\{[N(x,y) - U(x)]^{\beta}[J(x,y) - V(y)]^{(1-\beta)}\big\}$$

giving rise to the wage sharing condition

$$N(x,y) - U(x) = \beta[N(x,y) + J(x,y) - U(x) - V(y)] \tag{5}$$

Substitution of the value functions leads to an expression for the wage of worker type x in vacancy type y as a function of exogenous parameters:[23]

$$\begin{aligned} w(x,y) =& \beta pf(x,y) + \frac{(1-\beta)b(r+\sigma)}{r+\sigma+\beta m(\theta)} \\ &+ \frac{(1-\beta)\beta m(\theta)p}{r+\sigma+\beta m(\theta)} \times [\phi f(x,y_M) + (1-\phi)f(x,y_C)] \end{aligned} \tag{6}$$

[22] Allowing for both over and undereducation is akin to assuming $\pi_{ij} = 1 \ \forall \ \{i,j\}$ in Wong (2003).
[23] For substitution methods see the appendix section B.

3.5 Equilibrium

To solve the model, firms are assumed to have free entry into either type of vacancy $V(y_M) = 0, \quad V(y_C) = 0$ in the steady state. Also, because $\dot{u} = 0$, the share of either type of workers flowing into and out of unemployment at any given time must be equal giving rise to the following equilibrium conditions for workers with high and low levels of education respectively:

$$m(\theta)(1-\gamma)u = \sigma(1-\psi-(1-\gamma)u) \tag{7}$$

$$m(\theta)\gamma u = \sigma(\psi - \gamma u) \tag{8}$$

Equations 7 and 8 can be solved for γ and u giving rise to the following equilibrium conditions:

$$u = \frac{\sigma}{m(\theta)+\sigma} \tag{9}$$

$$\gamma = \psi$$

In the absence of constraints on which workers may match with which jobs, the share of unemployed x_L workers is equal to the share of x_L workers in the population meaning that the type of workers which firms are hiring is determined exogenously. This follows from the common pool of unemployment, and the fact that all workers the same job finding probability regardless of their type. Using the expression for u and the free entry conditions, $V(y_M) = 0$ and $V(y_C) = 0$ one can solve for the equilibrium triplet $\{u, \theta, \phi\}$.

From the expressions for the free entry of firms, and the observation $\gamma = \psi$ the following two conditions along with (9) will describe an equilibrium:

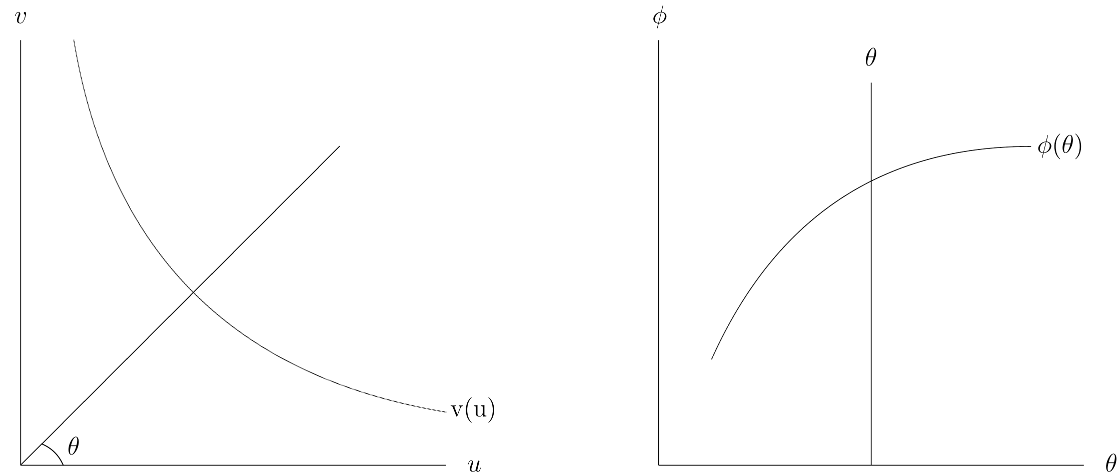
$$k(y_M) = \frac{m(\theta)}{\theta}\left(\psi J(x_L, y_M) + (1-\psi)J(x_H, y_M)\right) \tag{10}$$

$$k(y_C) = \frac{m(\theta)}{\theta}\left(\psi J(x_L, y_C) + (1-\psi)J(x_H, y_C)\right) \tag{11}$$

Solving the free entry for manual vacancies gives

$$\theta = \frac{m(\theta)(1-\beta)}{k(y_M)}\left(pF_M - \frac{b(r+\sigma)}{r+\sigma+\beta m(\theta)} - \frac{\beta m(\theta)p}{r+\sigma+\beta m(\theta)}\left[\phi(F_M - F_C) + F_C\right]\right) \tag{12}$$

Figure 3: A Graphical Depiction of Equilibrium



$$F_M = \gamma f(x_L, y_M) + (1-\gamma) f(x_H, y_M)$$
$$F_C = \gamma f(x_L, y_C) + (1-\gamma) f(x_H, y_C) \tag{13}$$

and this may be substituted into the free entry condition for cognitive vacancies to obtain the share of manual vacancies the firm will post, ϕ.

$$\phi = \frac{[r+\sigma+\beta m(\theta)][F_C k(y_M) - F_M k(y_C)]}{(F_M - F_C)\beta m(\theta)(k(y_M) - k(y_C))} - \frac{b(r+\sigma)}{\beta m(\theta) p(F_M - F_C)} - \frac{F_C}{F_M - F_C} \tag{14}$$

Finally ϕ may be substituted back into the low skill vacancy condition to obtain an expression for θ:

$$\theta = \frac{m(\theta)(1-\beta)p(F_M - F_C)}{(r+\sigma)[k(y_M) - k(y_C)]} \tag{15}$$

3.6 Market Conditions

Market conditions in the model are given by the parameter for prices, p. Comparative statics with respect to this parameter show how agents react to a price change, and are used to simulate different states of demand in the economy. First, in equilibrium there will be a change in labor market tightness. Provided that $F_M < F_C$ and $k(y_M) < k(y_C)$, equation (15) describes how a decrease in demand will lead to fewer vacancies relative to the unemployment rate. The first of these restrictions is guaranteed by the production function, while the second is by assumption. Since $m(\theta)$ is increasing in theta, and is in the denominator of the Beveridge curve condition, (9), unemployment rates rise in response to the change of state. This supports the use of rising unemployment rates as an indicator of a downturn.

Whether or not this price change also increases the share of manual vacancies depends on the relative change in θ and ϕ. The sign is not obvious because job creation in general will lead to more manual and cognitive jobs. Figure 4 depicts the case where this share increases, and comparative static exercises for these conditions are provided in the Appendix. Partial differentiation of (14) shows that following a downturn, the share of manual vacancies will increase as long as

$$\frac{b(r+\sigma)}{\beta m(\theta)p^2[F_M - F_C]} < 0.$$

This condition is negative as long as the term $[F_M - F_C]$ is negative, which is true for all production functions increasing in both arguments.[24] The intuition behind this shift is as follows: When aggregate demand falls, wages also fall reducing the cost of employing a worker. As long as it is more expensive to post a cognitive skill vacancy, then the firm will move towards hiring less educated (less expensive) workers since it can compensate for their lower productivity in the job by paying them less.

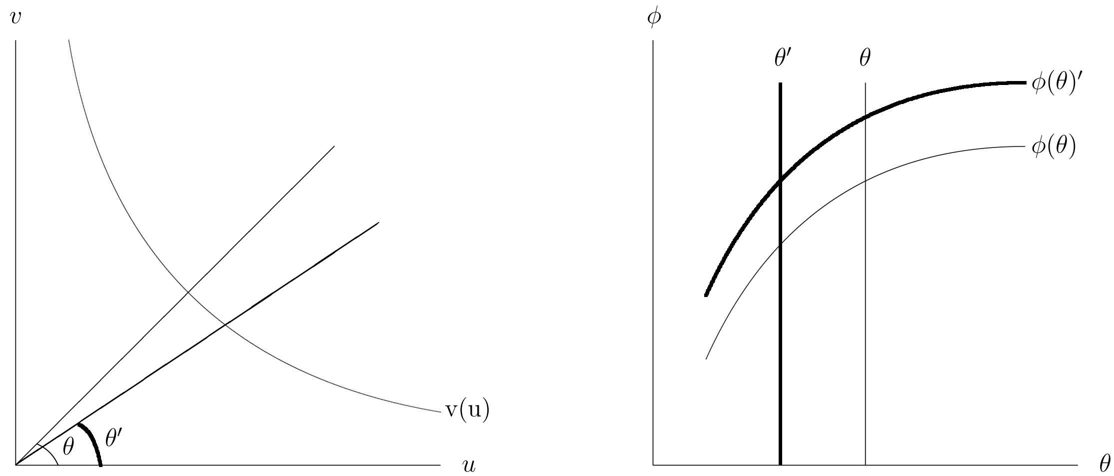
Overeducation in the model is represented by the share of x_H workers in y_M jobs. This is given by the expression

$$[1 - \psi - (1-\gamma)u]\phi, \tag{16}$$

that shows overeducation is a function of worker types, ψ unemployment rates, u, and the

[24] This also holds for the weaker case where high educated workers are more productive in cognitive jobs than manual jobs, while low education workers are equally (and less) productive in both jobs.

Figure 4: Equilibrium under a price change



share of low skill vacancies, ϕ, and this expression motivates the estimation specification in the next section of the paper. Because this expression is increasing in ϕ the model generates more overeducation as a the share of manual vacancies increases in equilibrium.[25]

This class of models is therefore able to generate the following equilibrium results: Overeducation increases in response to unfavorable changes in labor market conditions, and this relationship is affected by the skill requirements of jobs. In response to a downturn, employers change how they post vacancies in two ways. Firms will post fewer vacancies, and the share of these vacancies which require manual skills increases. Changes in the skill requirements of jobs during downturns are therefore important contributors to the incidence of overeducation, as shown in equation (16). This behavior is consistent with the positive relationship between the unemployment rate, at the time of job formation, and the share of manual skill requirements in new employment relationships documented in Section 2.3.

[25]In equilibrium both over and undereducation are possible, a phenomenon found in the data.

4 Estimates of Mismatch

To measure relationship between labor market conditions on the mismatch of workers to jobs I estimate a reduced form model using three different measures of overeducation. The first measure, *Over* is a binary indicator based on the distance between the O*NET education requirements and the worker's reported education in years, $E_j - E_i$. This indicator suggests workers are overeducated when their excess years of education cross a threshold. The second measure, $Over_{GH}$ is the binary measure based on the market returns to education, borrowed from Gottschalk and Hansen (2003). Estimates on both these measures are performed using the probit model.[26] The third measure is simply the continuous measure of distance, $D_{ij} = E_j - E_i$, estimated with OLS. While the binary measures enable the isolation of overeducated workers from the undereducated, this linear measure illustrates the relative importance of these two types of mismatch.

The reduced form specification given by equation (17) expresses overeducation as a function of the following elements of the model, motivated by equation (16): worker characteristics, x, labor market conditions, u, and job skill requirements, ϕ. Personal characteristics, $\boldsymbol{x}$, include dummies for education levels, experience and its quadratic, job tenure and marital status, while the vector $\boldsymbol{u}$ contains the various measure of the local unemployment rate to capture labor market conditions. Skill requirements are given by the O*NET factors $\boldsymbol{s}$, and $\boldsymbol{\delta}$ control for annual time trends and differences in economic and political differences across provinces with the appropriate fixed-effects.

$$D_{ijt} = \boldsymbol{u}'_{\ell t}\boldsymbol{\mu} + \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + \boldsymbol{s}'_{jt}\boldsymbol{\kappa} + \boldsymbol{\delta}_{pT} + \epsilon_{ijt} \tag{17}$$

Identification is based on the assumption that local unemployment rates are due to exogenous sources of variation in the economy. It is unlikely that mismatch, which is measured at

[26]Throughout the paper I report average marginal effects from all probit specifications.

the individual level, could have a meaningful impact on ER level unemployment rates. At the same time, I acknowledge the possibility that other unobserved factors at the ER level may correlate with the local unemployment rates, and therefore estimates of the unemployment rate may be biased. Because I intend to capture the impact of local labor market conditions, rather than identifying the causal impact of the unemployment rate specifically, I am content with the estimation strategy.

Because the data is a rotating panel, observations may not be truly independent. The implication for the OLS and probit estimators is inefficiency. While it may be possible to improve the standard errors by adopting a GLS framework, an underlying assumption of the error correlation structure would be necessary. In addition, efficiency gains may not be realized due to the clustering of standard errors. Since the source of identifying variation in labor market conditions is at the ER level, standard errors are penalized accordingly.[27]

4.1 Labor Market Conditions

In order to illustrate the impact of the local unemployment rate on mismatch, specifications 1-3 in Table 2 show the relative importance of current and past measures of labor market conditions for the three measures of mismatch by estimating (17). Comparing the three specifications, it is clear that labor market conditions at the time of hire, representing the environment in which workers have searched for jobs, are contributors to overeducation. Current unemployment rates could also impact mismatch, but this relationship would likely be due to attrition as more mismatched workers might transition into unemployment or voluntarily switch jobs. Section 5 addresses this issue and finds results similar to these.

With respect to the binary measures of overeducation, the positive coefficients on local unemployment rates at the time of hire in specifications 1 and 2 suggest that, given the threshold for overeducation of $\alpha = 1$, an increase in local unemployment rates from 5% to 9% would lead

[27]Moulton (1990) provides the leading example of why this is necessary.

to an average increase in the probability of being overeducated by half a percentage point. These results support the intuition from Bowlus (1995); Hagedorn and Manovskii (2010) that labor market conditions at the time of hire are correlated with match quality and provide evidence that overeducation is a relevant, and observable, measure of match quality.

As an alternative to the binary measures of mismatch, this table includes estimates of the linear distance measure $D_{ij} = E_j - E_i$ in specification 3. This measure captures the overall effect on mismatch, as well as allowing for the possibility that binary measures miss important variation within the three groups of mismatched workers they define. These estimates suggest that the overall impact of higher local unemployment rates is overeducation, since a negative impact indicates a decrease in job requirements relative to a worker's education level. More specifically, the coefficient for local unemployment rates in specification 5 indicates that an increase in the local unemployment rate from 5% to 9% would lead to an average increase in overeducation of 0.2 years of schooling. As labor market conditions worsen, employers may begin filling jobs with more educated workers, effectively bumping workers down the ladder. This is consistent with findings for wages from the overeducation literature which attribute the wage penalty to overeducation to a lesser job, and ongoing work discussing recent macroeconomic conditions in the United States (Beaudry, Green, and Sand, 2013).

As evidence that measures of over and undereducation deserve separate treatment, comparative results are presented in Appendix Table 7. It is possible that undereducation is the result of workers who have gained sufficient work experience to mitigate the observable mismatch documented in this paper. These workers therefore, while appearing mismatched, may in fact be in suitable jobs. In addition, it is possible that job requirements have changed over time leading workers with longer tenure to appear undereducated. Because of these confounding factors, this paper focuses on overeducation.

4.2 Skill Requirements

As a response to an economic downturn, the model presented in Section 3 shows that firms may choose to create more low skill vacancies. Reasons for this behavior might include stimulus packages which promote labor intensive manual skill jobs, a shifting of responsibilities to lesser paying occupations (for example from manager to supervisor), or an unwillingness to fill high paying cognitive skill jobs during periods of economic uncertainty.

To show the relative importance of skill requirements, I provide corresponding specifications 4-6 in Table 2 which are also conditioned on the skill requirements, $\boldsymbol{s}$, of the jobs which are being created. The skill requirements are the result of factor analysis on the O*NET data and include two cognitive and three manual measures. If some of the impact of labor market conditions is due to changes in the type of job, conditioning estimates on the skill requirements of the job will reduce the impacts.

Comparing the two sets of estimates from Table 2 confirms the importance of skill requirements. First, a comparison of specifications 1 and 3 (or 2 and 4) shows that the impact of past unemployment rates on overeducation is reduced and statistically indifferent from zero when conditioned on the skill requirements of the job. I interpret this as evidence that changes in the nature of job creation are an important mechanism in the relationship between mismatch and labor market conditions. The skill requirements themselves show that holding a job with higher cognitive skill requirements decrease the likelihood that a worker is overeducated. This suggests that workers are overeducated because they are obtaining manual skill jobs, which require less education on average.[28] A similar elimination of the relationship between labor market conditions and overall mismatch is found in a comparison of the two linear distance specifications 3 and 6.

These results are quite robust and hold for a number of specification changes including the

[28]Specifications 3 and 4 use the GH measure of overeducation and indicate similar patterns, suggesting that these results are not an artifact of how overeducation is defined.

Table 2: Estimates of Overeducation

	(1) Pr(Over)	(2) Pr(Over$_{GH}$)	(3) $E_j - E_i$	(4) Pr(Over)	(5) Pr(Over$_{GH}$)	(6) $E_j - E_i$
Current Urate	0.084	0.058	0.323*	0.074	0.076	0.194
×100	(0.086)	(0.069)	(0.259)	(0.118)	(0.074)	(0.298)
Urate at Hire	0.095**	0.089***	-0.476**	-0.053	0.053	0.225
×100	(0.041)	(0.033)	(0.204)	(0.056)	(0.041)	(0.214)
S_1				-0.174***	-0.008***	1.014***
(COG)				(0.005)	(0.003)	(0.031)
S_2				0.049***	0.001*	-0.395***
(MAN)				(0.005)	(0.002)	(0.015)
S_3				0.073***	0.002**	-0.438***
(MAN)				(0.002)	(0.002)	(0.006)
S_4				-0.002	-0.003***	-0.126***
(MAN)				(0.001)	(0.001)	(0.005)
S_5				-0.027***	0.001***	0.184***
(COG)				(0.002)	(0.001)	(0.007)
HS	-0.734***		3.001***	-0.982***		4.615***
	(0.009)		(0.054)	(0.013)		(0.066)
PS	-0.362***	0.024***	2.042***	-0.582***	0.017***	3.410***
	(0.007)	(0.003)	(0.042)	(0.005)	(0.004)	(0.033)
BA	-0.261***	0.018***	1.212***	-0.292***	0.016***	1.512***
	(0.010)	(0.002)	(0.034)	(0.008)	(0.003)	(0.018)
Exp	-0.002**	-0.006***	0.006**	-0.000	-0.005***	-0.006***
	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)
Exp^2	0.002*	0.008***	0.011**	-0.001	0.008***	0.036***
x 100	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.003)
Married	-0.019***	-0.071***	0.097***	-0.005***	-0.065***	0.017***
	(0.003)	(0.003)	(0.019)	(0.002)	(0.003)	(0.005)
Tenure	-0.000***	-0.0001***	0.002***	0.000***	-0.000**	-0.0004***
	-(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.0001)
N	1450984	785895	1744784	1450984	617881	1744784
R_p^2	0.252	0.267	0.417	0.441	0.272	0.713

Specifications 1,2,4,5 are Probit estimates of the probability of overeducation, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 5 and 6 are OLS regressions on the linear distance measure. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. Workers with education below high school are excluded from overeducation regressions because by definition, LHS is the lowest possible education requirement. $Over_{GH}$ measure based on Gottschalk and Hansen (2003) and is only defined for workers with more than HS education.

replacement of quadratic and linear measures of tenure and experience with dummies, controls for temporary jobs or firm size, various combinations of the five skill requirements, different overeducation threshold values α and to the use of the linear probability model instead of the probit model.[29][30] Estimates were also performed on various sub samples of workers based on job tenure or experience, and on a reduced sample containing only a single observation per individual, leading to similar results. The most conservative estimates are presented in this table, and restricting the local unemployment rates to a more typical value for a recession in Canada, for example 7%-15%, result in larger coefficients for overeducation impacts which are not conditional on skills.

5 Sample Selection

One possible source of bias in the estimates of overeducation is sample selection. Several studies have documented differences in the job duration (Bowlus, 1995) and mobility patters (Sicherman, 1991) of workers who are mismatched. Workers who have excess education may be more likely to switch to "better jobs" where the return to their skill is higher (Robst, 1995). In other words, overeducated workers are more likely to select into a state of job mobility and because of this, job mobility has been used as a measure of mismatch (Moscarini and Vella, 2008). Table 3, generated using the linked rotating panel structure of the LFS, suggests that overeducated workers are less likely to stay in their jobs compared to a relatively well matched worker.

Because of these potential differences, estimates may be subject to selection bias. If overeducated workers are more likely to switch out of their jobs, then the share of overeducated workers in the sample is too small. It is possible, for example, that those who are very overeducated because of labor market conditions select out of their jobs less often than those who

[29]These results are forthcoming in the Appendix, pending RDC disclosure.

[30]A reasonable threshold for the standard-deviation based measure, $\alpha\sigma_D$ ranges from approximately one year of education to four years of education.

Table 3: Mismatch and Job Separations

	Over_t	Matched_t
Switch_{t+1}	0.063	0.053
Unemp_{t+1}	0.027	0.034
Tenure_t	71.439	75.816

were overeducated because of other reasons such as the commuting time or the pay. In this case, the impact of labor market conditions might appear much smaller than the actual effect.

I address this potential selection issue using the methodology popularized in Heckman (1979), which accounts for the self-selection decisions of workers. Despite some evidence that selection is present, accounting for any potential selection bias in the estimation strategy does not appear to affect the main results of the paper.

5.1 Selection Correction

The selection correction method treats the selection bias as a form of omitted variable bias. When the sample in question excludes some observations in a non-random fashion, such as overeducated workers who have higher job mobility than matched workers, inferences from the observed sample of overeducated workers may not necessarily apply to the population.

The sample selection framework specifically models two separate components: the selection decision given by equation (19), and the outcome equation given by (18) which is observed only when a worker selects into the sample according to the indicator $h = 1$.[31]

$$y_i = \begin{cases} \tilde{\boldsymbol{x}}_i'\tilde{\boldsymbol{\beta}} + e_{1i} & \text{if } h_i = 1 \\ \\ missing & \text{if } h_i = 0 \end{cases} \tag{18}$$

$$Pr(h_i = 1|\boldsymbol{z}) = \boldsymbol{z}'\boldsymbol{\gamma} + e_{2i} \tag{19}$$

A key assumption in the model is give by the relationship $e_{2i} = \rho e_{1i} + \eta_i$. If selection into the sample is random, then $\rho = 0$ and equation (18) may be estimated by OLS. In the absence

[31] The case in this paper considers not selecting out of the sample rather than selecting into it.

of this, however, the error terms are correlated and the selection equation introduces a bias into the outcome equation. In doing so the outcome equation becomes:

$$E[y_i|h_i = 1] = \tilde{\boldsymbol{x}}_i'\tilde{\boldsymbol{\beta}} + \rho\sigma\frac{\phi(\boldsymbol{z}_i'\boldsymbol{\gamma})}{\Phi(\boldsymbol{z}_i'\boldsymbol{\gamma})} \tag{20}$$

and therefore it is necessary to control for selection by removing the bias term. The outcome equation, conditional on the selection relationship, is estimated simultaneously by full maximum likelihood according to:

$$\ln L_i = \begin{cases} w_i \ln \Phi\left\{\frac{\boldsymbol{z}_i\boldsymbol{\gamma} + (y_i - \tilde{\boldsymbol{x}}_i\tilde{\boldsymbol{\beta}})\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{w_i}{2}\left(\frac{y_i - \tilde{\boldsymbol{x}}_i\tilde{\boldsymbol{\beta}}}{\sigma}\right)^2 - w_i \ln\sqrt{2\pi\sigma} & \text{if } h_i = 1 \\ w_i \ln \Phi(-\boldsymbol{z}_i\boldsymbol{\gamma}) & \text{if } h_i = 0 \end{cases} \tag{21}$$

where w_i represent LFS final population weights.[32]

The selection model above assumes OLS estimation of the outcome equation, which is suitable for estimates of the simple linear distance measure D_{ij}. For binary measures, a version of the selection estimator due to Van de Ven and Van Praag (1981) provides a similar correction where the second stage is also a probit model.

Although it is possible to achieve identification from the functional form assumptions in these models, the distribution of covariates may influence the efficacy of this approach.[33] Therefore an exclusion restriction is included in the current selection equation. The selection equation is given by (22)

$$\begin{aligned} Pr(h_{ijt+1} = 1) &= \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z_{ijt}} e^{-s^2/2} ds \\ z_{ijt} &= \zeta\bar{h}_{\ell-it+1} + \boldsymbol{u}_{\ell t}'\boldsymbol{\mu} + \boldsymbol{x}_{ijt}'\boldsymbol{\beta} + \boldsymbol{s}_{jt}'\boldsymbol{\kappa} + \boldsymbol{\delta}_{pT} \end{aligned} \tag{22}$$

where h_{ijt+1} is the probability a worker stays in their job in the following month and the exclusion restriction, $\bar{h}$, is the probability that a worker's peers also stay in their jobs. The

[32] Maximum Likelihood estimation is preferable to the simpler two-step estimator, as shown in Puhani (2000).

[33] The Heckman selection technique generates λ from the inverse mills ratio of the selection equation estimates. The outcome equation can then be conditioned on this variable, to control for selection. This approach is valid because probit estimation of the first stage is non-linear and therefore λ is not perfectly collinear with other covariates even in the absence of an exclusion restriction. Problems arise, however, when the majority of the covariates are near the median value, in the range where the probit model is approximately linear. A thorough discussion of this issue may be found in Bushway, Johnson, and Slocum (2007).

instrument $\bar{h}$ represents the selection decisions of peers, calculated as the average of h for all other workers of the same age in the same ER and month. This is a relevant instrument because the probability of peers switching jobs is correlated to the current individual's decision. I also believe it is a valid instrument because I can think of no reason why the job search decisions of a worker in the past (when they were hired) should be affected by the current decision of peers to switch jobs.[34]

Controlling for selection bias does not appear to change the main results of this paper: unemployment rates at the time of hire correlate with overeducation, and this relationship appears to be the result of changes in the nature of job creation with respect to skills. Table 4 shows that conditioning estimates of the probability of overeducation on the skill requirements of jobs renders local unemployment rates insignificant, accounting for the selection decisions of workers. Whether or not selection is in fact an issue in the sample is questionable given the χ^2 statistic from specification 1.[35] Because this statistic is small the null hypothesis, that the error terms are independent in the first and second stage regressions, cannot be rejected. In other words, selection bias is not likely in the outcome regression if performed independently. Compared to Table 2 estimates of the conditional correlation between local labor market conditions and overeducation are slightly lower, suggesting the sample selection bias was positive but small.

6 Wage Outcomes

This section attempts to connect the current findings to the literature on the wage impacts of under and overeducation. If wage penalties found in the literature are due to overeducation, and if overeducation is the result of increased manual skill jobs, then controlling for skill requirements in the wage estimation should reduce estimates of the penalty for overeducation.

To test this hypotheses I estimate a modified wage equation and compare it to a specification

[34]Even though these workers are from the same cohort, the date of hire at the most recent job varies widely.
[35]Appendix Table 8 presents selection equation estimates.

Table 4: Estimates Accounting for Sample Selection

	(1)	(2)	(3)	(4)
Outcome Eq:	Pr(Over$_i$)	Pr(Over$_i$)	$E_j - E_i$	$E_j - E_i$
Unemp Rate	0.086	-0.086	0.366	-0.817**
(Current)	(0.078)	(0.106)	(0.309)	(0.349)
Unemp Rate	0.080**	-0.027	-0.399*	0.421*
(At Hire)	(0.036)	(0.049)	(0.216)	(0.236)
S_1		-0.152***		1.002***
(COG)		(0.005)		(0.005)
S_2		0.044***		-0.355***
(MAN)		(0.004)		(0.016)
S_3		0.063***		-0.389***
(MAN)		(0.002)		(0.006)
S_4		-0.002		-0.079***
		(0.003)		(0.005)
S_5		-0.024***		0.190***
		(0.002)		(0.008)
Selection Eq:	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)
Fraction of	1.252***	1.252***	1.251***	1.251***
Peers Stay	(0.055)	(0.055)	(0.055)	(0.055)
N	1372357	1372357	1372357	1372357
σ	-0.006	-0.053	1.514	1.217
χ^2	0.00	12.25***	85.59***	1382154***

Specifications 1 and 2 are Probit selection estimates conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Specifications 3 and 4 are Heckman regressions on the linear distance measure. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. Workers with education below high school are excluded from overeducation regressions because by definition, LHS is the lowest possible education requirement. χ^2 is a Wald statistic is to test for correlation in the error terms, $H_0 : \rho = 0$. Peers Stay is the exclusion restriction in the first stage regression for selection into job staying, the observed sample in first stage mismatch regressions.

similar to that found in Verdugo and Verdugo (1989). This equation, given by (23) resembles a Mincer wage regression, conditional on the vector $\boldsymbol{m}$ containing binary measures for under and overeducation, $Pr(Over)$, $Pr(Under)$.

$$\ln w_{ijt} = \boldsymbol{m}'\boldsymbol{\phi} + \boldsymbol{u}'_{\ell t}\boldsymbol{\mu} + \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + \boldsymbol{s}'_{jt}\boldsymbol{\kappa} + \boldsymbol{\delta}_{pT} + \epsilon_{ijt} \tag{23}$$

Results are reported in specifications 1 and 2 of Table 5. Specifications 3 and 4 control for the linear distance D_{ij} and its quadratic rather than the binary measures, as a robustness check.

Comparisons of odd and even-numbered specifications highlight the importance of skill requirement controls in the context of the literature on wage penalties. First, I replicate the findings of significant wage penalties(bonuses) for over(under)education in the odd numbered specifications. Second, the even numbered specification show a decrease in wage penalty of up to 50% conditional on skill requirements.[36] Because manual skill jobs pay less than cognitive skill jobs, and because overeducated workers are found in jobs with proportionally more manual skill requirements, it is possible that the overeducation wage penalty is reflecting the lower wages paid to manual tasks. A similar mechanism may help to explain a portion of why labor market entry during periods of high unemployment, affect future wages of workers Oreopoulos, von Wachter, and Heisz (2012), although testing this conjecture is beyond the scope of the LFS data.

7 Conclusion

This paper shows that overeducation, measured in several differing ways, arises partially as a result of local labor market conditions and that changes to the type of jobs may be the relative channel by which labor market conditions lead to education mismatch between a worker and their job. I provide evidence of this by showing that downturns lead to overeducation through increases in the share of manual skill jobs. These results are the some of the first findings

[36]The importance of alternative mismatch indicators, entering both linear and quadratic, are also diminished although to a lesser degree.

Table 5: Wages and Labor Market Conditions

	(1)	(2)	(3)	(4)
	$\ln w$	$\ln w$	$\ln w$	$\ln w$
Over	-0.177***	-0.089***		
	(0.014)	(0.007)		
Under	0.176***	0.039***		
	(0.011)	(0.003)		
D_{ij}			0.084***	0.050***
			(0.004)	(0.002)
D_{ij}^2			-0.603***	-0.476***
$\times 100$			(0.018)	(0.018)
S_1		0.112***		0.084***
(COG)		(0.010)		(0.007)
S_2		-0.011***		0.001
(MAN)		(0.003)		(0.003)
S_3		-0.048***		-0.035***
(MAN)		(0.004)		(0.003)
S_4		0.026***		0.029***
		(0.007)		(0.006)
S_5		0.024***		0.017***
		(0.002)		(0.002)
LHS	-0.868***		-1.002***	
	(0.033)		(0.034)	
HS	-0.641***	0.096***	-0.768***	0.149***
	(0.024)	(0.005)	(0.025)	(0.005)
PS	-0.424***	0.244***	-0.535***	0.324***
	(0.018)	(0.006)	(0.019)	(0.009)
BA	-0.178***	0.373***	-0.244***	0.523***
	(0.014)	(0.015)	(0.014)	(0.011)
PG		0.484***		0.697***
		(0.015)		(0.018)
Exp	0.025***	0.023***	0.025***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Exp^2	-0.046***	-0.044***	-0.048***	-0.045***
x 100	(0.001)	(0.001)	(0.001)	(0.001)
Married	0.071***	0.063***	0.070***	0.063***
	(0.008)	(0.067)	(0.007)	(0.007)
Tenure	0.001***	0.001***	0.001***	0.001***
Weeks	(0.000)	(0.000)	(0.000)	(0.000)
Job Switch	0.135***	0.129***	0.135***	0.131***
	(0.005)	(0.004)	(0.005)	(0.004)
Permanent	0.112***	0.080***	0.105***	0.084***
	(0.013)	(0.012)	(0.012)	(0.007)
N	1410361	1410361	1410361	1410361
R^2	0.360	0.379	0.335	0.370

Specifications OLS estimates of the return to over and undereducation conditional on measures of job skill requirements and local labor market conditions. Estimates are also conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Standard errors in parentheses clustered at the economic region. Wages are deflated using provincial CPI measures with base year 2002. Results weighted with LFS final weights. S_r are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

on mismatch in North America from objective measures, and explore the possibility that job heterogeneity is one contributor to education mismatch.

The general model of job search with two sided heterogeneity presented in this paper illustrates one potential reason for this change in skill requirements. Economic downturns, which also affect labor market conditions, may induce employers to post a different type of job than they otherwise might. Under minimal assumptions on the production process, an increase in the availability of manual skill jobs then results in overeducation as workers and firms meet in the job market. This appears to be a result of this class of models which has not received any attention thus far.

Empirical evidence of these relationships is provided from reduced form estimates on data from Canada's LFS. Poor local labor market conditions at the time of hiring are shown to contribute to the incidence of overeducation using an estimation strategy to account for sample selection bias among the overeducated. The skill requirements of jobs, from factor analysis on the O*NET database, play an important role in the incidence of mismatch. Increases in overeducation from economic downturns are eliminated when conditioning estimates on these job requirements. This finding is robust and is the main contribution of the paper. In addition, I show that the importance of skill requirements extends beyond the incidence of overeducation and also explains a substantial component of the wage penalty previously attributed to overeducation.

References

Albrecht, James and Susan Vroman. 2002. "A matching model with endogenous skill requirements." *International Economic Review* 43 (1):283–305.

Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent

Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4):1279–1333.

Barlevy, Gadi. 2001. "Why are the Wages of Job Changers So Procyclical." *Journal of Labor Economics* 19 (4):837–878.

———. 2002. "The sullying effect of recessions." *The Review of Economic Studies* 69 (1):65–96.

Bauer, Thomas. 2002. "Educational mismatch and wages: a panel analysis." *Economics of Education Review* 21:221–229.

Beaudry, Paul and John DiNardo. 1991. "The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle." *Journal of Political Economy* 99 (4):665–688.

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2013. "The Great Reversal in the Demand for Skill and Cognitive Tasks." Working Paper 18901, National Bureau of Economic Research.

Boudarbat, Brahim and Victor Chernoff. 2009. "The Determinants of Education-Job Match among Canadian University Graduates." Discussion Paper 4513, IZA.

Boudarbat, Brahim, Thomas Lemieux, and Crag Riddell. 2010. "The Evolution of the Returns To Human Capital in Canada, 1980-2005." *Canadian Public Policy* 36 (1):63–89.

Bowlus, Audra and Haoming Liu. 2003. "The long-term Effects of Graduating from High School During a Recession: Bad Luck or Forced Opportunity." Working Paper 2003-7, CIBC Center for Human Capital and Productivity.

Bowlus, Audra J. 1995. "Matching Workers and Jobs: Cyclical Fluctuations in Match Quality." *Journal of Labor Economics* 13 (2):335–350.

Brochu, Pierre and David Green. Forthcoming. "The Impact of Minimum Wages on Labour Market Transitions." *The Economic Journal* .

Burdett, Kenneth and Melvyn G Coles. 1999. “Long-Term Partnership Formation: Marriage and Employment.” *The Economic Journal* 109 (456):307–334.

Bushway, Shawn, Brian D Johnson, and Lee Ann Slocum. 2007. “Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology.” *Journal of Quantitative Criminology* 23 (2):151–178.

Cattell, Raymond B. 1966. “The scree test for the number of factors.” *Multivariate Behavioral Research* 1:245–276.

Chassamboulli, Andri. 2011. “Cyclical Upgrading of Labor and Employment Differences across Skill Groups.” *The B.E. Journal of Macroeconomics* 11.

Desjardins, Richard and Kjell Rubenson. 2011. “An Analysis of Skill Mismatch using Direct Measures of Skills.” Education Working Paper 63, OECD.

Devereux, Paul. 2002. “Occupational Upgrading and the Business Cycle.” *Labour* 16 (3):423–452.

———. 2004. “Cyclical Quality Adjustment in the Labor Market.” *Southern Economic Journal* 70 (3):600–615.

Devereux, Paul J and Robert A Hart. 2007. “The spot market matters: evidence on implicit contracts from Britain.” *Scottish Journal of Political Economy* 54 (5):661–683.

Duncan, Greg J. and Saul D. Hoffman. 1981. “The incidence and wage effects of overeducation.” *Economics of Education Review* 1 (1):75 – 86.

Finnie, Ross. 2001. “Graduates’ earnings and the job skills-education match.” *Education Quarterly Review* 7 (2):7–21.

Firpo, Sergio, Nicole Fortin, and Thomas Lemieux. 2011. “Occupational Tasks and Changes in the Wage Structure.” Working Paper 5542, IZA.

Frenette, Marc. 2004. “The overqualified Canadian Graduate: the role of the academic program in they incidence, persistence, and economic returns to over qualification.” *Economics of Education Review* 23 (1):29–45.

Gottschalk, Peter and Michael Hansen. 2003. “Is the Proportion of College Workers in Non-college Jobs Increasing?” *Journal of Labor Economics* 21 (2):pp. 449–471.

Grant, Darren. 2003. “The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from the National Longitudinal Surveys.” *Industrial and Labor Relations Review* 56:393–716.

Groot, Wim and Henritte Maassen van den Brink. 2000. “Overeducation in the labor market: a meta-analysis.” *Economics of Education Review* 19 (2):149 – 158.

Hagedorn, Marcus and Iourii Manovskii. 2010. “Job Selection and Wages over the Business Cycle.” Manuscript, University of Pennsylvania.

Heckman, James J. 1979. “Sample selection bias as a specification error.” *Econometrica* 47 (1):153–161.

Ingram, Beth and George Neumann. 2006. “The Returns to Skill.” *Labour Economics* 13:35–59.

Kahn, Lisa B. 2010. “The long-term labor market consequences of graduating from college in a bad economy.” *Labour Economics* 17:303–316.

Kaiser, Henry. 1958. “The varimax criterion for analytic rotation in factor analysis.” *Psychometrika* 23:187200.

Kambourov, Gueorgui and Iourri Manovskii. 2009a. “Occupational Mobility and Wage Inequality.” *Review of Economic Studies* 76:731–759.

———. 2009b. “Occupational Specificity of Human Capital.” *International Economic Review* 50 (1):63–115.

Leuven, Edwin and Hessel Oosterbeek. 2011. "Overeducation and Mismatch in the Labor Market." Discussion Paper 5523, IZA.

Marimon, R. and F. Zilibotti. 1999. "Unemployment vs. Mismatch of Talent: Reconsidering Unemployment Benefits." *Economic Journal* 109:266–291.

McDonald, James T. and Christopher Worswick. 1999. "Wages, Implicit Contracts, and the Business Cycle: Evidence from Canadian Micro Data." *Journal of Political Economy* 107 (4):884–892.

McGuinness, Séamus. 2006. "Overeducation in the Labour Market." *Journal of Economic Surveys* 20 (3):387–418.

Mortensen, Dale T and Christopher A Pissarides. 1999. "Unemployment Responses to Skill-biasedTechnology Shocks: the Role of Labour Market Policy." *The Economic Journal* 109 (455):242–265.

Moscarini, Giuseppe. 2001. "Excess Worker Reallocation." *Review of Economic Studies* 63 (3):593–612.

Moscarini, Giuseppe and Francis Vella. 2008. "Occupational Mobility and the Business Cycle." Working Paper 13819, NBER.

Moulton, Brent R. 1990. "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units." *The Review of Economics and Statistics* 72 (2):334–338.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics* 4 (1):1–29.

Peri, Giovanni and Chad Sparber. 2009. "Task Specialization, Immigration, and Wages." *American Economic Journal: Applied Economics* 1 (3):135–169.

Pissarides, Christopher. 1990. *Equilibrium Unemployment Theory*. Basil Blackwell: Cambridge MA.

Poletaev, Maxim and Chris Robinson. 2008. "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys 1984-2000." *Journal of Labor Economics* 26 (3):387–420.

Puhani, Patrick. 2000. "The Heckman Correction for Sample Selection and Its Critique." *Journal of Economic Surveys* 14 (1):53–68.

Robst, John. 1995. "Career mobility, job match, and overeducation." *Eastern Economic Journal* 21 (4):539–550.

Rubb, Stephen. 2003. "Overeducation in the labor market: a comment and re-analysis of a meta-analysis." *Economics of Education Review* 22:621–629.

Shimer, Robert and Lones Smith. 2000. "Assortative matching and search." *Econometrica* 68 (2):343–369.

Sicherman, Nachum. 1991. "Overeducation in the Labor Market." *Journal of Labor Economics* 9:101122.

Sloane, Peter. 2003. "Much ado About Nothing? What does the Overeducation Literature Really Tell us?" In *Overeducation in Europe*, edited by Felix Büchel, Andries de Grip, and Antje Mertens. Northhampton, MA: Edward Elgar Publishing, 11–47.

Tsai, Yuping. 2010. "Returns to overeducation: A longitudinal analysis of the U.S. labor market." *Economics of Education Review* 29:606–617.

Van de Ven, Wynand P. and Bernard M. Van Praag. 1981. "The demand for deductibles in private health insurance: A probit model with sample selection." *Journal of Econometrics* 17 (2):229 – 252.

Verdugo, Richard R. and Naomi T Verdugo. 1989. "The Impact of Surplus Schooling on Earnings." *The Journal of Human Resources* 24 (4):629–643.

Wong, Linda Y. 2003. "Can the Mortensen-Pissarides Model with Productivity Changes Explain US Wage Inequality?" *Journal of Labor Economics* 21 (1):70–105.

Yamaguchi, Shintaro. 2012a. "Changes in Returns to Task-Specific Skills and Gender Wage Gap." Working paper, McMaster University.

———. 2012b. "Tasks and Heterogeneous Human Capital." *Journal of Labor Economics* 30 (1):1–53.

Yuen, Jennifer. 2010. "Job-education match and mismatch: Wage differentials." Tech. rep., Statistics Canada.

Appendix

A The O*NET

The O*NET database, which is the successor to the Dictionary of Occupational Titles (DOT), represents the most detailed database of job characteristics available in North America. The current paper makes use of version 17.0 of the O*NET database, which has 974 different occupations classified on a version of the SOC coding system. The purpose of the O*NET is to attribute several characteristics to each occupation. These characteristics are divided into six groups: "Worker Characteristics," "Worker Requirements," "Experience Requirements," "Occupational Requirements," "Workforce Characteristics" and "Occupation-Specific Information." Each of these six groups contains up to four sub-categories of information, leading to a great deal of overlap across various categories. For example, mathematics is represented both as a "Skill" under "Experience Requirements" and an "Ability" under "Worker Characteristics." Because there is a great deal of overlap within the O*NET, the current analysis is limited to information about the education and the ability requirements of jobs.

To merge the LFS and the O*NET data, the O*NET job categories were collapsed to the SOC level. A concordance provided by the standards division of Statistics Canada allows the Standard Occupational Classification system (SOC) codes, and associated O*NET data, to be integrated into the LFS.[37] After merging with the LFS, the sample contains workers in 327 different occupations. Samples of the O*NET questionnaire are given below

In recent versions of the O*NET, education requirements are assessed by a group occupational experts. An occupational expert is a worker in the occupation who is deemed, due to rank or experience, to have expert knowledge about the occupation. The reported educational requirements are given in the O*NET data for each expert, for discrete education milestones.

[37]This paper uses the O*NET database version 17.0, where the job data are coded according to the SOC 2010 system. A concordance (or "crosswalk"), from the National Crosswalk Service Center, transform these to SOC 2000 codes. There is minimal information loss in this process because code changes from 2000 - 2010 versions are limited to 8 occupations.

To generate an index of educational requirements, these categories are first converted to years of education. Fortunately the LFS data are collected with similar discrete measures and major categories such as high school and undergraduate education correspond directly. The LFS has more detail on workers who have less than high school education, but does not detail postgraduate studies. By contrast, the O*NET is quite detailed beyond the undergraduate level, but has a lower bound of less than high school. Because of this lower bound, it is not possible for workers with less than high school education to be overeducated using the distance measure D_{ij}.

Measures of skill requirements are derived from the O*NET category "Abilities". This category appears to have the most comprehensive and general set of elements, and I allow the common factor model estimation procedure to chose the relevant factors from the 52 different abilities, denoted by $k \in \{1, \ldots, 52\}$, for each O*NET occupation. Each ability, has a measure of "importance" I_k as well as a "level of complexity" C_k for a particular occupation. Both measures are standardized to a scale $\in (0, 10)$ and combined to generate a single measure $a_k j$ for each ability k in each occupation j, according to $a_{jk} = I_{jk}^{a} \times C_{jk}^{1-a}$.[38]

A.1 Factor Analysis

To extract the relevant information about occupation specific skill, summary measures of skill requirements $S_{rj}, r = 1, \ldots, 4$ are generated from these 52 ability measures using Factor analysis. Although some of the literature on specific skills uses principal component analysis, (Yamaguchi, 2012a,b), factor analysis was chosen for this application because the goal is to identify underlying commonalities among the various ability ratings rather than simply reducing the dimensionality of the data. Unlike principal component analysis, factor analysis ignores the unique variation in underlying skill measures when generating the main factors. Because

[38]These two measures, I_k and C_k are highly correlated, and principal factors generated for the combined measures are remarkably similar to those generated for individual measures. Results reported in this paper use a=1/2, but results are robust to variation in this parameter.

of the nature of the O*NET database and its propensity for duplicate information, it is likely that much of the unique variation is attributable to noise. In addition, factor analysis is more suitable for orthogonal rotation which leads to superior interpretability without sacrificing the order of factors (which may be the case with principal components).

Factor analysis is able to identify unique sources of variation, or eigenvectors, in the O*NET ability data of dimension k by estimating the common factor model:

$$\boldsymbol{a} = \boldsymbol{s}\boldsymbol{\Lambda}' + \boldsymbol{e}, \tag{24}$$

where $\boldsymbol{a}$ is the vector of ability ratings and $\boldsymbol{s}$ is the resulting vector of factors. The matrix $\boldsymbol{\Lambda}$, referred to as the factor loading matrix, attributes the original ability ratings to the resulting factors, akin to assigning them weights. The common factor model assumes that the correlation matrix of $\boldsymbol{a}$ is given by;

$$\boldsymbol{R} = \boldsymbol{\Lambda}\boldsymbol{I}\boldsymbol{\Lambda}' + \boldsymbol{\Psi}. \tag{25}$$

and that $\boldsymbol{\Psi}$ represents the uniqueness element in the ability measures which will not be attributed to common factors. The model estimates $\boldsymbol{\Psi}$ first, then computes each column of the factor loading matrix $\boldsymbol{\Lambda}$ in succession for all factors, $1, \ldots, 52$. Because the common variation is attributed successively to the leading factors in order, not all of the resulting factors will be relevant. In this case, only the leading 5 factors appear to be meaningful, and are kept for analysis. The scree test borrowed from Cattell (1966) is used to select factors which have eigenvalues exceeding the mean, a popular rule of thumb in the literature. A plot of the scree test is shown in Figure 8.

The factor analysis procedure is manipulated in two ways to assist in the interpretation of the resulting factors. First, I apply weights based on the population of employed males in each occupation from the LFS data. This step is common in the literature and affects the scaling of the factors. A standard deviation in the resulting factor therefore represents a standard deviation of the corresponding skill in the Canadian workforce. The second manipulation is an orthogonal factor rotation, as described in Kaiser (1958). The original factors are generated so that the factors account for the maximum amount of variance possible, in successive order. As a result, a large number of the 52 ability measures will contribute heavily to multiple factors, making it difficult to distinguish between them. By contrast, the "Varimax" rotation procedure maximizes the factor loading variance for each factor, so that the ability measures now contribute more heavily to a single factor. The Because the rotation is orthogonal, it re-organizes the to improve interpretability, without sacrificing their independence

Table 9 presents the rotated factor loadings for the 5 relevant skill measures. By examining how each of the 52 original abilities contribute to the resulting factors it is possible to interpret the factors. Factor 1 appears to represent cognitive skill requirements such as reasoning and communication. Factors 2 and 3 capture manual aspects of an occupation, and might be interpreted as sensory/perception and strength/dexterity respectively. Finally, factors 4 and 5 differentiate within earlier factors. Factor 4 separates coordination and strength, while factor 5 isolates numerical skill from other cognitive traits.

B Solving for Equilibrium Wages

Solving the value functions, I first assume that the equilibrium value of employment always exceeds unemployment. Similarly, free entry means that the value to a firm of a filled vacancy is always positive. Re-arranging (4) and (2) leads to the expressions:

$$E(x,y) = \frac{w(x,y) + \sigma U(x)}{r+\sigma} \tag{26}$$

$$J(x,y) = \frac{pf(x,y) - w(x,y)}{r+\sigma} \tag{27}$$

Substitution of these simplified expressions for the value of a filled job into the wage sharing condition (5) gives the following expression:

$$w(x,y) = \beta pf(x.y) + (1-\beta)rU(x) \tag{28}$$

It is also necessary to simplify the expression for the value of unemployment. Substituting (26) and (28) into (1) gives an expression for the asset value of an unemployed worker x.

$$U(x) = \frac{b(r+\sigma)}{r(r+\sigma+\beta m(\theta))} + \frac{\beta m(\theta) p}{r(r+\sigma+\beta m(\theta))} \times [\phi f(x,y_M) + (1-\phi) f(x,y_C)] \tag{29}$$

Combining (28) and (29) leads to (6) which can be expressed separately for each pair (x,y):

$$\begin{aligned}
w(x_H,y_C) &= \beta pf(x_H,y_C) + \tfrac{(1-\beta)b(r+\sigma)}{r+\sigma+\beta m(\theta)} + \tfrac{(1-\beta)\beta m(\theta)p}{r+\sigma+\beta m(\theta)} \times [\phi f(x_H,y_M) + (1-\phi) f(x_H,y_C)] \\
w(x_H,y_M) &= \beta pf(x_H,y_M) + \tfrac{(1-\beta)b(r+\sigma)}{r+\sigma+\beta m(\theta)} + \tfrac{(1-\beta)\beta m(\theta)p}{r+\sigma+\beta m(\theta)} \times [\phi f(x_H,y_M) + (1-\phi) f(x_H,y_C)] \\
w(x_L,y_C) &= \beta pf(x_L,y_C) + \tfrac{(1-\beta)b(r+\sigma)}{r+\sigma+\beta m(\theta)} + \tfrac{(1-\beta)\beta m(\theta)p}{r+\sigma+\beta m(\theta)} \times [\phi f(x_L,y_M) + (1-\phi) f(x_L,y_C)] \\
w(x_L,y_M) &= \beta pf(x_L,y_M) + \tfrac{(1-\beta)b(r+\sigma)}{r+\sigma+\beta m(\theta)} + \tfrac{(1-\beta)\beta m(\theta)p}{r+\sigma+\beta m(\theta)} \times [\phi f(x_L,y_M) + (1-\phi) f(x_L,y_C)]
\end{aligned}$$

C The Relative Changes of ϕ and θ

The depiction of equilibrium in Section 3 is based on the assumptions that $\phi_\theta > 0$ and $\phi_{\theta\theta} < 0$. This section illustrates these comparative statics and the conditions under which they hold:

$$\frac{\partial \phi}{\partial \theta} = \frac{m'(\theta)(r+\sigma)\left[(F_C k(y_M) - F_M k(y_C)) + pb(k(y_M) - k(y_C))\right]}{(F_M - F_C)\beta m(\theta)^2 (k(y_M) - k(y_C))}$$

This first order partial

$$\frac{\partial \phi}{\partial \theta} > 0 \quad if \quad \frac{F_C - pb}{F_M - pb} > \frac{k(y_C)}{k(y_M)}.$$

This condition has an interpretation in terms of the profitability of various types of vacancies. The ratio of differences, between productivity and reservation wages, over the type of workers must be greater than the ratio of vacancy costs in order for the share of low skill jobs to increase as more jobs become available.

Under these same conditions, the second order partial

$$\frac{\partial^2 \phi}{\partial \theta^2} = \frac{(r+\sigma)\left[(F_C k(y_M) - F_M k(y_C)) + pb(k(y_M) - k(y_C))\right]}{(F_M - F_C)\beta m(\theta)^2 (k(y_M) - k(y_C))} \left(m''(\theta) - \frac{2m'(\theta)}{m(\theta)} \right)$$

is negative as long as the matching function has the properties $m'(\theta) > 0$ and $m''(\theta) < 0$, which are satisfied by common matching functions such as the Cobb-Douglas.

D Figures and Tables

Table 6: The Relationship between Unemployment and Skill Requirements

	Urate @ hire	Current Urate	Urate @ hire	Current Urate	Urate @ hire	Current Urate
S_1	-0.003	0.009***	-0.012***	0.001	-0.002	0.001
(COG)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
S_2	0.025***	0.024***	0.015***	0.017***	0.018***	0.017***
(MAN)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
S_3	0.016***	0.004**	-0.006***	-0.014***	-0.001	-0.014***
(MAN)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Prov. FE			✓	✓	✓	✓
Year FE					✓	✓
N	14010	14010	14010	14010	14010	14010
R^2	0.184	0.112	0.679	0.473	0.729	0.473

OLS regressions of local unemployment rates on skill requirement measures. Also conditioned on other skill requirements measures. LFS data collapsed to mean values by economic region and month.

Table 7: Estimates of Mismatch

	(1) Pr(Under)	(2) Pr(Under)	(3) Pr(Under)	(4) Pr(Over)	(5) Pr(Over)	(6) Pr(Over)
Current Urate	0.060		-0.122	0.110		0.095
×100	(0.097)		(0.077)	(0.074)		(0.098)
Urate at Hire		-0.055	0.158		0.118**	0.108***
×100		(0.067)	(0.116)		(0.051)	(0.046)
N	1744784	1744784	1744784	1744784	1744784	1744784
R_p^2	0.328	0.327	0.266	0.301	0.299	0.252

Probit estimates conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Marginal effects at the mean reported instead of coefficients. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights.

Table 8: First Stage Regressions - Sample Selection

Selection Eq:	Pr(Stay$_i$)
Fraction of	1.252***
Peers Stay	(0.055)
Unemp Rate	-2.288***
(Current)	(0.684)
Unemp Rate	1.105***
(At Hire)	(0.392)
LHS	-0.234***
	(0.017)
HS	-0.168***
	(0.019)
PS	-0.034
	(0.022)
BA	0.016
	(0.020)
Exp.	0.001
	(0.001)
Exp^2	-0.013***
x 100	(0.002)
Married	0.225***
	(0.004)
Tenure	0.002***
	(0.000)
N	1372357

Probit selection equation from estimates in Table 4, also conditional on provincial and year fixed-effects. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. Peers Stay is the exclusion restriction in the first stage regression for selection into job staying, the observed sample in first stage mismatch regressions.

Table 9: Rotated Factor Loadings

O*NET Ability	Factor1	Factor2	Factor3	Factor4	Factor5
Oral Comprehension	0.88	-0.30	-0.23	-0.06	-0.07
Written Comprehension	0.85	-0.28	-0.31	-0.06	0.12
Oral Expression	0.85	-0.28	-0.29	-0.14	-0.08
Written Expression	0.85	-0.27	-0.32	-0.08	0.05
Fluency of Ideas	0.89	-0.21	-0.13	0.00	0.04
Originality	0.88	-0.18	-0.12	0.00	0.01
Problem Sensitivity	0.90	-0.02	-0.11	0.11	0.13
Deductive Reasoning	0.91	-0.18	-0.15	0.04	0.11
Inductive Reasoning	0.91	-0.19	-0.12	0.08	0.04
Information Ordering	0.84	-0.10	-0.15	0.14	0.29
Category Flexibility	0.78	-0.22	-0.12	0.17	0.31
Mathematical Reasoning	0.67	-0.20	-0.18	0.07	0.61
Number Facility	0.63	-0.13	-0.19	0.04	0.63
Memorization	0.81	-0.04	-0.13	0.05	0.16
Speed of Closure	0.74	0.23	-0.03	0.16	0.30
Flexibility of Closure	0.63	0.09	0.02	0.53	0.25
Perceptual Speed	0.38	0.27	0.06	0.66	0.32
Spatial Orientation	-0.13	0.94	0.18	-0.03	0.05
Visualization	0.39	0.35	0.20	0.55	0.11
Selective Attention	0.59	0.17	-0.04	0.46	0.13
Time Sharing	0.65	0.37	-0.02	0.18	-0.19
Arm-Hand Steadiness	-0.37	0.38	0.59	0.46	-0.16
Manual Dexterity	-0.48	0.41	0.56	0.41	-0.16
Finger Dexterity	-0.12	0.26	0.47	0.66	-0.07
Control Precision	-0.39	0.65	0.35	0.43	-0.17
Multilimb Coordination	-0.40	0.67	0.47	0.27	-0.14
Response Orientation	-0.22	0.85	0.30	0.21	-0.14
Rate Control	-0.36	0.74	0.28	0.31	-0.16
Reaction Time	-0.28	0.76	0.31	0.36	-0.11
Wrist-Finger Speed	-0.20	0.51	0.34	0.50	-0.20
Speed of Limb Movement	-0.32	0.62	0.60	0.16	0.04
Static Strength	-0.42	0.56	0.64	0.11	-0.10
Explosive Strength	0.25	0.18	0.50	-0.19	-0.02
Dynamic Strength	-0.41	0.54	0.67	0.08	0.03
Trunk Strength	-0.46	0.39	0.69	0.14	-0.08
Stamina	-0.37	0.46	0.75	0.06	-0.08
Extent Flexibility	-0.45	0.43	0.67	0.22	-0.08
Dynamic Flexibility	-0.05	0.16	0.42	-0.15	-0.02
Gross Body Coordination	-0.37	0.51	0.72	0.09	-0.02
Gross Body Equilibrium	-0.13	0.60	0.62	0.21	0.03
Near Vision	0.63	-0.08	-0.12	0.29	0.26
Far Vision	0.33	0.72	-0.03	0.23	0.15
Visual Color Discrimination	0.18	0.46	0.26	0.58	0.15
Night Vision	-0.15	0.93	0.16	-0.03	0.04
Peripheral Vision	-0.15	0.95	0.16	-0.02	-0.02
Depth Perception	-0.18	0.80	0.25	0.27	-0.09
Glare Sensitivity	-0.18	0.88	0.23	0.11	0.01
Hearing Sensitivity	0.14	0.67	0.18	0.49	-0.15
Auditory Attention	0.02	0.58	0.20	0.57	-0.05
Sound Localization	-0.09	0.92	0.20	0.05	0.03
Speech Recognition	0.84	-0.15	-0.26	-0.20	-0.14
Speech Clarity	0.81	-0.20	-0.30	-0.27	-0.12

Figure 5: Map of Economic Regions in Canada

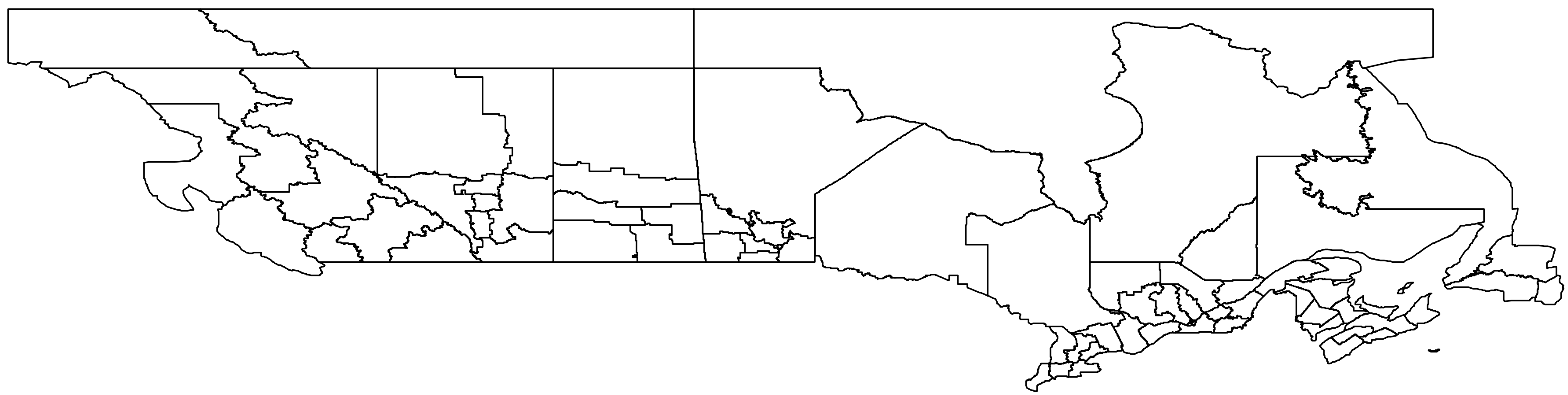


Figure 6: Educational Requirements

Instructions for Completing Education and Training Questions

In these questions, you are asked about the education and experience requirements for this job. Please read each question carefully and mark your answer by putting an **X** in the box beside your one best answer.

REQUIRED LEVEL OF EDUCATION

1. If someone were being hired to perform this job, indicate the level of education that would be required:

(Note that this does not mean the level of education that you personally have achieved.)

- ☐ **Less than a High School Diploma**
- ☐ **High School Diploma** (or GED or High School Equivalence Certificate)
- ☐ **Post-Secondary Certificate** - awarded for training completed after high school (for example, in Personnel Services, Engineering-related Technologies, Vocational Home Economics, Construction Trades, Mechanics and Repairers, Precision Production Trades)
- ☐ **Some College Courses**
- ☐ **Associate's Degree** (or other 2-year degree)
- ☐ **Bachelor's Degree**
- ☐ **Post-Baccalaureate Certificate** - awarded for completion of an organized program of study; designed for people who have completed a Baccalaureate degree but do not meet the requirements of academic degrees carrying the title of Master.
- ☐ **Master's Degree**
- ☐ **Post-Master's Certificate** - awarded for completion of an organized program of study; designed for people who have completed a Master's degree but do not meet the requirements of academic degrees at the doctoral level.
- ☐ **First Professional Degree** - awarded for completion of a program that
  - o requires at least 2 years of college work before entrance into the program,
  - o includes a total of at least 6 academic years of work to complete, and
  - o provides all remaining academic requirements to begin practice in a profession.
- ☐ **Doctoral Degree**
- ☐ **Post-Doctoral Training**

1 O*NET Education and Training Questionnaire

Figure 7: Skill Requirements

Instructions for Making Abilities Ratings

These questions are about job-related activities. An *ability* is an enduring talent that can help a person do a job. You will be asked about a series of different abilities and how they relate to *your current job* – that is the job you hold now.

Each ability in this questionnaire is named and defined.

For example:

Arm-Hand Steadiness	**The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.**

You are then asked to answer two questions about that ability:

A ***How important is the ability to your current job?***

For example:

How important is ARM-HAND STEADINESS to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
1	2	3	~~4~~	5

*Mark your answer by putting an **X** through the number that represents your answer.*
Do not mark on the line between the numbers.

***If you rate the ability as Not Important to the performance of your job, mark the one [~~1~~] then skip over question B and proceed to the next ability.**

B ***What level of the ability is needed to perform your current job?***

To help you understand what we mean by **level**, we provide you with examples of job-related activities at different levels for each ability. For example:

What level of ARM-HAND STEADINESS is needed to perform *your current job*?

	Light a candle		Thread a needle		Cut facets in a diamond	
1	~~2~~	3	4	5	6	7
						Highest Level

*Mark your answer by putting an **X** through the number that represents your answer.*
Do not mark on the line between the numbers.

1 O*NET Abilities Questionnaire

Figure 8: Scree Plot of Rotated Eigenvectors