THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

WP 16-08

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MATCHING SKILL AND TASKS: CYCLICAL FLUCTUATIONS IN THE OVERQUALIFICATION OF NEW HIRES

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This Draft: March 2016

Abstract

This paper demonstrates that downturns can affect job match quality by influencing job tasks. Cognitive and manual task shares and education-based overqualification measures are generated from Canada's Labour Force Survey and the O*NET database. Manual tasks are shown to be countercyclical among newly formed jobs. Task measures also displace the predictive power of labor market conditions for the probability of overqualification. The paper develops and calibrates a search model with two-sided heterogeneity that can account for these empirical findings. Predictions differ from prior models because production processes and vacancy posting costs differ. A single percentage point increase in unemployment is accompanied by an increase in the share of manual task vacancies by 6 percentage points, leading to an increase in overqualification by 3.5 percentage points. A policy experiment shows that increased unemployment benefits may not reduce overqualification.

Keywords: Labor Market Conditions, Tasks, Overeducation, Job Match Quality, Mismatch, Job Search

JEL Codes: J23; J24; J63

*I would like to thank Keith Bender, Louise Grogan, Chris McKenna, Chris Minns, Miana Plesca, Chris Robinson, and participants at the 2013 CLSRN and EEA meetings, 2014 SOLE meetings and CELMR workshop on educational and skills mismatch, the 2015 SES meetings and IZA/CEDEFOP joint workshop on skills and skill mismatch and a 2016 seminar at Finance Canada. Access to data used in this paper was provided by the Statistics Canada Research Data Centre Network. All errors and opinions expressed are my own. This work has also benefited from financial support from the Social Sciences and Humanities Research Council.

1 Introduction

The costs of recessions are often characterized in terms of the number of unemployed, the frequency of layoffs or the duration of unemployment spells. However, those workers that find jobs during recessions may also experience some costs. For example, Bowlus (1995) uses job duration measures to show that that matches formed in recessions may be of lower quality. Low quality matches featuring overqualified workers are characterized by lower pay and decreased job satisfaction (Allen and van der Velden, 2001; Groot and Maassen van den Brink, 2000; McGuinness, 2006; Peiró et al., 2010; Rubb, 2003; Sloane, 2003; Tsang, 1987). Cyclical overqualification may be costly for a substantial number of workers. Even through the Great Recession, at least 3.6 million jobs were formed each month in the US (Bureau of Labor Statistics, 2015). Furthermore, the literature suggests that up to 35% of North American workers are overqualified (Leuven and Oosterbeek, 2011). These numbers suggest that there is scope for an understanding of why job match quality changes in a downturn and whether policies affecting job formation might help to reduce the associated costs.

This paper establishes an empirical relationship between economic downturns, job tasks, and overqualification. Jobs formed in downturns use relatively more manual tasks than jobs formed at other times. A cyclical change in the distribution of tasks is shown using composite task measures from the Occupational Information Network (O*NET) database mapped into Canada's Labour Force Survey (LFS). The microdata also suggest that tasks are significant predictors for the likelihood of overqualification among individuals. In some cases tasks completely displace the correlation between labor market conditions and overqualification. This intermediating role for tasks is found across overqualification measures based on expert ratings, the within-occupation education distribution and the occupational education premium.

I develop a search model that can account for these empirical relationships. The model features random matching, high and low-skill workers and firms that choose whether to post vacancies with cognitive or manual tasks. Overqualification, or the share of high-skill workers in manual task jobs, increases when productivity falls. This occurs because firms post a greater share of manual vacancies when productivity is low. When that manual task vacancies are relatively inexpensive to post they become attractive at low levels of productivity, since the relative increase in output from a cognitive vacancy is reduced. These predictions are different from previous models of this type, such as Gautier (2002) or Wong (2003), where low-type vacancy shares are decreasing in aggregate productivity. Assumptions leading to the results in this paper are consistent with body of empirical evidence on job matches and mismatches. Production and wages depend on both the worker and the vacancy type and all worker-vacancy combinations have the potential to generate positive output. These modeling decisions increase the competition for cognitive vacancies by decreasing the surplus amount required to sustain the pairing of a high-skill worker and a manual vacancy. The model in this paper is also similar to others in the literature that do not consider changes in aggregate productivity and focus instead on structural phenomenon such as skill-biased technological change (Albrecht and Vroman, 2002; Dolado et al., 2009).

The model is calibrated to the Canadian economy for the period 1997-2012 and shows that a single percentage point increase in unemployment leads to a 5.8 percentage point increase in the manual task share. Precisely because of this increase in manual tasks, overqualification increases by 3.5 percentage points. Model predictions have several distinct advantages over reduced-form empirical evidence, including the ability to account for the potential endogeneity of job tasks through individual occupational choices and the ability to provide general equilibrium effects. The joint nature of job formation decisions suggests that the latter is non-trivial. Unemployment benefits are examined as a potential policy response to cyclical overqualification. The policy experiment shows that increased unemployment benefits may compound, rather than alleviate, the incidence of overqualification in a downturn. Increased benefits make unemployment more attractive for workers and raise the surplus required to sustain a match. This favors manual task vacancies because their lower posting costs make them profitable at lower levels of output.

Cyclicality on both sides of the labor market could affect overqualification. The skill supplied by job applicants has been shown to be cyclical (see Barlevy (2001); Devereux (2004) for example). Data on job-to-job transitions high-skill workers move up the ladder in an upswing to jobs which pay more (Devereux, 2002). Measures of firm or occupational "quality" have been used in the existing literature to suggest changes in job characteristics (Kahn, 2010; Speer, 2016). However, wage-based measures of job characteristics are likely subject to influence from worker skills and other firm-level factors. The task-based approach in this paper is important because it provides a more nuanced understanding of the demand for skills that is rooted in the job itself.

Literature demonstrating the cyclicality of skill demand (or job tasks) is relatively sparse. Jaimovich and Siu (2012) show that labor market polarization is concentrated during recessions where the destruction of routine-task jobs is concentrated. Devereux (2000) finds that firms re-assign their existing workers to "lower" tasks in a downturn. One innovation of this paper is to show that job formation also affects the cyclicality of tasks.[1] The focus on job creation

[1]Cyclical task changes from new job creation during the Great Recession could include low-skill construction jobs, so-called "shovel-ready" infrastructure projects. The American Recovery and Reinvestment Act of 2009

is further motivated by evidence that cyclicality among unemployment rates is dominated by flows *out* of unemployment (see Shimer (2012) for the US and Campolieti (2011) for Canada).

Skill demand is difficult to analyze empirically because job vacancy data detailed enough to distinguish job tasks are relatively uncommon.[2] One exception is the state of Minnesota where region-level occupation-based vacancy data are available for the period 2005-2013. Figure 1 demonstrates that the share of manual tasks among posted job vacancies is higher in regions with high unemployment rates. Although the data are specific to one US state, they provide important evidence of the cyclicality of job tasks and motivate further analysis. The combination of Canada's LFS and the O*NET yields data with large sample sizes and detailed occupational task information that facilitate the analysis in this paper.

The paper contributes to the literature linking job match quality and economic conditions by providing Canadian evidence to accompany existing findings from the US (Acemoğlu, 1999; Bowlus, 1995; Hagedorn and Manovskii, 2013). Prior research on job match quality in Canada has been focused on describing the extent of overqualification across demographic groups and university fields of study and its implications for wages Yuen (2010); Finnie (2001); Boudarbat and Chernoff (2009); Uppal and LaRochelle-Côté (2014). The results of this paper also contribute to the literature relating wage penalties to past labor market conditions. Unemployment rates at hire, and during job spells, have been linked to worker wages in Canada, the US and Europe (McDonald and Worswick, 1999; Beaudry and DiNardo, 1991; Bellou and Basiş, 2012). Since manual task jobs pay less, the finding that cyclical task changes cause overqualification may help to explain the link between job match quality and future wage penalties described by Hagedorn and Manovskii (2013).

The rest of the paper proceeds as follows. Section 2 outlines the data and illustrates the relationship between tasks, overqualification and unemployment rates during job formation. Section 3 presents a search model which shows that overqualification changes because shares of job vacancies depend on economic conditions. In Section 4 the model is calibrated to the Canadian economy from 1997-2012. Quantitative predictions from aggregate productivity changes are provided and a policy experiment examines the consequences of changing unemployment benefits. Section 5 concludes.

detailed over $100 billion for infrastructure projects, including 27.5 billion for highway and bridge construction, $8 billion for intercity rail projects, $4.6 billion for flood protection and navigation, and $4 in wastewater treatment (Public Law 111-5, 2009). Canada's $30 billion stimulus spending included $12 billion devoted to immediate infrastructure projects requiring low-skill labor including the construction of roads and bridges, broadband internet access, electronic health records, laboratories and border crossings (Department of Finance, 2009).

[2]The Job Openings and Labor Turnover Survey (JOLTS) for the US and the Survey of Employment, Payrolls and Hours (SEPH) for Canada provide information by industry but not occupation.

2 Data and Empirical Motivation

This section demonstrates that past labor market conditions can be linked both to job match quality and to changing job tasks. Overqualification and the share of manual job tasks are defined and shown to correlate with regional unemployment rates at the time of job formation. Job match quality is also shown to depend on tasks, suggesting that tasks are one channel through which the business cycle affects overqualification.

2.1 Data

Analyzing the effect of economic conditions on a worker's job tasks and overqualification status requires particularly detailed data. Because tasks and job match quality are both determined when jobs are formed, it is appropriate to examine the effect of economic conditions during job formation.[3] Ideally, nationally representative data containing large samples of newly hired workers would be available. This data should also have large sample sizes within disaggregated occupation codes in order to develop measures of job tasks and overqualification. Many large datasets with a panel dimension, such as the Current Population Survey (CPS), may not contain a sufficient number of newly hired workers because the sampling windows for each individual are relatively short. Fortunately, Canada's Labour Force Survey (LFS) makes an alternative approach possible. The LFS contains consistent job tenure information for almost all employed workers. This variable allows a researcher to link currently observed workers to the labor market conditions they faced when their job was formed. An added benefit of this approach is that it allows for the analysis of jobs with substantial duration, precisely those which may be the most costly in the case of overqualification. Observing only contemporaneous hires may over-expose the sample to low quality matches that would not last long enough to be of consequence.

This paper uses monthly samples of employed workers from the LFS for the years 1997-2012. The data are restricted to employed males ages 16-65 and exclude those who are unionized, part-time, and self-employed following the literature relating past labor market conditions to future wages. The resulting sub-sample is focused around workers who are least likely to appear overqualified as a result of particular characteristics of their employer. Individuals are sampled for six months making it possible to link workers to form a short panel. Labor market conditions are generated from the confidential LFS at the Economic Region (ER) level using

[3] In the data, both job tasks and overqualification measures are occupation-based and therefore do not vary during the job duration. It is possible that employers may alter the tasks of employees without reassigning occupational titles. A substantial change of tasks, however, may reasonably be considered a new job or occupation. For an analysis of within-employer occupation changes see Devereux (2000).

counts of labor force participants, unemployed workers and sampling weights for the period 1987-2012. The sample is extended back in time to capture past labor market conditions available during all years for which consistent regional boundaries are retrospectively encoded.[4] Unfortunately the sample of employed workers cannot be extended to cover years prior to 1997 because many important worker characteristics, including wages, were not available for respondents prior to the survey redesign.

To demonstrate the importance of labor market conditions during job formation, sample means for workers with less that one month job tenure are presented in Table 1. Descriptive statistics are given separately for less-favorable labor markets, where the regional unemployment rate is above average, and more favorable labor markets with lower regional unemployment rates. Workers hired in less-favorable labor markets are slightly older with more experience, earn about \$0.6 CAD less per hour and are more likely to have some post-secondary education.

2.2 Cyclical Tasks

Task measures offer an alternative characterization of occupations by representing them as a bundle of basic job requirements that are present in all jobs with varying intensity. The task measures in this paper (which might also be called skill requirements) are represented by the vector S, containing 5 elements s^r denoted $r = 1, \ldots, 5$. Each of the r elements is a composite measure, or factor, generated from the "abilities" category of the O*NET data. The factor analysis procedure used to generate these measures is weighted so that a single standard deviation in any one task measure represents a standard deviation of that task in the Canadian occupation distribution. The procedure is similar to the approach of Poletaev and Robinson (2008) and is described in the Data Appendix. In this paper, the analysis focuses on the two most significant factors that together account for 62% of the variation in the Canadian occupation distribution. The first is a cognitive measure, representing reasoning and communication tasks. The second is a manual measure, representing sensory and physical coordination tasks.

The distribution of job tasks among employed workers appears to vary with labor market conditions. Figure 2 plots a moving average of the leading two task measures against the unemployment rate at the time of job formation. The share of manual tasks increases dramatically among those jobs which are formed in regional labor markets with high unemployment. The opposite may be true for cognitive tasks, although the pattern is somewhat less striking.

[4] Economic region is a Census geographic division. The data contain 73 ERs. An assumption is also made that the number of workers that re-locate outside of their current ER while staying with the current employer is negligible because workers crossing sampling boundaries are not identified with the same respondent code.

A more rigorous empirical examination suggests a causal link from regional unemployment rates to tasks. The empirical model

$$\bar{s}_{\ell t} = c_0 + c_1 u_{\ell t-k} + \bar{X}'_{\ell t} C_2 + \delta_\ell + \epsilon_{\ell t} \tag{1}$$

is estimated for the leading two task measures. The dependent variable $\bar{s}_{\ell t}$ is the average task share in region ℓ in month t. Unemployment rates when the job match was formed (in period $t-k$) are denoted by $u_{\ell t-k}$. The vector X includes time varying demographic controls at the regional level including education level shares, average experience and its quadratic, average job tenure and marital status shares. The parameters δ and τ represent economic region and time fixed effects, respectively. This specification isolates the change in task shares that may be attributed to within-region cyclicality in labor market conditions. Estimates in Panel A of Table 2 show that increased regional unemployment rates at the time of job formation decrease the relative cognitive task intensity. The corresponding effect on manual task shares is estimated in Panel B. Manual tasks are found to be robustly countercyclical at the regional level across all specifications. The estimated coefficients suggest that a single percentage point increase in the unemployment rate increases the manual task intensity of newly formed jobs by one-tenth of a standard deviation.

2.3 Cyclical Overqualification

A worker is considered to be overqualified if their years of educational attainment exceeds the "required" amount for their job. However, defining this required level of education is not straightforward and thus the overqualification literature does not yet agree on a single measure. This paper provides evidence from three conceptually different measures with the aim of capturing overqualification in a generally sense. According to the first measure, overqualified workers have educational attainment that exceeds the ratings of occupational experts in the O*NET data by at least one half of a standard deviation. This amounts to approximately one excess year of education.[5] The second measure uses information from the distribution of educational attainment within each occupation and is common in the literature. According to this measure, overqualified workers have educational attainment exceeding the occupational median by more than one standard deviation. The third and final measure is an adaptation of the measure proposed by Gottschalk and Hansen (2003) (GH). Overqualified workers are those with secondary school education or higher who work in an occupation that pays them an education premium

[5] Sensitivity tests reveal that the empirical results in this paper are robust to a range of definitions from 0.5-1.5 years of excess schooling.

below 10%.[6]

Overqualification appears to vary with regional unemployment rates in the Canadian data. The bottom panel of Table 1 shows new hires are more likely to be overqualified if they are in less favorable labor markets. Overqualification rates among in regional labor markets with above average unemployment rates are 24% using the O*NET measure, 38% using the median measure, and 62% using the GH measure. Corresponding rates for the more favorable labor markets are 22%, 35% and 61%.

Reduced form estimates provide more substantive evidence that regional labor market conditions affect overqualification. Individual level estimates for all three measures are given in Panel A of Table 3. Marginal effects evaluated at the mean from the probit model

$$Pr(OQ_{it}) = \Phi(a_0 + a_1 U_{\ell,t-k} + a_2 U_{\ell,t} + X_{it}' A_3). \tag{2}$$

are presented in columns 1-3. The parameter of interest, a_1, captures the effect of regional unemployment rates during job formation on a worker's propensity to be overqualified. Estimates are conditional on current unemployment rates, a vector of demographic characteristics X, and a full set of time and regional dummies. Standard errors are clustered at the region level. Estimates from the O*NET and median measures in columns 1 and 2 suggest that an increase in regional unemployment rates from 5% to 9% would increase in the probability of being overqualified by approximately half a percentage point. In the aggregate these impacts are economically significant.[7] A downturn of this magnitude would increase the number of overqualified workers in Canada by the entire population of Kingston. In the US, a comparable change would overqualify a population the size of Phoenix or Philadelphia. Estimates using the GH measure are almost six times larger. Larger impacts may be partly a result of wage compression during a downturns, which could reduce the number of jobs that pay substantial education premiums.

Conditional logit estimates in columns 4-6 show that the cyclical relationship is preserved when accounting for individual-specific heterogeneity. These estimates provide an important robustness check because unobserved characteristics are known to affect overqualification (Bauer,

[6] The education premium is given by the coefficient on a high school education dummy in a log-wage regression specific to the 4-digit occupation and year of observation. This measure assumes that an education premium is paid only when skills are required. Gottschalk and Hansen (2003) use college (or university) educated workers. However, the majority of post-secondary education is at the community college level in Canada. The wide variety of these programs and their vocational nature suggests that they may provide a poor measure of general skill. Therefore I measure overqualification at the high school level.

[7] Partial equilibrium effects on this scale are in line with others in the literature. For example, Oreopoulos et al. (2012) find that a single percentage point increase in regional unemployment rates at graduation induce job mobility at a rate of 0.003% and affect starting wages by 0.01-0.02%.

2002; Tsai, 2010; Iriondo and Pérez-Amaral, 2013). However, it is worth noting that conditional logit estimates identify a_1 using only those individuals whose overqualification varies over time. Thus, estimates reflect the cyclicality of overqualification only among job switchers.

This paper shows that cyclical job tasks are an important contributor to overqualification. Panel B presents descriptive evidence in favor of this argument by estimating equation (2) with the addition of the task measure vector, S. In the presence of task measures, the unemployment rate impacts from panel A are reduced across all specifications with the exception of column 5. In many cases they also become statistically insignificant. Tasks evidently displace some of the predictive power that past labor market conditions have for the propensity of overqualification. Instead, having accepted a job with lower cognitive and higher manual tasks increases the propensity of overqualification.[8] This paper offers one possible explanation for the scarring effect of entering the labor market during a downturn (Bowlus and Liu, 2003; Kahn, 2010; Liu et al., 2012; Oreopoulos et al., 2012). Both job match quality and wages may deteriorate in a downturn because of changes in the tasks among available jobs.

This evidence is not definitive because the empirical task measures, which are based on occupation codes, are unlikely to be exogenous. Conditional logit estimation may minimize selection issues but is unlikely to fully overcome them because occupational choice may be influenced by time-varying factors. The partial equilibrium nature of reduced form estimates are also limiting in this context. In light of the evidence that unfilled job vacancies also change with labor market conditions, they likely mask important firm behavior. For these reasons the analysis turns to a general equilibrium model in order to quantify the cyclicality of tasks and their subsequent effects on overqualification.

3 Model

This section outlines a job search framework that describes the incidence of overqualification in the labor market. The model features high and low-skill workers and cognitive and manual task job vacancies. The hierarchy in skill and tasks enables the model to describe overqualification, the share of high-skill workers in manual task jobs.[9] Taking into account aggregate productivity, firms choose whether to post a vacancy and which type of vacancy to post. Firms face a tradeoff

[8]The results are robust to alternative specifications with controls for immigrant status, temporary employment and various combinations of the task vector elements. The results were also found to be robust to the sample-selection estimator developed by Van de Ven and Van Praag (1981), which can account for potential underreporting of mismatches arising from job mobility. These results are available upon request.

[9]Other models adopting a "circular" view of mismatch, such as Barlevy (2002); Moscarini and Vella (2008); Gautier et al. (2010), do not rank skills or tasks.

in this decision because cognitive vacancies are more productive yet also more expensive. Given a fixed pool of workers, these decisions directly affect the incidence of unemployment and overqualification in equilibrium.

This model reproduces several important empirical facts about job match quality that are described by Sicherman (1991). These empirical facts are as follows: Overqualified workers earn more than workers that are well matched and underqualified workers earn more than they would have in their "more suitable" match, a manual task job. These facts suggest that job tasks affect production conditional on worker characteristics. They also suggest that most economies are likely to be in a "mixing" equilibrium where both over and underqualified matches form. This model is able to reproduce the empirical facts because the output of a match will depend positively on both the firm and worker type, each independently of the other. Other papers, such as Albrecht and Vroman (2002); Dolado et al. (2009); Gautier (2002), assume low skill workers are unproductive in cognitive vacancies, effectively ruling out underqualification. However, this assumption is at odds with the empirical finding that underqualified workers exist in large numbers across several countries (Leuven and Oosterbeek, 2011). Still other papers assume that a certain workers can and cannot be mismatched (Chassamboulli, 2011), or that wages differ by worker type because of differences in their unemployment benefits rather than their productivity Wong (2003).

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 task (or skill requirement) $s \in \{s_C, s_M\}$. Manual jobs s_M are less productive than cognitive jobs. The endogenous variable ϕ represents their share amongst all job vacancies. 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

$$m(u, v) = m(1, \theta)u, \qquad \theta = \frac{v}{u}$$

where u denotes the unemployment rate. Only unemployed workers search for jobs, meeting firms with empty vacancies at a rate of $m(\theta)$.

Cognitive and manual jobs dissolve according to the exogenous probabilities σ_C and σ_M, respectively. The model is able to deliver the desired predictions about firm behavior without the additional complexity of on-the-job search or endogenous job destruction. The interest rate in the economy is given by the parameter $r > 0$ and economic conditions are affected by changes in the productivity parameter z, which is also strictly positive.

Workers

In this economy there is a continuum of risk-neutral and infinitely lived workers of mass 1. The share ψ is exogenously assigned type x_L. Workers can be either employed or unemployed and the share of unemployed who are endowed with a low level of education is represented by γ. In a given period, an unemployed worker receives a present value return of

$$rU(x) = b + m(\theta)\big(\phi \max\{N(x, s_M) - U(x), 0\} + (1-\phi)\max\{N(x, s_C) - U(x), 0\}\big) \quad (3)$$

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

$$rN(x, s) = w(x, s) + \sigma_s\big(U(x) - N(x, s)\big) \quad (4)$$

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 fill with a worker, or remain empty at a cost of k_s. An empty vacancy of type s therefore gives a firm the present value return of

$$rV(s) = -k_s + \frac{m(\theta)}{\theta}\Big(\gamma \max\{J(x_L, s) - V(s), 0\} + (1-\gamma)\max\{J(x_H, s) - V(s), 0\}\Big) \quad (5)$$

The expected net return of a type s vacancy filled by a type x worker is given by

$$rJ(x, s) = zf(x, s) - w(x, s) + \sigma_s\big(V(s) - J(x, s)\big). \quad (6)$$

A filled vacancy produces $f(x, s)$. Output is characterized by the discrete pairings of x and s.

$$f(x, s) > \begin{cases} f(x', s) & if \quad x' < x \\ f(x, s') & if \quad s' < s \end{cases}$$

More output is produced with higher x or s. This is suggested by the empirical record on wage determination. Workers who are overqualified, still earn slightly more than properly qualified workers on average, but less than they would have earned in a job more suited to their skill level. It is reasonable to assume that more educated workers are more productive than less educated workers, regardless of the job. Additionally, a cognitive job may be more productive than a manual job because technological advances allow for the use of more sophisticated forms of capital. For example, a manual laborer in a factory may be less productive than an engineer who can program robots to perform similar tasks. An overqualified worker is denoted by the pair $\{x_H, s_M\}$ because a highly educated worker would have been more productive and earned higher wages in a cognitive task job.

Wage Determination

Following the literature, wages are determined by Nash bargaining. The parameter β represents the worker's share of the total surplus created by a match.

$$N(x,s) - U(x) = \beta[N(x,s) + J(x,s) - U(x) - V(s)] \tag{7}$$

Substituting equations (3)-(6) into the bargaining equation and following the steps outlined in Appendix Section A.1, an expression for the wage of worker x in vacancy s is found:

$$w(x,s) = \beta z f(x,s) + (1-\beta) r \left(\frac{b + z\beta m(\theta)\left[\frac{\phi}{r+\sigma_M} f(x,s_M) + \frac{1-\phi}{r+\sigma_C} f(x,s_C)\right]}{r + r\beta m(\theta)\left[\frac{\phi}{r+\sigma_M} + \frac{1-\phi}{r+\sigma_C}\right]} \right) \tag{8}$$

Because the output of high and low-skill workers differs in both types of vacancies, the current model is able to generate an education premiums in cognitive and manual jobs. This feature is important because it is consistent with the empirical literature. Wages have been shown to depend on both worker and job characteristics and almost all occupations pay an education premium for college educated workers in the US (Allen and van der Velden, 2001; Gottschalk and Hansen, 2003).[10]

3.2 Equilibrium

Multiple equilibria are possible in a search model with two sided heterogeneity (Wong, 2003). I examine only the "mixing" equilibrium because this is the equilibrium that is supported by the data. The equilibrium features well matched, overqualified and underqualified workers. It will turn out that the parameter values from calibrating the model in Section 4 also support this equilibrium.

To support mixing, high-skill workers must be willing to accept manual task jobs. For the first to be true, high-skill workers must earn high enough wages in manual task jobs or have

[10] One limitation of this approach is that the model does not predict different unemployment rates across worker types.

low enough unemployment benefits so that they are unwilling to wait for a cognitive task job to arrive. In other words the marginal cost of rejecting the overqualified job opportunity must be higher than the marginal benefit of waiting for a suitable match. It is reasonable to assume that this assumption should hold as long as the generosity of unemployment benefits is limited, or if the productivity of the high-skill worker is still high enough in a manual task job to generate a sufficiently large education premium. Firms that post cognitive vacancies must also be willing hire low-skill workers if the two should meet. The expected surplus of an $\{x_L, s_C\}$ pairing should not be lower than the alternative pairing $\{x_H, s_C\}$. The lower wages paid to low-skill workers and the production process depending relatively more on the task of the job (physical capital) than on the worker skill (human capital) make this possible. Differences in job posting costs help to support a mixing equilibrium because lower posting costs prevent manual task jobs, that generate lower output, from being unambiguously less attractive to the firm.[11] Proofs are formally presented in Appendix section A.3.

In equilibrium, firms are assumed to have free entry into either type of vacancy. Also, because $\dot{u} = 0$, the flow into and out of unemployment at any given time must be equal for each type of worker.

$$m(\theta)(1-\gamma)u = (1-\psi-(1-\gamma)u)(\phi\sigma_M + (1-\phi)\sigma_C) \tag{9}$$

$$m(\theta)\gamma u = (\psi - \gamma u)(\phi\sigma_M + (1-\phi)\sigma_C) \tag{10}$$

Equilibrium conditions 9 and 10 can be solved for γ and u to obtain:

$$u = \frac{(\phi\sigma_M + (1-\phi)\sigma_C)}{m(\theta) + (\phi\sigma_M + (1-\phi)\sigma_C)} \tag{11}$$

$$\gamma = \psi \tag{12}$$

Expression (11) is simply the Beveridge curve condition. The common unemployment pool for both worker types means that all workers have the same job finding probability. This symmetry explains why the share of unemployed x_L workers is equal to the overall share of x_L workers in the population in equation (12).

The two free entry conditions, $V(s_M) = 0$ and $V(s_C) = 0$ can be combined to find:

$$\phi = \frac{k_C(r+\sigma_C)[b - zrF_M] - k_M(r+\sigma_M)[b - zrF_C]}{zr\beta m(\theta)[F_M - F_C](k_M - k_C)} + \frac{k_C}{k_M - k_C} \tag{13}$$

[11] It is possible to support the mixing equilibrium with a single posting cost provided that job separation rates are sufficiently different. However, it is perhaps less palatable to place constraints on job destruction rates.

where

$$F_M = \gamma f(x_L, s_M) + (1-\gamma) f(x_H, s_M)$$

$$F_C = \gamma f(x_L, s_C) + (1-\gamma) f(x_H, s_C)$$

Finally, equation (13) can be substituted back into either free entry condition to obtain an expression for labor market tightness:

$$\theta = \frac{m(\theta)(1-\beta)z(F_M - F_C)}{(r+\sigma_M)k_M - (r+\sigma_C)k_C} \tag{14}$$

A solution for the equilibrium triplet $\{u, \theta, \phi\}$ follows from (11), (13) and (14). Appendix Section A.4 derives a closed form solution, assuming Cobb-Douglas matching.

3.3 Economic Conditions and Productivity

Aggregate productivity in the model is given by the parameter z. Because the model solution describes a steady state, I follow Pissarides (2009), Shimer (2005) and others approximating cyclicality by comparing steady states. Equation (14) shows that a low state, z', will have fewer vacancies per unemployed worker relative to a high state, z, whenever cognitive jobs are more expensive to post and yield higher expected output than manual jobs. Since $m(\theta)$ is increasing in θ and is itself located in the denominator of the Beveridge curve condition, unemployment rates rise with productivity. Adopting the Cobb-Douglas meeting function $m(\theta) = \theta^{1-\xi}$, which is common in the literature, equation (14) can be written as:

$$\theta^{\xi} = \frac{(1-\beta)z(F_M - F_C)}{(r+\sigma_M)k_M - (r+\sigma_C)k_C}.$$

With this matching technology it is straightforward to show that

$$\frac{\partial \theta}{\partial z} = \frac{z^{\frac{1-\xi}{\xi}}}{\xi}\left(\frac{(1-\beta)(F_M - F_C)}{(r+\sigma_M)k_M - (r+\sigma_C)k_C}\right)^{\frac{1}{\xi}}$$

is positive. Partial differentiation of (13) shows that the share of manual vacancies will increase when $\frac{\partial \theta}{\partial z} > 0$, as shown above.

$$\begin{aligned}\frac{\partial \phi}{\partial z} = &-\frac{m'(\theta)\frac{\partial \theta}{\partial z}[F_C k_M (r+\sigma_M) - F_M k_C (r+\sigma_C)]}{(F_M - F_C)[k_M - k_C]\beta m(\theta)^2} \\ &+\frac{b[k_M(r+\sigma_M) - k_C(r+\sigma_C)]\left\langle z m'(\theta)\frac{\partial \theta}{\partial z} + m(\theta)\right\rangle}{r\beta(F_M - F_C)(k_M - k_C)z^2 m(\theta)^2}\end{aligned} \tag{15}$$

This comparative static is negative when $k_C(r + \sigma_C) > k_M(r + \sigma_M)$ and $F_M k_C(r + \sigma_C) < F_C k_M(r + \sigma_M)$.[12] The first condition requires the discounted cost of posting a cognitive vacancy to be greater than the discounted cost of posting a manual vacancy. Pissarides (1994) also assumes that higher paying jobs are more costly to post. It is reasonable to assume that cognitive-type jobs may be contracted to head-hunting agencies that charge placement fees, or advertised in expensive circulars such as *The Economist*. By contrast, manual-type jobs are more likely to be advertised inexpensively in local newspapers or on-line job banks. Other recruiting costs including the interview process are also likely to be higher for jobs with a high cognitive task intensity. The interpretation of the second condition is that the expected productivity gains of a cognitive job over a manual job must outweigh the additional job posting costs.

Overqualification in the model is represented by the share of x_H workers in s_M jobs and is given by the expression

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

which simplifies to

$$(1 - \gamma)\phi. \tag{17}$$

This expression shows that overqualification should depend on worker types, ψ, and the tasks of vacancies, ϕ, rather than directly upon labor market conditions. Because ϕ is a function of θ, task changes are the mechanism by which cyclical economic conditions are transmitted to job match quality. In other words, overqualification depends on the relative demand for different types of skill, rather than depending directly on labor market tightness. This mechanism is consistent with the empirical evidence offered in Section 2.3.

One consequence of an economic downturn may be more overqualification. The model generates variation in job match quality across economic states in part because higher unemployment rates imply longer search durations, increasing the waiting costs for unemployed high-skill workers. The amount of surplus required to support a match decreases, making it more likely that high skill workers will accept the lower paying manual task jobs. This may benefit the firm. High-skill workers are still able to increase output because $f(x_H, s) > f(x_L, s)$. The firm experiences some benefit from a high-skill worker without paying the costs associated with a cognitive vacancy. Allowing low-skill workers to match with cognitive jobs, the case which is ruled out in other similar models, increases this benefit for the firm and is an important reason for the vacancy posting behavior described by this model. Low-skill workers take some of the

[12] These conditions are discounted versions of the prior assumptions that $F_M < F_C$ and $k_M < k_C$.

cognitive job offers, further increasing the cost high-skill workers face if they wait for a more "suitable" offer.

The importance of vacancy posting costs is also apparent in expression (15). As z decreases, the marginal benefit of posting both job types falls relative to fixed marginal posting costs. At low enough z, cognitive jobs may become less lucrative than manual jobs even if they are more lucrative when productivity is high. Figure 3 illustrates this intuition in a highly simplified setting. The productivity threshold at which costs exceed output for manual jobs, z_M, is lower than the comparable threshold for cognitive jobs z_C. At $z > z^*$, cognitive jobs are more lucrative while the opposite is true when $z < z^*$.

4 Calibration

Using the LFS data, the model is calibrated to match the Canadian economy during the period 1997-2012. The share of low-skill workers, $\gamma = 0.447$, is derived from the share of employed males with high school education or less. The quarterly interest rate of $r = 0.008$, matches the Bank of Canada 10 year bond rate.[13] Unemployment benefits are set at 55%, the basic rate awarded by Canadian employment insurance. For simplicity, I follow the literature and assign equal bargaining power, $\beta = 0.5$, to firms and workers. The matching function is parameterized as a Cobb-Douglas, $m(\theta) = \theta^{1-\xi}$, and the aggregate productivity parameter, z, is normalized to 1. The job arrival rate is derived from an unemployment duration of 1.469 quarters, which is the average value for workers in the sample. Using the observed average job duration quarters and the economy average unemployment rate of 7.2%, the aggregate separation rate is 0.048. Using the observation that manual jobs in the LFS separate at exactly twice the rate of cognitive jobs and adjusting weights for the relative shares of cognitive and manual jobs, the individual job destruction rates are $\sigma_M = 0.056$ and $\sigma_C = 0.033$.

Several other parameters in the model do not have an intuitive counterpart in the Canadian data. These are calibrated by matching other statistics against the LFS data. Normalizing the output of a low skill manual job, $f(x_L, s_M) = 1$, I derive the other output quantities, the matching elasticity, and vacancy posting costs $k_M = 0.193$, $k_C = 0.339$ from the relative wages of corresponding matches, the unemployment rate, the share of manual skill vacancies and the job arrival rate. The share of cognitive and manual vacancies in the data is determined by assigning occupations to the manual category if the relative magnitude of the leading manual task measure s^2 exceeds the leading cognitive measure s^1.

[13]This information is taken from the period April 2005-March 2014, where the average annual interest rate was 0.032.

The calibration results are detailed in Table 4. Panel A shows the calibrated parameters and Panel B compares the moments used to calibrate these results to their values in the LFS data. The model matches the data well for u, ϕ and $m(\theta)$. Wage ratios are less accurate because the education premium in manual skill jobs is too low. However, the calibration reproduces the correct ranking of wages, rewarding high-skill over low-skill labor and cognitive over manual tasks. The calibrated values for production are ranked: $f(x_H, s_C) > f(x_L, s_C) > f(x_H, s_M) > f(x_L, s_S)$. This ranking suggests that job tasks contribute more to productivity than worker skills. Such a ranking may reflect the potential of workers to adapt to their jobs, while the machinery on the job is unlikely to adapt to the worker.

4.1 The Effects of a Productivity Change

Changes in the productivity parameter demonstrate the model's behavior across economic conditions. When productivity falls, characterized by a decrease in the parameter z, unemployment increases, the job matching rate falls and the number of vacancies decreases. Of particular interest is the relative share of manual skill vacancies, ϕ. As the unemployment rate rises due to a fall in productivity, firms increase the relative share of manual skill jobs. The behavior of the calibrated model is consistent with the comparative static discussed in Section 3.3 because the calibrated parameter values satisfy the assumptions discussed there.

The model is used to make quantitative predictions about overqualification in a downturn. Consider Case V in Table 5, which corresponds to average economic conditions in Canada for the period 1997-2012. With an unemployment rate of 7% roughly 60% of the job vacancies favor manual tasks and the model economy has an overqualification rate of 33%. A productivity decrease, leading to a single percentage point increase in the unemployment rate, moves the model economy to a state where the share of overqualified workers rate rises to just over 36% (Case II). Overqualification rises because of the share of manual vacancies increases to almost 66%. This is a general equilibrium response that includes changes in the number of employed workers, the overall number of vacancies, and the share of manual vacancies. The model also predicts an increase in the fraction of separations that are attributed to manual jobs. In a downturn there is more turnover among manual task jobs, which then fill with high-skill workers. Increased turnover among manual jobs was apparent during the Great Recession in the US when construction and manufacturing accounted for almost half of all layoffs (Şahin et al., 2014). It is also consistent with recent findings that suggest economic downturns are when "routine" task jobs, which are more likely be of the manual flavor, are destroyed (Autor, 2010; Jaimovich and Siu, 2012).

4.2 Policy Experiment: Unemployment Benefits

This section uses the model to suggest how changes in the generosity of unemployment benefits might affect Overqualification. Unemployment benefits are often manipulated during recessions in order to smooth the impact of cyclical job losses. The average extension to the unemployment benefit in the US during the Great Recession was 83 weeks and in Canada the benefit amount is based on the local unemployment rate. Conventional wisdom suggests that increased generosity might alleviate mismatch by affording workers longer search periods during which to overcome matching frictions.

In this model, increases in unemployment benefits may not improve job match quality. The comparative static

$$\frac{\partial \phi}{\partial b} = \frac{k_C(\sigma_C + r) - k_M(\sigma_M + r)}{zr\beta m(\theta)[F_M - F_C](k_M - k_C)}$$

reveals that the firms expected costs for cognitive jobs matter. Whereas Hagedorn et al. (2013) show that the *quantity* of job vacancies created decreases with benefit generosity, this policy experiment suggests that the *type* of job vacancies created changes as well. Because cognitive jobs are more expensive for the firm to post and fill, firms may increase the share of manual skill jobs they post leading to more mismatch.[14] When benefits are more generous it takes more surplus to overcome a worker's reservation wage. If posting costs are high relative to productivity, which may be the case for cognitive vacancies when aggregate productivity is low, cognitive vacancies may be less feasible to post.

This propensity to firms reduce the share of manual skill jobs dampens the effect of productivity changes on overqualification. Table 6 below compares the quantitative predictions of the model to productivity changes under different unemployment benefit values, b. The first rows show the predictions of the model as calibrated in the previous section with $b = 0.55$. A fall in the productivity parameter by 0.16 leads to a single percentage point increase in the unemployment rate. Firms respond by increasing the share of manual skill jobs by 5.8 percentage points and overqualification rises by 3.5 percentage points. Rows 3 and 4 depict an equivalent fall in z under a regime of lower unemployment benefits ($b = 0.5$). With lower benefits, workers take jobs more freely and there is less unemployment overall. However, the market is less volatile. The comparable productivity decrease increases unemployment by slightly less than before, 0.9 percentage points. The share of manual job vacancies also starts lower, $\phi = 0.55$ and increases less. The comparable downturn increases the share of manual skill jobs by only 4.3 percentage points, instead of 5.8, and increases overqualification by 2.4 percentage points instead of 3.5.

[14]These findings differ from circular models of mismatch, such as Marimon and Zilibotti (1999), where increases in unemployment benefits decrease mismatch in a recession.

Lines 5 and 6 show the converse case where unemployment benefits increase to $b = 0.6$. In this case, the response of u, ϕ, and overqualification to a change in z are amplified.

5 Conclusion

This paper establishes stylized facts about job formation in economic downturns using data from Canada's LFS and the O*NET. The relative share of employment in manual task-intensive jobs increases with the regional unemployment rate during job formation. The empirical evidence suggests that job tasks are an important transmission mechanism by which economic conditions affect overqualification rates. General equilibrium effects from the calibrated search model show that firms may exploit their relatively favorable position in the labor market during a downturn. They are able to hire high-skill workers in lower paying manual task jobs, increasing overqualification rates. These predictions are new to the literature and arise from the model because of alternative assumptions that may be considered more consistent with the empirical evidence on job matches and mismatches.

The framework in this paper may help to explain why overqualified workers suffer wage penalties. Manual task jobs are lower paying jobs and the findings in this paper suggests that jobs formed in a recession will be dis-proportionately of this type. The potential surplus of a job match may be restricted by the task even if workers supply a high level of skill. The mechanism proposed in this paper is also consistent with a scarring effect from graduating during a recession. Overqualification in the initial job could be one reason for wage penalties among recent graduates. Persistent wage penalties may follow among those who remain in their initial job and for those whose career trajectory is affected by the initial match.

This paper suggests a limited scope for policy aimed directly at reducing overqualification. First, overqualification represents an alternative to unemployment and therefore may be a welfare improving option for some workers. The model in this paper predicts that overqualification increases in a downturn because workers are not willing to wait for a better job offer to arrive. Second, the policy experiment conducted in this paper challenges the conventional wisdom that increased unemployment benefits would improve job matches by affording workers a longer search period. Instead, a longer search duration decreases the expected value of posting a job and induces firms to post the lower-cost manual type job vacancies. Finally, the cyclical component of overqualification can be expected to decrease in the recovery phase as the share of cognitive vacancies increases. Reductions in cyclical overqualification are perhaps best addressed as part of the greater effort to dampen business cycle fluctuations.

Important areas for further research remain. The analysis could be extended to measures of job match quality besides overqualification. The education-based measures in this paper are relevant to policymakers interested in subsidizing levels of education because "excess" education is indicative of idle skill and foregone productivity. However, field of study or the quality of educational institutions where degrees have been obtained may also affect job match quality. Other dimensions, such as geography or individual preferences, may be important in fully characterizing the match between a worker and their job, although Green and McIntosh (2009) find that overqualification "on paper" coincides with unused skill in practice for 47% of workers. The empirical results in this paper focus on filled job vacancies because the analysis of unfilled vacancies is beyond the scope of nationally representative data currently available for the US or Canada. Testing the findings of this paper with detailed job vacancy data therefore remains an important avenue for future research.

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Table 1: Recently hired males in Canada 1997-2012.

Personal Characteristics	**Region Unemployment Above Average** mean	se	n	**Region Unemployment Below Average** mean	se	n
Age	31.999	(0.034)	120704	31.016	(0.027)	185606
Experience	12.328	(0.034)	120704	11.455	(0.026)	185606
Job Tenure	2.541	(0.003)	120704	2.583	(0.002)	185606
Real Wage	12.610	(0.001)	120704	13.215	(0.001)	185606
Educ: LHS	0.198	(0.001)	120704	0.193	(0.001)	185606
Educ: HS	0.328	(0.001)	120704	0.383	(0.001)	185606
Educ: PS	0.319	(0.001)	120704	0.279	(0.001)	185606
Educ: BA	0.155	(0.001)	120704	0.145	(0.001)	185606
OQ Measures						
O*NET	0.242	(0.001)	91822	0.216	(0.001)	139768
Median	0.383	(0.001)	120704	0.345	(0.001)	185606
GH	0.622	(0.002)	70890	0.605	(0.001)	113356

Source: LFS 1997-2012, males with job tenure less than one month, age 16-65, reporting wage and occupation. Sample split at the average regional unemployment rate for new-hires, which is 7.6%. Public sector employees, self-employed and unionized workers are excluded. Age and potential experience measured in years, job tenure measured in weeks. Education categories are less than high school (LHS), high school (HS), non-university post-secondary (PS) and university degree of higher (BA). Real wages exclude zeros. OQ measures are binary indicators for overqualification that are detailed in Section 2.3 of the text.

Table 2: The Effect of Local Unemployment Rates on Job Tasks

Panel A: COG Task Measure	$\bar{s}^1$ (1)	$\bar{s}^1$ (2)	$\bar{s}^1$ (3)	$\bar{s}^1$ (4)
Urate at Hire × 100	-1.939***	-0.269	-0.108	-0.432***
	(0.252)	(0.531)	(0.115)	(0.134)
Region FE	✓	✓	✓	✓
Time FE		✓		✓
Dem. Controls			✓	✓
N	14010	14010	14010	14010
R^2	0.643	0.807	0.722	0.736

Panel B: MAN Task Measure	$\bar{s}^2$ (1)	$\bar{s}^2$ (2)	$\bar{s}^2$ (3)	$\bar{s}^2$ (4)
Urate at Hire × 100	0.912***	0.975**	0.746***	1.019***
	(0.327)	(0.393)	(0.135)	(0.161)
Region FE	✓	✓	✓	✓
Time FE		✓		✓
Dem. Controls			✓	✓
N	14010	14010	14010	14010
R^2	0.683	0.813	0.817	0.820

Source: Canadian LFS 1997-2012 and O*NET 17.0. Cell-level data by economic region and month. Estimates are the impact of regional unemployment rates when jobs were formed on the regional shares of cognitive and manual task measures, s^1 and s^2 receptively. Task measures are the two leading components from factor analysis on O*NET ability requirements described in the text in Section 2.2. Coefficients $\times 100$. Standard errors in parentheses are robust to heteroskedasticity. Demographic controls are cell-level means of potential years of experience, a marital status indicator, job tenure in months and years of education. Estimates also conditioned on current unemployment rates.

Table 3: Unemployment rates at Hire and the Probability of Overqualification

	Probit			**Conditional Logit**		
	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Panel A:	O*NET	Median	GH	O*NET	Median	GH
Without Tasks	(1)	(2)	(3)	(4)	(5)	(6)
Urate at	0.071**	0.035	0.296***	1.995***	2.541***	2.306***
Hire × 100	(0.036)	(0.049)	(0.099)	(0.858)	(0.767)	(0.685)
Current Urate	✓	✓	✓	✓	✓	✓
Dem. Controls	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓			
Time FE	✓	✓	✓			
Year FE				✓	✓	✓
N	1450984	1744784	1007150	99102	51487	115820
Pseudo R^2	0.025	0.139	0.044			

Panel B:						
With Tasks	(1)	(2)	(3)	(4)	(5)	(6)
Urate at	-0.016	0.018	0.164	1.038	3.276**	1.930**
Hire × 100	(0.032)	(0.052)	(0.104)	(1.635)	(1.311)	(0.853)
s^1(COG)	-0.174***	0.002	-0.191***	-3.591***	-2.744***	-1.433***
	(0.005)	(0.004)	(0.002)	(0.057)	(0.039)	(0.021)
s^2(MAN)	0.052***	-0.002	0.097***	1.152***	1.534***	0.713***
	(0.005)	(0.002)	(0.004)	(0.034)	(0.029)	(0.018)
s^3(MAN)	0.074***	-0.009***	0.066***	1.545***	1.380***	0.406***
	(0.002)	(0.002)	(0.002)	(0.035)	(0.028)	(0.018)
s^4(MAN)	-0.002***	-0.015*	-0.174***	-0.080***	-0.485***	1.242***
	(0.003)	(0.008)	(0.002)	(0.028)	(0.023)	(0.022)
s^5(COG)	-0.027***	-0.024***	0.002	-0.565***	-0.181***	0.157***
	(0.002)	(0.003)	(0.005)	(0.029)	(0.021)	(0.019)
Current Urate	✓	✓	✓	✓	✓	✓
Dem. Controls	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓			
Time FE	✓	✓	✓			
Year FE				✓	✓	✓
N	1450984	1744784	1007150	99102	51487	115820
Pseudo R^2	0.445	0.142	0.259			

Source: Canadian LFS 1992-2012. Measures of overqualification (OQ) are binary and described in the text in Section 2.3. Urate at hire is the regional unemployment rate when workers obtained their job. Coefficients scaled up ×100. Columns 1-3 contain probit marginal effects evaluated at the mean. Columns 4-6 contain conditional logit coefficients instead of marginal effects because no constant term is estimated. Demographic controls include dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status and job tenure. Results also conditional on current regional unemployment rate. Standard errors in parentheses clustered at the economic region. s^1-s^5 are task measures from the O*NET described in the text in Section 2.2. Time dummies monthly. Results weighted with LFS final weights.

Table 4: Calibration Results

Panel A: Parameters Calibrated from Model Moments

Model Element	Parameter	Calibrated Value
Low worker Cog Job Output	$f(x_L, s_C)$	1.139
High worker Man Job Output	$f(x_H, s_M)$	1.080
High worker Cog Job Output	$f(x_H, s_C)$	1.198
Manual Posting Cost	k_M	0.138
Cognitive Posting Cost	k_C	3.314
Cobb-D Matching Parameter	ξ	0.627

Panel B: Calibrated Model Moments

Model Element	Variable	Model	Data
Unemployment Rate	u	0.072	0.072
Share Man vacancies	ϕ	0.600	0.600
Prob. Find a Job	$m(\theta)$	0.671	0.671
Wage Ratios	$w(x_L, s_C)/w(x_L, s_M)$	1.072	1.046
	$w(x_H, s_M)/w(x_L, s_M)$	1.072	1.150
	$w(x_H, s_C)/w(x_L, s_M)$	1.133	1.159

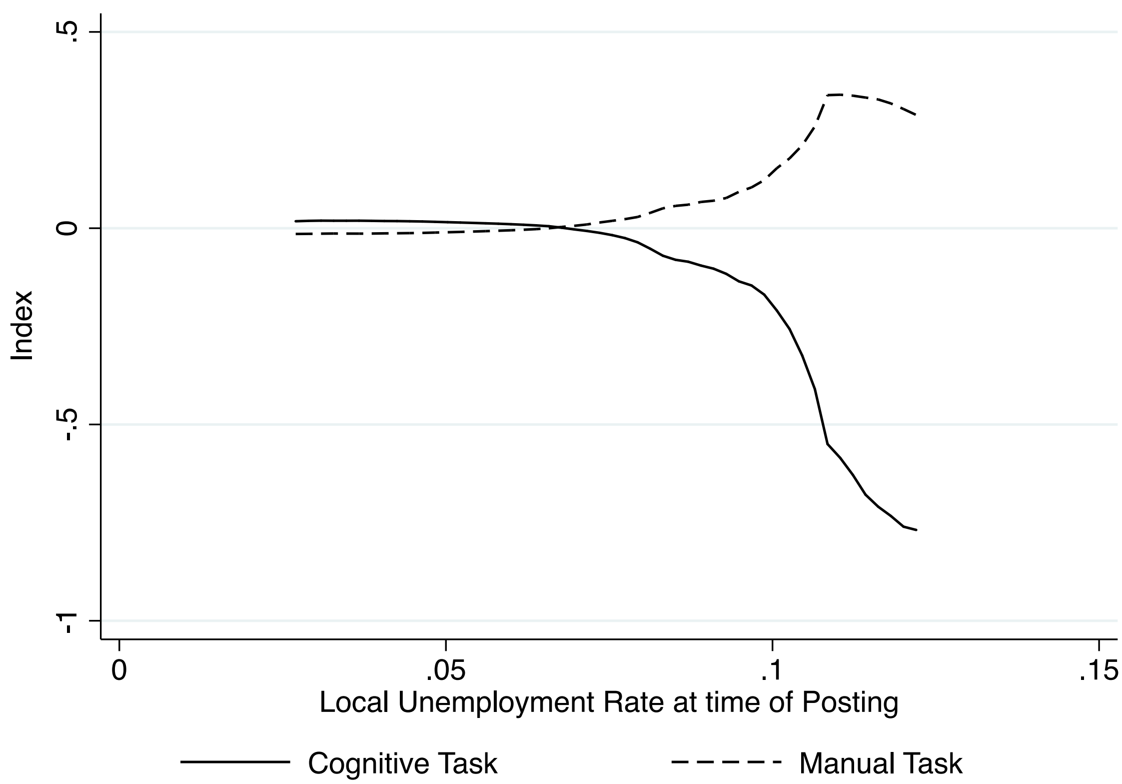
Table 5: Productivity Changes

Case	z	u	ϕ	$m(\theta)$	OQ	$\phi\sigma_M$	$(1-\phi)\sigma_C$
I	0.8000	0.0851	0.6810	0.5877	0.3766	0.0443	0.0104
II	0.8400	0.0818	0.6582	0.6050	0.3640	0.0428	0.0111
III	0.9400	0.0751	0.6170	0.6470	0.3412	0.0401	0.0124
IV	1.0000	0.0719	0.6003	0.6713	0.3319	0.0390	0.0130
V	1.0400	0.0700	0.5916	0.6871	0.3271	0.0385	0.0133
VI	1.1700	0.0649	0.5732	0.7371	0.3170	0.0373	0.0139
VII	1.1800	0.0645	0.5723	0.7408	0.3165	0.0372	0.0139
VIII	1.3300	0.0601	0.5641	0.7956	0.3120	0.0367	0.0142

Table 6: Productivity Changes at different values of b

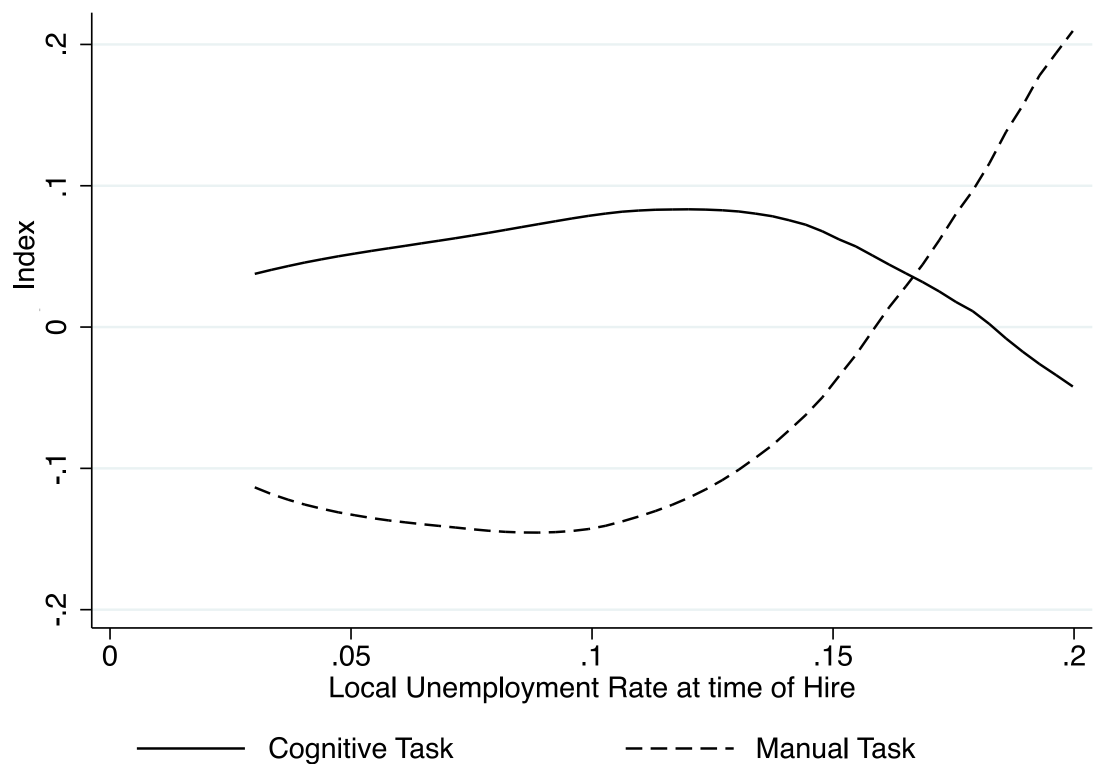
b=0.55	z	u	ϕ	$m(\theta)$	OQ	$\phi\sigma_M$	$(1-\phi)\sigma_C$
	1.0000	0.0719	0.6003	0.6713	0.3319	0.0390	0.0130
	0.8400	0.0818	0.6582	0.6050	0.3640	0.0428	0.0111
b=0.50							
	1.0000	0.0700	0.5545	0.6713	0.3066	0.0360	0.0145
	0.8400	0.0790	0.5977	0.6050	0.3305	0.0389	0.0131
b=0.60							
	1.0000	0.0738	0.6461	0.6713	0.3573	0.0420	0.0115
	0.8400	0.0845	0.7186	0.6050	0.3974	0.0467	0.0091

Figure 1: Cyclical Tasks among Posted Job Vacancies in Minnesota



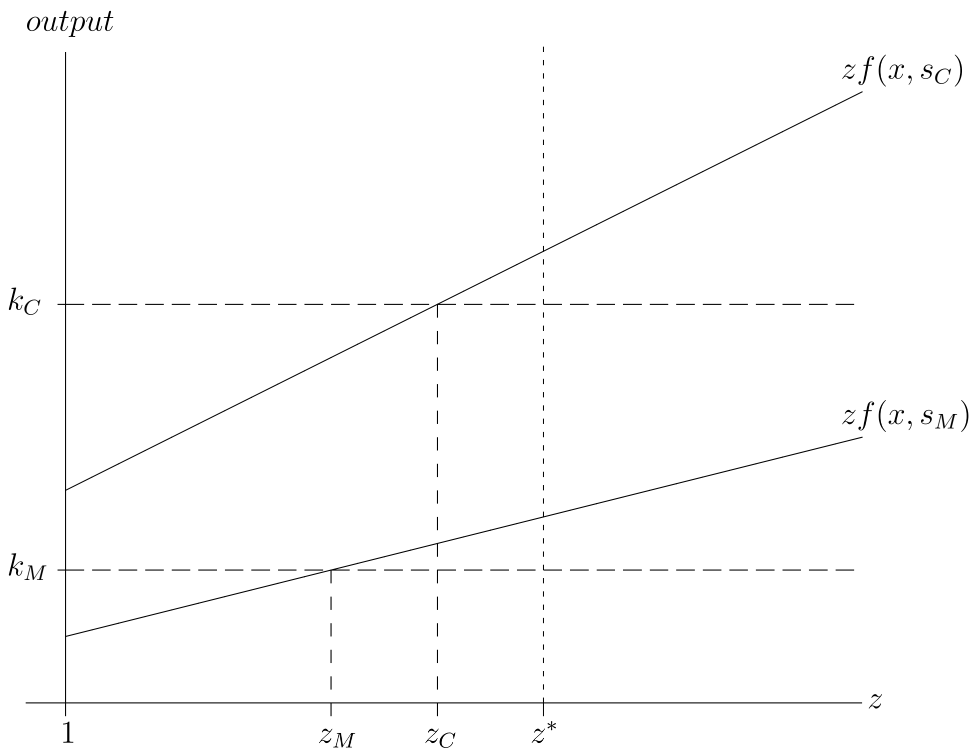
Plots are local moving averages of cognitive and manual task measures among of posted job vacancies in the state of Minnesota (on the Y axis) against the regional unemployment rates (on the X axis). The smoother uses an Epanechnikov kernel with a bandwidth of 0.15. Task measures are the leading factors from a factors analysis procedure carried out on the O*NET "ability requirements" data. Unemployment rates are sourced from the Minnesota Local Area Unemployment Statistics at the Economic Development Region level. Job vacancy counts are from the Minnesota Job Vacancy Survey. Data are available biannually for the period 2005 - 2013.

Figure 2: Task Measures and Local Economic Conditions During Job Formation



Plots are local moving averages relating the shares of cognitive and manual tasks among filled jobs in Canada to regional unemployment rates at the time these jobs were formed. The smoother uses an Epanechnikov kernel with bandwidth 0.015. Task measures are the leading factors from a factors analysis procedure carried out on the O*NET "ability requirements" data. A single standard deviation represents the population standard deviation of that particular task. Regional unemployment rates are measured monthly at the Economic Region (ER) level from the period 1987-2012. Results are trimmed to the range (3-20%).

Figure 3: Output and posting costs of Vacancies by Type



The firm's marginal benefit of posting a cognitive or manual job is represented by the expected output, zF_C and zF_M. Job posting costs are fixed amounts k_C and k_M. The point z^* represents the productivity level at which the marginal benefit exceeds the marginal cost by the same amount for both job types.

A Model Solutions Appendix

A.1 Wages

In the mixing equilibrium the value of employment exceeds unemployment. Free entry among firms ensures that the value of a filled vacancy is always positive. Re-arranging (6) and (4) leads to the expressions:

$$N(x,s) = \frac{w(x,s) + \sigma_s U(x)}{r + \sigma_s} \tag{A.1}$$

$$J(x,s) = \frac{zf(x,s) - w(x,s)}{r + \sigma_s} \tag{A.2}$$

Substituting these simplified expressions into the wage sharing condition (7) gives the following expression:

$$w(x,s) = \beta z f(x,s) + (1-\beta) r U(x) \tag{A.3}$$

Therefore the value functions for filled vacancies and employed workers can be written as

$$N(x,s) = \frac{\beta z f(x,s) + [(1-\beta)r + \sigma_s]}{r + \sigma_s} U(x) \tag{A.4}$$

$$J(x,s) = \frac{(1-\beta) z f(x,s) - (1-\beta) r}{r + \sigma_s} U(x) \tag{A.5}$$

It is also necessary to simplify the expression for the asset value of unemployment. Substituting (A.4) into (3) gives the expression for a worker of type x.

$$\begin{aligned} rU(x) =& b + m(\theta) \left(\frac{\phi}{r + \sigma_M} \Big[z\beta f(x, s_M) + (r(1-\beta) + \sigma_M) U(x) \Big] \right. \\ & \left. + \frac{1-\phi}{r + \sigma_C} \Big[z\beta f(x, s_C) + (r(1-\beta) + \sigma_C) U(x) \Big] - U(x) \right) \end{aligned} \tag{A.6}$$

which simplifies to

$$U(x) = \frac{b + z\beta m(\theta) \left[\frac{\phi}{r+\sigma_M} f(x, s_M) + \frac{1-\phi}{r+\sigma_C} f(x, s_C) \right]}{r + r\beta m(\theta) \left[\frac{\phi}{r+\sigma_M} + \frac{1-\phi}{r+\sigma_C} \right]} \tag{A.7}$$

Combining (A.3) and (A.7) leads to (8):

$$w(x,s) = \beta z f(x,s) + (1-\beta) r \left(\frac{b + z\beta m(\theta) \left[\frac{\phi}{r+\sigma_M} f(x, s_M) + \frac{1-\phi}{r+\sigma_C} f(x, s_C) \right]}{r + r\beta m(\theta) \left[\frac{\phi}{r+\sigma_M} + \frac{1-\phi}{r+\sigma_C} \right]} \right)$$

A.2 Equilibrium Conditions

From the expressions for the free entry of firms, and the observation $\gamma = \psi$, the following two conditions along with (11) will describe an equilibrium:

$$k_M = \frac{m(\theta)}{\theta} \left(\psi J(x_L, s_M) + (1-\psi) J(x_H, s_M) \right) \tag{A.8}$$

$$k_C = \frac{m(\theta)}{\theta} \left(\psi J(x_L, s_C) + (1-\psi) J(x_H, s_C) \right) \tag{A.9}$$

Solving the free entry for manual vacancies gives

$$\theta = \frac{(1-\beta) m(\theta)}{k_M (r + \sigma_M)} \left(z F_M - \frac{rb + zr\beta m(\theta) \left[\frac{\phi F_M}{r+\sigma_M} + \frac{(1-\phi) F_C}{r+\sigma_C} \right]}{r + r\beta m(\theta) \left[\frac{\phi}{r+\sigma_M} + \frac{(1-\phi)}{r+\sigma_C} \right]} \right) \tag{A.10}$$

A similar expression can be found for cognitive vacancies. These two solutions can be equated to eliminate $\theta / m(\theta)$ and solved for the share of manual vacancies,

$$\phi = \frac{k_C (r + \sigma_C)[b - zrF_M] - k_M (r + \sigma_M)[b - zrF_C]}{zr\beta m(\theta)[F_M - F_C](k_M - k_C)} + \frac{k_C}{k_M - k_C} \tag{A.11}$$

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

$$\theta = \frac{m(\theta)(1-\beta) z (F_M - F_C)}{(r + \sigma_M) k_M - (r + \sigma_C) k_C} \tag{A.12}$$

A.3 Proofs of Existence

This section details the conditions required to support a mixing equilibrium. The proofs follow closely to Wong (2003).

First, a high-skill worker must be willing to accept a manual skill job. This will occur only if such a pairing generates a non-negative surplus:

$$N(x_H, s_M) - U(x_H) + J(x_H, s_M) \geq 0$$

Substituting in from equations (A.4) and (A.5) we obtain

$$zf(x_H, s_M) \geq U(x_H).$$

Substitution of equation (A.7) for $U(x_H)$ and re-arranging gives the weak inequality

$$zf(x_H, s_M) - b \geq \frac{z\beta m(\theta)(1-\phi)}{r+\sigma_C}\Big[f(x_H, s_C) - f(x_H, s_M)\Big]. \tag{A.13}$$

This result shows that a mixing equilibrium exists if the marginal cost of a high-skill worker rejecting a manual job offer exceeds the marginal benefit of waiting for a cognitive offer to arrive.

Second, the mixing equilibrium requires firms posting cognitive vacancies to accept low-skill workers. This requires the expected surplus of filling a cognitive vacancy with a low-skill worker to be no less than the expected surplus from filling it with a high skill worker:

$$N(x_L, s_C) + J(x_L, s_C) - U(x_L) \geq N(x_H, s_C) + J(x_H, s_C) - U(x_H)$$

Substituting in from equations (A.4) and (A.5) we obtain the weak inequality

$$\frac{zf(x_L, s_C) - rU(x_L)}{r+\sigma_C} \geq \frac{zf(x_H, s_C) - rU(x_H)}{r+\sigma_C} \tag{A.14}$$

Substitution of equation (A.7) for $U(x_H)$ gives

$$[f(x_H, s_C) - f(x_L, s_C)] \leq \frac{\beta m(\theta)\phi}{r+\sigma_M}\Big\langle[f(x_H, s_M) - f(x_L, s_M)] - [f(x_H, s_C) - f(x_L, s_C)]\Big\rangle \tag{A.15}$$

This weak inequality holds when the output loss from employing a low-skill worker instead of a high-skill worker is low enough among cognitive jobs. This is more likely to be true when job tasks are important relative to worker skills for production. Also, the right hand side will exceed the left hand side when the discounted losses from low-skill workers in manual jobs exceed the losses for low-skill workers in cognitive jobs by a sufficient amount. The rate at which workers accept manual task jobs $m(\theta)\phi$ affects this expression because decreases in the rate at which workers meet with cognitive vacancies increase the firm's cost of waiting for a high skill worker to arrive.

A.4 A Closed Form Solution with Cobb-Douglas Matching Technology

This section demonstrates that it is possible to solve the model explicitly when the matching function is a Cobb-Douglas. Parameterizing the matching function as $m(u,v) = u^{\xi}v^{1-\xi}$ we may also write: $m(\theta) = \theta^{1-\xi}$. Substituting this expression into equation (A.10) gives

$$\theta = \left[\frac{(1-\beta)z(F_M - F_C)}{(r+\sigma_M)k_M - (r+\sigma_C)k_C}\right]^{\frac{1}{\xi}} \tag{A.16}$$

Finally, substituting equation (A.16) into (11) and simplifying:

$$\phi = \frac{k_C}{(k_C - k_M)} + \frac{k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]}{z\beta(k_C - k_M)(F_C - F_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi}} \tag{A.17}$$

Substituting the above two expressions into equation (11) gives

$$\begin{aligned} v = &\Bigg[\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{1/\xi} \\ &\times\Bigg(z\beta(F_C - F_M)(k_M\sigma_C - k_C\sigma_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi} \\ &+k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]\Bigg)\Bigg]\Bigg/ \\ &\Bigg[z\beta(k_M - k_C)(F_C - F_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{2(1-\xi)/\xi} \\ &+z\beta(F_C - F_M)(k_M\sigma_C - k_C\sigma_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi} \\ &+k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]\Bigg] \end{aligned} \tag{A.18}$$

B Data Appendix

B.1 The O*NET

The O*NET (Occupational Information Network) database is the successor to the Dictionary of Occupational Titles (DOT). It represents the most detailed source 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 more detailed version of the Standard Occupational Classification system (SOC) coding system. The purpose of the O*NET is to attribute 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. For example, mathematics is represented both as a "Skill" under "Experience Requirements" and an "Ability" under "Worker Characteristics."

This paper merges the LFS and the O*NET data. First, the O*NET job categories were collapsed to the SOC level, a process which amounts to dropping the last two digits added by the O*NET. A concordance from the National Crosswalk Service Center transforms these to SOC 2010 codes to SOC 2000 codes, a process which affects only 8 occupations. A concordance provided by the standards division of Statistics Canada maps the SOC 2000 codes into the Canadian NOCS06 codes that are used in the LFS. [15] The resulting LFS sample contains 327 different 4-digit SOC occupations.

B.1.1 The O*NET Overqualification Measure

This paper uses education requirements to generate one measure of overqualification. In recent versions of the O*NET, education requirements are assessed by a group of 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. Education requirement rankings, using discrete education milestones, are reported for each surveyed expert (See Figure B.1 for the questionnaire). To generate an index of educational requirements from the average response, categories are 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

[15] At the time this paper was written the SOC NOCS concordance had been verified by the custodians of the NOCS06, but not the SOC.

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 overqualified.

The O*NET binary overqualification measure labels a worker as overqualified when the distance between worker education and occupation requirements $D_{ij} = E_j - E_i$ exceeds a threshold of $\sigma_D/2$. This threshold is half of a standard deviation of the distance D and classifies workers with one "excess" year of education as overqualified.[16]

B.2 Task Measures

In addition to characterizing occupations in terms of education requirements, task measures are generated from the O*NET data. These measures provide job characteristics that are much more informative to the econometrician than occupation codes and can be used to compare occupations in a meaningful way. Tasks not only provide a richer understanding of the nature of certain jobs, but also provide job characteristics which are not collinear with the education requirements used to generate measures of overqualification.

An important way the task measures in this paper differ from those in the polarization literature (Autor et al., 2003; Firpo et al., 2011), is the subset of the O*NET data from which they are generated. The methodology in this paper is purposely agnostic about which O*NET elements might best describe a task. Instead, information is drawn from the entire "ability" category, which appears to be the most comprehensive and consistent grouping of occupation characteristics. In the polarization literature, particular elements from various categories of the O*NET, or its predecessor the Dictionary of Occupational Titles (DOT), are hand-picked. This approach may be well suited in that literature where nuanced job characteristics such as routine and non-routine tasks are particularly helpful in understanding issues around off-shoring and the displacement of workers by technology.

Measures of the tasks for each occupation are derived from the O*NET category "Abilities." This category was chosen because it appears to have the most comprehensive and general set of elements. Each of the 52 abilities, indexed by k, 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_{kj}, for each ability, k, in each occupation, j, according to $a_{jk} = I_{jk}^{a} \times C_{jk}^{1-a}$.[17] The common factor model estimation procedure

[16] $\sigma_D \approx 1.9$ years of education.

[17] 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. The ability questionnaire is provided in Figure B.2. Results reported in this paper use a=1/2, but results are robust to variation in this parameter.

identifies the relevant underlying factors from the 52 different abilities.

B.2.1 Factor Analysis

Summary measures of job tasks s^r are generated from these 52 ability measures using factor analysis. The procedure follows closely to Poletaev and Robinson (2008) and generates 5 tasks of significance. Some of the literature on specific skills uses principal component analysis, (Yamaguchi, 2012a,b), however factor analysis was used in this paper. The main advantage of factor analysis is that it identifies underlying commonalities among the various ability ratings in addition to reducing the dimensionality of the data. Unique variation in the underlying ability measures is ignored when generating the main factors. Factor analysis is also more suitable for orthogonal rotation, which improves the interpretability of resulting task measures without sacrificing the order of factors.

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:

$$A = S\boldsymbol{\Lambda}' + e, \tag{B.19}$$

where A is the vector of ability ratings and 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 A is given by;

$$\boldsymbol{R} = \boldsymbol{\Lambda I \Lambda}' + \boldsymbol{\Psi}, \tag{B.20}$$

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 possible 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.

The factor analysis procedure is manipulated in two ways to assist in the interpretation of the resulting factors. First, weights from the LFS data are applied based on the population of employed males in each occupation. This step affects the scaling of the factors and improves their cardinal interpretation. A standard deviation in the resulting factor (or task measure) represents a standard deviation of the corresponding task in the Canadian occupation distribution. 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 how the factors, S, relate to the original abilities. By contrast, the "Varimax" rotation procedure maximizes the factor loading variance for each factor, so that each ability measure will contribute more heavily to a single factor. Because the rotation is orthogonal, it re-organizes the data to improve factor interpretability without sacrificing independence.

By examining how each ability contributes to a factor (see the factor loading Table B.3) it is possible to interpret each task (Ingram and Neumann, 2006). For example, the leading factor, s^1, is highly correlated with O*NET 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 tasks and could be classified as a cognitive measure. By contrast, s^2 correlates positively with manual abilities including several aspects of visual perception, "reaction time" and the "speed of limb movement." Similar interpretations are developed for the remaining factors, leading to the tasks presented in Table B.1.[18] Table B.2 presents the five occupations scoring highest for each of the two leading factor scores.

Table B.1: Factor Analysis Output

Component	Cog/Man	Requirement Interpretation	Proportion
S_1	COG	Reasoning / Communication	34
S_2	MAN	Sensory / Coordination	28
S_3	MAN	Physical Strength	14
S_4	MAN	Coordination vs Strength	9
S_5	COG	Numeracy vs Communication	4

Five task 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 orthogonal rotation.

[18]The first and fifth are measures of cognitive tasks, while factors 2-4 appear to represent manual tasks. 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 tasks, while factors 4 and 5 provide some differentiation within these broader tasks.

Table B.2: NOCS06 Occupations with Highest Factor Scores

Highest Cognitive Scores

NOCS06	Occupation Title	s^1	s^2
D011	Specialist Physicians	3.202	-0.245
D012	General Practitioners and Family Physicians	3.202	-0.245
C011	Physicists and Astronomers	2.870	-0.584
E021	Psychologists	2.307	-1.093
C172	Air Traffic Control and Related Occupations	2.430	0.058

Highest Manual Scores

NOCS06	Occupation Title	s^1	s^2
C171	Air Pilots, Flight Engineers & Flying Instructors	1.111	2.677
G722	Outdoor Sport and Recreational Guides	1.111	2.677
H711	Truck Drivers	-0.390	2.671
H712	Transit Operators	0.057	2.547
H736	Boat Operators	0.087	2.443

Figure B.1: O*NET Questionnaire: 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
  - requires at least 2 years of college work before entrance into the program,
  - includes a total of at least 6 academic years of work to complete, and
  - provides all remaining academic requirements to begin practice in a profession.
- ☐ **Doctoral Degree**
- ☐ **Post-Doctoral Training**

1 O*NET Education and Training Questionnaire

Figure B.2: O*NET Questionnaire: Ability 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

Table B.3: Rotated Factor Loadings

O*NET Ability	Factor 1 (s^1)	Factor 2 (s^2)	Factor 3 (s^3)	Factor 4 (s^4)	Factor 5 (s^5)
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

Factors 1-5 are generated using factor analysis on the O*NET 17.0 using employment counts from Canadian occupation distribution for the years 1997-2012 as weights.