Matching Skill and Tasks: Cyclical Fluctuations in the Overqualification of New Hires

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Abstract

This paper shows that downturns affect job formation through their influence on job tasks. Jobs formed in a recession have relatively more manual tasks, increasing the probability that workers are overqualified. These findings are illustrated with data combining Canada's Labour Force Survey (LFS) for the period 1997-2012, the O*NET, and measures comparing actual and required education within occupations. A search model with two-sided heterogeneity is calibrated using this data. The model shows that a one percentage point increase in unemployment increases the manual task share by 6% and overqualification by 3.5%. Empirical estimates using the LFS data are consistent with the model predictions.

Keywords: Labor Market Conditions, Tasks, Overqualification, Mismatch
JEL Codes: J22; K42

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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, matches that form in recessions may be of lower quality Bowlus (1995).[1] Low quality matches in which workers are overqualified are less desirable because of lower pay and decreased job satisfaction (Allen and van der Velden, 2001; Groot and Maassen van den Brink, 2000; Leuven and Oosterbeek, 2011; McGuinness, 2006; Peiró, Agut, and Grau, 2010; Rubb, 2003; Sloane, 2003; Tsang, 1987). These costs may affect a substantial number of workers. Even through the Great Recession, monthly new hires in the US remained above 3.6 million (Bureau of Labor Statistics, 2015). The prevalence of new hires suggests that there is scope for an understanding of why job match quality changes in a downturn and whether policy might play a role in the reduction of these potential costs.[2]

This paper establishes two stylized facts that reveal a relationship between economic downturns, job tasks, and overqualification. First, the task composition of jobs is shown to vary with economic conditions at the time of job formation. Composite measures of cognitive and manual tasks are generated from the Occupational Information Network (O*NET) database following a procedure similar to Poletaev and Robinson (2008). The share of newly formed jobs which are manual-task intensive are found to increase in a downturn. This can be interpreted as a relative change in the demand for skill. Second, these job tasks are shown to explain a substantial component of the cyclicality of overqualification. A large nationally representative dataset with worker and job characteristics, as well as retrospective detail about labor market conditions, is created by integrating Canada's Labour Force Survey (LFS) and the O*NET database. The data show that job tasks have significant predictive power for the probability of overqualification. The findings are robust to various definitions of overqualification including expert ratings of required education, the distribution of education among the employed and the market premium for education for each occupation.

I develop a search model with high- and low-skill workers, and cognitive and manual task jobs. Calibrating the model to match the Canadian economy for the period 1997-2012 suggests that a one percentage point increase in unemployment may increase the manual task share by 6% and subsequently increase overqualification by 3.5%. The role of job tasks as a mechanism by which economic conditions affect overqualification rates is also demonstrated using the model. High-skill workers from the unemployment pool are more likely to accept jobs for which they are overqualified in a downturn because the chances of obtaining

[1] Bowlus (1995) finds that job matches in the US last longer if formed in booms rather than recessions.

[2] The focus on job creation is also motivated by the fact that the cyclicality of unemployment is dominated by the flow *out* of unemployment (see Shimer (2012) for the US and (Campolieti, 2011) for Canada).

a more suitable match decrease. Overqualification increases as firms increase the share of manual task-intensive vacancies, exploiting the willingness of high-skilled workers to accept these lower paying jobs. These predictions differ from those of previous models of this type, including Albrecht and Vroman (2002) and Wong (2003). The predictions differ because alternative assumptions are made about the production processes and vacancy posting costs. The results appear to be more consistent with the existing empirical evidence on job matches and mismatches, as well as being consistent with the stylized facts demonstrated in this paper. A simple policy experiment shows that increased unemployment benefits may compound rather than alleviate the incidence of overqualification, because recessions can increase the firm's incentive to post less expensive manual task vacancies.

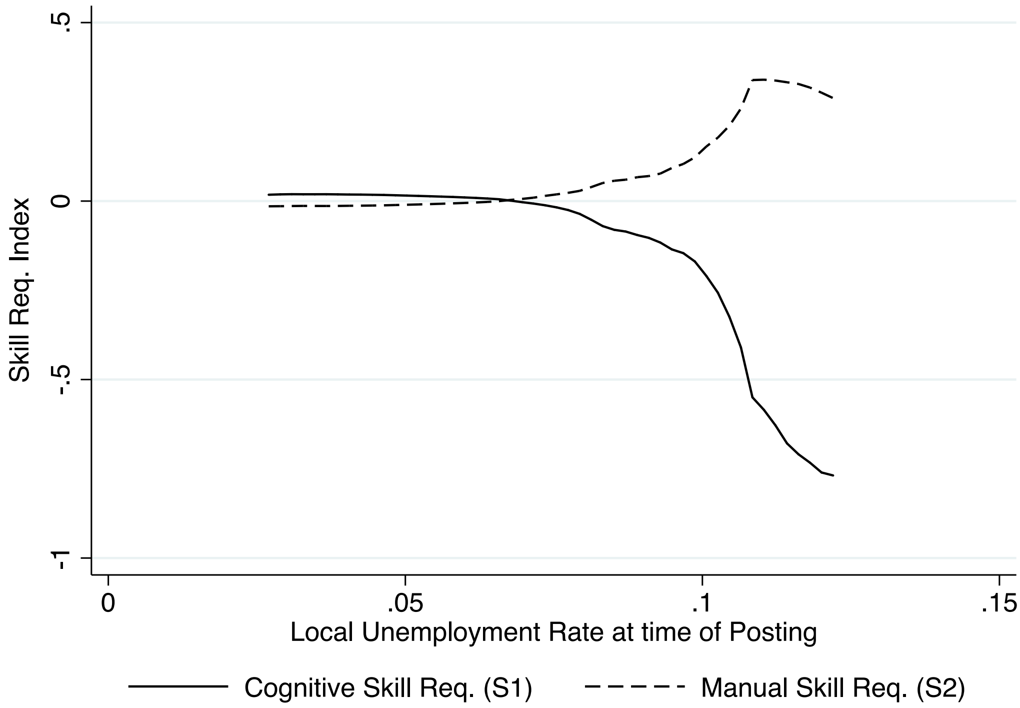
Cyclicality on both sides of the labor market could affect overqualification. The skill supplied by job applicants has been shown to be cyclical (see Barlevy (2001); Devereux (2002, 2004) for example). Data on job-to-job transitions shows that high-skill workers may move up the ladder in an upswing to better paying jobs. However, the literature about the potential cyclicality of skill demand (or job tasks) is relatively sparse. Jaimovich and Siu (2012) show that labor market polarization is concentrated during recessions and Devereux (2000) finds that firms may re-assign their existing workers to "lower" tasks in a downturn.[3] One obstacle limiting the examination of the demand for labor is the availability of job vacancy with sufficient detail to facilitate the analysis of job tasks.[4] Fortunately job vacancy data by occupation are available for the state of Minnesota. Figure 1 demonstrates that the share of manual tasks among posted job vacancies increases in regions of Minnesota with high unemployment rates over the period 2005-2013. Although the data are specific to a particular US state, they provide important evidence of the cyclicality of job tasks and motivate further analysis.

The results of this paper contribute to the literature relating wage penalties to past labor market conditions. Unemployment rates at hire, and over job duration, have been found to contribute to worker wages in Canada (McDonald and Worswick, 1999), the US (Beaudry and DiNardo, 1991), and Europe (Bellou and Basiş, 2010). The finding that cyclical task changes lead to overqualification may help to explain the finding that job match quality

[3]Examples of cyclical task changes in daily life could include the creation of low-skill construction jobs, including so-called "shovel-ready" infrastructure projects, during the Great Recession. The American Recovery and Reinvestment Act of 2009 detailed over \$100 billion for infrastructure projects. Some of the larger investments included 27.5 billion for highway and bridge construction, \$8 billion for intercity rail projects and \$4.6 billion for flood protection and navigation, and \$4 in wastewater treatment (Public Law 111-5, 2009). Similarly, \$12 billion of Canada's \$30 billion stimulus spending was devoted to immediate infastructure projects for roads, bridges, broadband internet access, electronic health records, laboratories and border crossings Department of Finance (2009).

[4]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. Human capital has been shown to be specific to the occupation rather than the industry Kambourov and Manovskii (2009). This suggests that tasks are better measured through occupational information.

Figure 1: Cyclical Tasks in Posted Job Vacancies



Plot is a local moving average smooth of the cognitive and manual tasks of posted job vacancies in Minnesota (on the Y axis) against the regional unemployment rates (on the X axis). Smoother uses an Epanechnikov kernel with a bandwidth of 0.15. The tasks are leading components from factors analysis on the O*NET ability requirements data. Local unemployment rates are from the Minnesota Local Area Unemployment Statistics, and are measured at the Economic Development Region level. Job vacancy counts are from the Minnesota Job Vacancy Survey. All data is collected for the second and fourth quarter for the period 2005 - 2013.

can explain future wage penalties (Hagedorn and Manovskii, 2013). This paper's findings are also related to the literature detailing the scarring effect of entering the labor market during a downturn (Bowlus and Liu, 2003; Kahn, 2010; Liu, Salvanes, and Sørensen, 2012; Oreopoulos, von Wachter, and Heisz, 2012).

The rest of the paper proceeds as follows. Section 2 outlines the data and illustrates the relationship of tasks and overqualification rates with respect to past labor market conditions. Section 3 presents the search model which shows that overqualification changes because the relative task intensity of job vacancies changes with economic conditions. The model is calibrated to Canada 1997-2012 and quantitative predictions are provided. Section 4 provides direct empirical evidence of the two stylized facts using LFS and O*NET data. Section 5 concludes.

2 Data and Summary Statistics

This section demonstrates that past labor market conditions can be linked both to job match quality and changing job tasks. Overqualification and the share of manual job tasks are found to be coincident with regional unemployment rates at the time of job formation. These observations suggest that hiring conditions may have important effects on job formation over the business cycle.

2.1 Data

Economic conditions at the time of job formation are the relevant conditions to assess job tasks and overqualification. Observable overqualification and job tasks are typically assessed using occupation codes and are therefore fixed for the duration of a single job. Short sampling windows, however, limit the ability to observe new job formation in large representative data sets such as the Current Population Survey (CPS). Fortunately Canada's Labour Force Survey (LFS) contains consistent and detailed job tenure information. The job tenure information is exploited to link currently employed workers in the sample to the regional labor market conditions during the month of job formation. This strategy is also more likely to capture overqualification spells of substantial duration, which are precisely those spells that may impart significant costs on workers over their career.

Regional labor market conditions to be linked to employed workers are generated from the confidential LFS by Economic Region (ER) for the period 1987-2012.[5] The sample is restricted to employed male respondents age 16-65 and excludes those who are unionized, part-time, and self-employed. These restrictions are similar to those in the US literature on the effects of past labor market conditions and implicit contracts, and include those workers which may be most comparable across countries. The restriction also excludes workers who might appear overqualified due to institutional peculiarities in unionized or public service work. The sub-sample used in this paper therefore includes those workers most likely to respond to changing tasks and least likely to find themselves overqualified for their job. Estimates of the incidence of mismatch are likely to be somewhat conservative for this reason.

[5] Economic region is a Census geographic division for analysis of economic activity. Because the LFS is the official source for Canadian unemployment rates, ER level unemployment rates are calculated directly from the data using counts of labor force participants, unemployed workers and sampling weights. The LFS sample includes 73 of the ERs providing a considerable amount of cross-sectional variation in labor market conditions. The linkage procedure is limited to 1987 because the 2012 ER boundaries in the dataset are not encoded prior to this date. 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. Employed workers themselves are observed from 1997 forward because many characteristics, including wages, were not available for waves entering prior to the 1996 survey redesign.

To demonstrate the importance of regional unemployment rates at the time of job formation, the top panel of Table 1 presents sample means for workers in the LFS data that began their job within the prior 4 weeks. Those hired into less favorable labor markets, where the regional unemployment rate is above average, are slightly older with more experience, earn about $0.6 CAD less per hour and are more likely to have some post-secondary education relative to those hired into labor markets with lower regional unemployment rates.

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 Economic Region-level unemployment rate for new hires, which is 7.6%. Also excluded are public sector employees and unionized workers. Age and potential experience measured in years, job tenure measured in weeks. Education categories less than high school (LHS), high school (HS), non-university post-secondary (PS), university degree (BA). Real wages exclude zeros. OQ measures are binary indicators for overqualification.

2.2 Overqualification

A worker is said to be overqualified if they have education or skill in excess of what might be considered the "required" amount for their job. Because the literature on overqualification or overeudcation is not in agreement on any single measure, this paper uses three different measures. The use of different measures also speaks to the robustness of the empirical results by demonstrating that the cyclicality of overqualification, and the intermediating role of tasks, are not an artifact of one particular measure.

The first measure is based on expert ratings of an occupation's education requirements from the O*NET.[6] Workers are assigned to the overqualified group if they have one half

[6] Appendix Section C outlines the O*NET database and the merging procedure with the LFS.

a standard deviation (chosen to account for approximately one year) of education or more than the O*NET education requirements. The second measure, referred to hereafter as the median measure, uses information from the distribution of the skill supply of workers in the data. This measure is taken from the overeducation literature and assigns workers to the overqualified group if they have more than one standard deviation of education above the median observed education in their occupation. This measure provides information about the extent to which a worker is overqualified relative to other workers within their occupation. The third and final measure is an adaptation of the market wage-based measure from Gottschalk and Hansen (2003) (GH). The measure is only defined for workers with at least secondary school education, and assigns individuals to the overqualified group if their occupation pays those with secondary school education a wage premium less than 10% above those who have less education.[7] This measure may capture the extent to which worker skills are utilized, assuming that wages at least partially reflect a worker's contribution to production.

The probability of overqualification appears to vary with regional unemployment rates during job formation across all three measures. The bottom panel of Table 1 shows that recently hired workers are more likely to be overqualified if they are in regional labor markets where the unemployment rate is above the average in the data. Overqualification rates among workers hired within the last four weeks 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%. The data appear consistent with existing evidence linking job match quality to economic conditions Acemoglu (1999); Bowlus (1995).

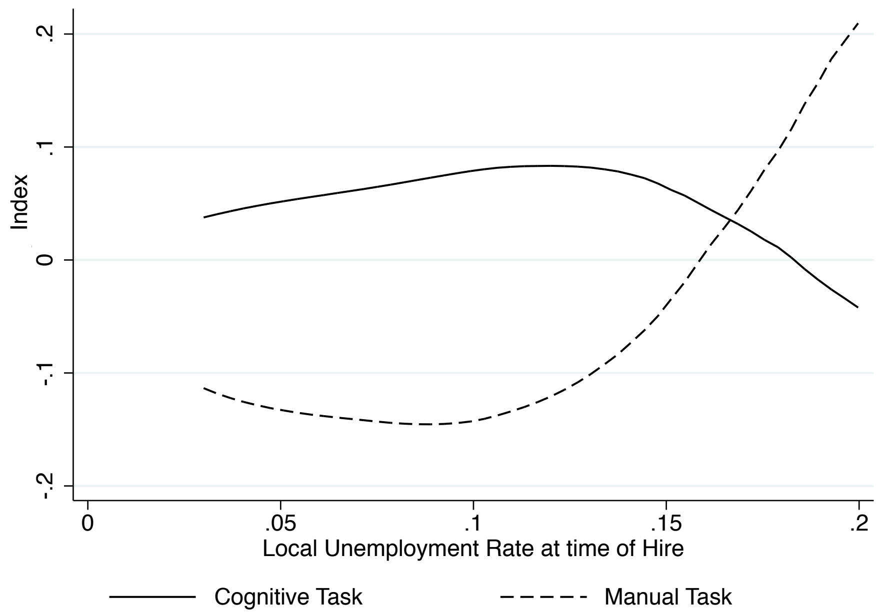
2.3 Tasks

To generate task measures for occupations, this paper follows a factor analysis procedure described in the Data Appendix which is similar to that of Poletaev and Robinson (2008). Occupation codes are replaced with a five element vector of the leading factors from the O*NET "abilities" category. The main factor is a cognitive measure, and the second is a manual measure. The factor analysis procedure is weighted so that a single standard devi-

[7] The wage premium is given by the coefficient on a high school education dummy in from a mincer regression in an individual's occupation and year of observation. Gottschalk and Hansen (2003) use college (or university) educated workers. In Canada, a measure defined only for university educated workers may not be satisfactory because the majority of post-secondary education is at the community college level. I generate the measure at the high school level instead of the more general post-secondary level because community colleges offer a more vocational education which may not capture the general skill which this paper documents. This is apparent by the fact, outside certain professional programs such as nursing, there are few continuation programs available. In fact, many university admission decisions are based on the high school grades of applicants even if the applicant has completed a community college diploma in a related field.

ation in any one task measure represents a standard deviation of the tasks in the Canadian occupation distribution.

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



Local moving average smooth relating the share of cognitive and manual tasks among filled jobs ind Canada to regional unemployment rates at the time these jobs were formed. Epanechnikov kernel with bandwidth of 0.015. Tasks are the leading factors from the O*NET database. A single standard deviation represents the population standard deviation of that particular task. Regional unemployment rates measured monthly at the Economic Region (ER) level 1987-2012. Results are trimmed to the range (3-20%).

Job tasks also appear to change with past labor market conditions. Figure 2 plots the leading two continuous task measures from the jobs of employed workers against the labor market conditions at the time these jobs were formed. The share of manual tasks increases dramatically among those jobs which are formed in regional labor markets with high unemployment. A second plot also suggests that the opposite may be true for cognitive tasks, although the pattern is somewhat less striking. These measures represent tasks in filled vacancies. It is not possible to observe changes in unfilled vacancies because this data is not available by occupation. However, the trends are supported by the evidence from Minnesota discussed previously.

There is a good reason to suspect that the cyclical patterns of overqualification rates and job tasks are related. Hagedorn and Manovskii (2013) show that wage effect of past labor market conditions may in fact be the result of job match quality. Changes in task measures provide one plausible explanation for why job match quality may vary with past biz cycle. This is true because match quality is determined when jobs are formed. Even if workers and jobs evolve to improve the job match quality this could not be observed.

This explanation is also consistent with the predictions of a search model. Job tasks, and subsequently overqualification, can depend on labor market conditions at the time of job formation because these conditions may affect the mix of available job vacancies across tasks.

3 Model

This section outlines a job search framework to describe the incidence of mismatch and overqualification in the labor market. The relative shares of cognitive and manual job vacancies, unemployment rates, and the incidence of overqualification are endogenous variables to be determined in equilibrium. The model features heterogeneous workers and vacancies with a hierarchical structure. This structure enables the model to make predictions about overqualification that would not arise from a "circular" view of matching (Barlevy, 2002; Moscarini and Vella, 2008; Gautier, Teulings, and Van Vuuren, 2010).

The model in this paper departs from other hierarchical search models with two sided heterogeneity, such as Albrecht and Vroman (2002), by making different assumptions about production and vacancy posting costs. This departure is critical for the relationship between economic conditions and overqualification. In this model both worker skills and job tasks can contribute to the productivity of a match independent of the other. This is motivated by two stylized facts laid out in Sicherman (1991). First, overqualified workers earn more than workers that are well matched. Second, underqualified workers earn more than they would have in a more suitable match. Taken together, these facts suggest an important role for job tasks in productivity and the existence of a "mixing" equilibrium where both over and underqualified matches form. The alternative assumption, that low skill workers produce nothing in a high skill (cognitive) job, may be too strong because underqualified workers are observed in significant numbers across several countries (Leuven and Oosterbeek, 2011). Many similar models generate overqualification at the expense of underqualification (Albrecht and Vroman, 2002; Dolado, Jansen, and Jimeo, 2009; Gautier, 2002). Chassamboulli (2011) illustrates that this approach may lead to increased rather than decreased high-skill (or cognitive task) jobs in a downturn.

Because I allow productivity to differ across workers in all job types, or across all tasks, the model generates education premiums for both job types. This feature is important because it permits the existence of overqualified workers by ensuring them a sufficient wage. Furthermore, it is consistent with the empirical literature. Wages have been shown to depend on both worker and job characteristics, Allen and van der Velden (2001), and almost all occupations pay an education premium for college educated workers in the US Gottschalk and Hansen (2003). A mixing equilibrium can also be supported if overqualified and well matched workers earn different wages because of differences in their non-market income.

The model in Wong (2003) employs this strategy, however, all workers in manual jobs produce the same amount.

In this paper I also assume that the costs of posting and filling a cognitive task job will be considerable. When cognitive vacancies are more expensive than manual task vacancies the firm has an incentive to post the manual task jobs even if it would hire a high-skill worker. This assumption is easily defended by observing that management positions may be contracted to head-hunting agencies or advertised in expensive circulars such as *The Economist*, whereas laborer positions are more likely to be advertised inexpensively in local newspapers or on-line job banks.

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) $s \in \{s_C, s_M\}$.[8] Manual jobs s_M are less productive than cognitive jobs, and the endogenous variable ϕ is 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 $m(\theta)$, while firms with vacancies meet unemployed workers at a rate of $m(\theta)/\theta$. Cognitive and manual jobs dissolve according to the exogenous probabilities σ_C and σ_M, respectively.[9] The interest rate in the economy is given by $r > 0$, and economic conditions are affected by changes in the productivity parameter z, which is also strictly positive.

Workers

In this economy there are a continuum of risk-neutral and infinitely lived workers of mass 1, the share ψ of which is exogenously assigned type x_L. Workers can be either employed or unemployed, and γ determines the share of unemployed who are endowed with a low level of education.[10] In a given period, an unemployed worker receives a present value return of

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

[8] Cognitive and manual jobs could also be considered high and low skill jobs respectively.

[9] The model behavior with a single job destruction rate is similar provided that vacancy posting costs differ by job type.

[10] Because search is random from a common unemployment pool, $\gamma = \psi$ in equilibrium.

where b is the unemployment benefit to a worker of either type.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

$$rN(x,s) = w(x,s) + \sigma_s\big(U(x) - N(x,s)\big) \tag{2}$$

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_s. An empty vacancy of type s therefore gives a firm the present value return of

$$rV(s) = -k_s + \frac{m(\theta)}{\theta}\Big(\gamma \max\{J(x_L,s)-V(s),0\} + (1-\gamma)\max\{J(x_H,s)-V(s),0\}\Big) \tag{3}$$

A reasonable assumption is that cognitive vacancies are more costly to post and fill. Firms likely recruit executives by advertising in circulars such as the Economist or through head-hunting agencies. Recruiting for manual labor jobs, on the other hand, likely involves the local newspaper.[11] This assumption is not strictly required for the behavior of the model because differences in separation rates across vacancy types may generate sufficient differences in $rV(s)$. However, it is perhaps more palatable for a calibration exercise to constrain vacancy posting costs rather than job destruction rates.

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

$$rJ(x,s) = zf(x,s) - w(x,s) + \sigma_s\big(V(s) - J(x,s)\big). \tag{4}$$

A filled vacancy produces according to the production function $f(x,s)$ where output is characterized by the discrete pairings of x and s:

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

Output is higher for higher x or s. It is reasonable to assume that more educated workers are more productive than less educated workers, regardless of the job. This is suggested by wages in the data. 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. 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. The wage data also support this task ranking.

[11]The interview process for jobs with a high cognitive task intensity is also likely to be more lengthy.

An overqualified worker is denoted by the pair $\{x_H, s_M\}$ job because this highly educated worker would have been more productive and earned higher wages in a cognitive task job. With a production function that increases with both arguments, the worker x_H can be more productive in a manual task job than the worker x_L even though they are not as well matched. Empirical findings support this production process because overqualified workers, although earning less than they would in a more suitable match, still earn more than other workers in the same job who have only the required level of education (Allen and van der Velden, 2001).

Wage Determination

Following the literature, wages are determined by Nash bargaining, where the parameter β represents the worker's share of the total surplus in the economy.

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

Substitution of the value functions, following the steps outlined in Appendix Section A.1, leads to an expression for the wage of worker x in vacancy s:

$$w(x,s) = \beta z f(x,s) + (1-\beta) r \left(\frac{b + z\beta m(\theta)\left[\frac{\phi}{r+\sigma_M} f(x,s_M) + \frac{1-\phi}{r+\sigma_C} f(x,s_C)\right]}{r + r\beta m(\theta)\left[\frac{\phi}{r+\sigma_M} + \frac{1-\phi}{r+\sigma_C}\right]} \right) \tag{6}$$

3.2 Equilibrium

Multiple equilibria are possible from search models with two sided heterogeneity (Wong, 2003). I examine only the equilibrium which is supported by the data. In this equilibrium, sometimes referred to as the "mixing equilibrium," some workers are well matched, some workers are overqualified and yet other workers are underqualified. Instead, the other equilibria are not supported by the data because they rule out one or more of these cases.

To solve the model for this equilibrium, firms are assumed to have free entry into either type of vacancy 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.

$$m(\theta)(1-\gamma)u = (1 - \psi - (1-\gamma)u)(\phi\sigma_M + (1-\phi)\sigma_C) \tag{7}$$

$$m(\theta)\gamma u = (\psi - \gamma u)(\phi\sigma_M + (1-\phi)\sigma_C) \tag{8}$$

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

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

$$\gamma = \psi \tag{10}$$

The expression (9) is simply the Beveridge curve condition, expressed as a weighted average of the job destruction rates. The common unemployment pool ensures that all workers the same job finding probability regardless of their type. This symmetry also explains why equation (10) equates the share of unemployed x_L workers is equal to the overall share of x_L workers in the population.

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

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

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 (11) can be substituted back into either free entry condition to obtain

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

A solution for the equilibrium triplet $\{u, \theta, \phi\}$ follows from (9), (11) and (12). A closed form solution, assuming Cobb-Douglas matching, is derived in the Appendix Section A.4.

Certain conditions on parameter values are required to support the mixing equilibrium. First, 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 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 bust 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 reasonably high in a manual task job.

The second assumption requires that firms who post cognitive vacancies must be willing to hire low-skill workers if the two should find each other during the search process. For the second assumption to be hold, the expected productivity loss from an underqualified worker should not be too high. In other words the expected surplus of this pairing should not be lower than it would be from the alternative pairing with a high-skilled worker. This can be satisfied by a production process that hinges relatively more on the task of the job relative to the worker skill. Another interpretation might be that the input of physical capital provides more to the output of a job relative to the input of labor or human capital. The proofs are formally presented in Appendix section A.3.

3.3 Market Conditions

Labor market conditions in the model are a product of aggregate productivity z. Because the model solution describes a steady state, I follow Pissarides (2009) and others approximating the cyclical results with comparative statics across steady states.[12] Equation (12) shows that a low state, z' will have fewer vacancies per unemployed worker relative to a high state, z, under the assumptions outlined earlier.[13] Since $m(\theta)$ is increasing in θ, and is in the denominator of the Beveridge curve condition, (9), unemployment rates rise in response to the change of state. Adopting the Cobb-Douglas meeting function $m(\theta) = \theta^{1-\xi}$, which is common in the literature, equation (12) 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. Whether or not this productivity change also increases the share of manual vacancies depends on the relative shifts of the θ and ϕ curves. The overall effect is not obvious because a productivity decrease will lead to fewer of both types of vacancy overall. To see how productivity changes lead to changes in vacancy shares, ϕ, it is necessary to consider direct, and indirect effects (through changes in θ). Partial differentiation of (11) shows that the share of manual vacancies will increase as long as $\frac{\partial\theta}{\partial z} > 0$:

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

This term is negative when $k_C(r+\sigma_C) > k_M(r+\sigma_M)$ and $F_M k_C(r+\sigma_C) < F_C k_M(r+\sigma_M)$. [14]

A shift in favor of manual skill jobs when z falls leads to an increase in overqualification. In this way, the second main prediction of the model leads to the first. Overqualification in

[12] Shimer (2005) argues that comparative steady states are a reasonable approximation for the cyclical behavior of the labor market in similar models.

[13] The reader is reminded of these assumptions. The expected output of a filled cognitive vacancy exceeds the output of a manual vacancy, $F_M < F_C$, and it is relatively more expensive to recruit for a cognitive position, $k_M < k_C$. Albrecht and Vroman (2002) specify a single posting cost but pin down ϕ by eliminating underqualified matches with the assumption that $f(x_L, s_C) = 0$.

[14] The second conditions can be interpreted as requiring any expected productivity gains of a cognitive job must outweigh the additional posting costs.

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

$$\frac{[1-\psi-(1-\gamma)u]}{(1-u)}\phi \tag{13}$$

which simplifies to

$$(1-\gamma)\phi. \tag{14}$$

Because ϕ is a function of θ, task changes are the mechanism by which cyclical economic conditions are transmitted to job match quality. This expression motivates the empirical specification in Section 4, and shows that overqualification should depend on worker types, ψ, and the tasks of vacancies, ϕ, rather than directly upon labor market conditions. In other words, overqualification depends on the relative demand for different types of skill, rather than depending directly on labor market tightness.

The model makes two key predictions. First, there is more overqualification in a downturn. Higher unemployment implies a longer unemployment duration. Therefore high-skill workers that happen to meet with lower paying vacancies, for which they are overqualified, are more likely to accept these jobs. Second, firms respond to a state of reduced productivity not only by posting fewer vacancies in total but also by posting relatively more manual skill (or low skill) vacancies. There are two reasons why firms shift the relative share of available jobs in this way. One reason is the cost. Jobs which require manual skill workers are less expensive to post, and to fill. The other reason is more strategic. Firms know that the unemployment pool contains relatively more high-skill workers in a downturn. As long as highly educated workers can produce slightly more than less educated workers in a manual skill job, firms have an incentive to exploit the buyers market. Firms know that they stand to gain by employing highly educated workers in manual skill jobs provided that the unemployment benefit is not too high.

3.4 Calibration

Using the LFS data, the model is calibrated to statistics for the Canadian economy for the period 1997-2012. The share of low-skill workers, γ=0.447, is derived from the share of employed males with high school education or less. This is consistent with the GH measure of overqualification presented in Section 2 and used in the empirical analysis to follow. The quarterly interest rate of $r = 0.008$, matches the Bank of Canada 10 year bond rate.[15] 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,

[15]This information is taken from the period April 2005-March 2014, where the average annual interest rate was 3.23 .

$m(\theta) = \theta^{1-\xi}$, and the aggregate productivity parameter, z, is normalized to 1. Using the observed average job duration of 1.469 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 productivity 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. To determine the share of manual skill vacancies, occupations are labeled as cognitive or manual based on the relative magnitude of the leading two tasks S_1 and S_2. The job arrival rate is derived from an unemployment duration of 1.469 quarters, which is the average value for workers in the sample. Panel A of Appendix Table B.1 shows the calibrated parameters, and Panel B compares the moments used to calibrate these results to values in the LFS. The model matches the data well for u, ϕ and $m(\theta)$, but wage ratios are less accurate. In particular, the education premium for workers in manual skill jobs is too low in the model. However, the calibration reproduces a ranking of wages that rewards 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.

3.5 Productivity Changes

Changes in the productivity parameter demonstrate the model behavior as economic conditions vary. When productivity falls, characterized by a decrease in the parameter z, the model simulates an economic downturn. Unemployment increases, the job matching rate falls and the number of vacancies also decrease. Of particular interest, however, is the relative share of manual skill vacancies, ϕ. As the unemployment rate rises, firms increase the relative share of manual skill jobs. Changes in these endogenous variables for small changes in z are illustrated by Figure B.1 in the Appendix.

As an experiment, the model is used to simulate the increase in overqualification which may arise as the economy enters a downturn. Consider Case V in Table 2. 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 roughly 36% (Case II). Overqualification rises because of the share of manual vacancies increases to 65%. This is a general equilibrium response, which includes changes in the overall number of vacancies, the number of employed workers, and the relative share of high and low skill vacancies. The model also predicts an increase in the fraction of separations which are attributed to manual skill jobs. This occurs in the model because there is more turnover among manual task jobs, which then fill with high-skill workers. This could be considered consistent with observations that construction and manufacturing accounted for almost half of all US workers laid off in the Great Recession Şahin et al. (2014), and the suggestion that economic downturns are when many of the "routine" task jobs are shed from an economy with Autor (2010); Jaimovich and Siu (2012).

Table 2: 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	0.8600	0.0803	0.6483	0.6136	0.3585	0.0421	0.0114
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

3.6 Unemployment Benefits

Unemployment benefits may affect worker incentives because they represent the outside option. In circular models of mismatch, such as Marimon and Zilibotti (1999), decreases in unemployment benefits lead to more mismatch. Workers cannot afford to wait as long in the unemployment pool for a more suitable match and therefore become more willing to accept mismatched jobs. In hierarchical models, however, this may not always be the case. In the current framework, the type of job posted by the firm plays an important role in determining the share of overqualified workers. Because cognitive jobs are more expensive for the firm to post and fill, firms may reduce the share of manual skill jobs they post leading to less mismatch. The comparative static

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

is positive whenever the now familiar condition $k_C(\sigma_C + r) > k_M(\sigma_M + r)$ holds. This comparative static reveals that the firms expected costs for cognitive jobs matter. When workers accept jobs sooner it is relatively more affordable for firms to create cognitive vacancies despite the increased posting costs. Because job destruction tilts towards cognitive jobs, firms also need to increase the share of vacancies in order to keep the desired number of cognitive jobs filled.

This propensity to reduce the share of manual skill jobs also dampens the effect of productivity changes on overqualification. Table 3 below compares the quantitative predictions of the model with different values of the unemployment benefit b. The first rows show the predictions of the model as calibrated to the Canadian economy from 1997-2012 with b=0.55. An fall in the productivity parameter of 0.16 leads to approximately a 1 percentage point increase in the unemployment rate. Firms respond by increasing the share of manual skill jobs by 5 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 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. 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.

Table 3: 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

4 Estimation

This section uses the combined LFS and O*NET data to provide direct evidence in favor of the model predictions.

4.1 Tasks and Past Labor Market Conditions

The first prediction of the model is that the share of available jobs which are manual-task intensive is higher in a downturn. The expression for the share of manual task jobs in a given economic region (ER) can be summarized as a function of unemployment rates, as well as many other exogenous parameters which may be fixed by economic regions across time, or by time across regions $\phi_{\ell t} = \phi(U_{\ell t}, \delta_\ell, \tau_t)$. For any job match formed in period $t-k$ and observed in period t, each element r of the of task vector is measured with error ϵ_r. The empirical specification to test this prediction is given by:

$$S_{r\ell t} = c_{r0} + c_{r1}U_{\ell t-k} + c_{r2} + \delta_\ell + \epsilon_{r\ell t}. \tag{15}$$

Using data collapsed to the ER-level, the definition of a regional labor market, task-shares are obtained for each region. Job tasks are given by the ER averages of the O*NET factors in formed jobs, S. These provide a measure that captures the relative shares of cognitive and manual jobs, ϕ. The vector X includes demographic controls including the ER-averages of education level dummies, experience and its quadratic, job tenure and marital status. The vector U contains regional unemployment rates at the economic region level, ℓ, both current and at the time of hire. The parameters δ and τ represent economic region and time fixed effects respectively.

Results show that the task-shares of newly formed jobs vary with local economic conditions. Panel A of Table 4 provides estimates of (15) for the leading cognitive task measure. Better local economic conditions appear to decrease the relative cognitive task intensity among recently formed jobs. The estimates for manual task shares in Panel B are more conclusive. The share of manual tasks in newly formed jobs increases with regional unemployment across all specifications. The coefficients suggest that a single percentage point increase in the unemployment rate leads to one-tenth of a standard deviation increase in the manual tasks of newly formed jobs. The tasks S are measured in standard deviation units of the employed population and the coefficient for regional unemployment rates is scaled up by a factor of 100.

4.2 Tasks and Cyclical Overqualification

The second prediction of the model is that changes in tasks are the mechanism by which economic downturns bring about overqualification. This is the main contribution of the paper. The Equilibrium expression for the share of overqualification the share of vacancies given by equation (13) can be written as a function of worker characteristics X and firm, or vacancy, characteristics S.

$$OQ_{\ell t} = a_0 + S'_{\ell t}A_1 + X'_{\ell t}A_2 + \epsilon_{a\ell t} \tag{16}$$

Table 4: The Effect of Local Unemployment Rates on Job Tasks

Panel A: COG Task Measure	S_1 (1)	S_1 (2)	S_1 (3)	S_1 (4)
Urate at Hire	-1.939***	-0.269	-0.108	-0.432***
	(0.252)	(0.531)	(0.115)	(0.134)
ER Fixed-effects	✓	✓	✓	✓
Time Dummies		✓		✓
Dem. Controls			✓	✓
R^2	0.643	0.807	0.722	0.736

Panel B: MAN Task Measure	S_2 (1)	S_2 (2)	S_2 (3)	S_2 (4)
Urate at Hire	0.912***	0.975**	0.746***	1.019***
	(0.327)	(0.393)	(0.135)	(0.161)
ER Fixed-effects	✓	✓	✓	✓
Time Dummies		✓		✓
Dem. Controls			✓	✓
R^2	0.683	0.813	0.817	0.820

Estimates are the impact of regional unemployment rates when jobs were formed on the employed shares of cognitive and manual task measures, S_1 and S_2 receptively. Coefficients $\times 100$. Standard errors in parentheses robust to heteroskedasticity. Task measures are the two leading components from factor analysis on O*NET ability requirements. Cell-level data by economic region and month. N=14010. Dem. 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.

Overqualification in the data can be measured at the individual level, because the O*NET data have been merged at the occupation level with the LFS data. Equation (16) can therefore be considered an aggregate of individual-level binary overqualification measures

$$Pr(OQ_{ijt} = 1 | S_{jt}, X_{it}) = \Phi(a_0 + S'_{jt}A_1 + X'_{it}A_2). \quad (17)$$

Estimates of equation 17 are presented in Tables 5-7 for the three different measures of overqualification. Table 5 presents estimates based on the O*NET overqualification measure. This measure classifies workers as overqualified if their years of education exceed those recommended in the O*NET database by at least 1/2 of a standard deviation (approximately one “excess” year of education). Table 6 presents similar estimates using an alternative measure of overqualification based on the median education observed for a worker’s occupation in the data. Results are also presented for the GH measure in Table 7. In this measure workers at least high school education are classified as overqualified if they are employed in an occupation where they are paid a premium of less than 10% above workers with less education.[16]

Within each table, specification 1 provides the marginal effect from a probit estimation of the effect of labor market conditions at hire on overqualification. The effect of the labor market condition is identified from the within-ER time changes because estimates are conditioned on a full set of time dummies and ER dummies. Standard errors are clustered at the ER level to match the identifying variation in labor market conditions. Specification 2 presents marginal effects from a binary sample selection model (Van de Ven and Van Praag (1981)). There may be scope for selection bias of workers into and out of jobs for which they are overqualified, in which case estimates in specification 1 are unsatisfactory. Several studies document differences in the job duration (Bowlus, 1995) and mobility patters (Sicherman, 1991) of workers with low match quality, suggesting that overqualified workers will switch to "better jobs" where the return to their skill is higher (Robst, 1995). If overqualified workers are more likely to switch out of their jobs, then the share of these types of job matches observed in the cross section sample is too small.[17] The selection equation for the probability of remaining in the job h_{ijt+1} is identified using an exclusion restriction measuring the probability that a worker's "peers" remain in their jobs is included.[18]

$$h_{ijt+1} = \zeta \bar{h}_{\ell-it+1} + X'_{it} A_2 + e_{2ijt} \tag{18}$$

This (negative) selection decision of a worker's peers, $\bar{h}$, is the average of h for all other workers of the same age, in the same ER and month. Peer mobility is relevant to the selection equation because the probability that observed peers remain is highly correlated to an individual's staying probability. Peer mobility should also be a valid exclusion restriction because a worker's overqualification is predetermined.[19] Finally, specification 3 presents coefficients from a conditional logit model that accounts for worker-specific time-invariant effects.[20] The estimates from this model should be interpreted with caution because identification is only achieved for workers who are observed switching jobs during the six month

[16]This measure is only defined for workers with high school education.

[17]This concern is relevant because workers rotate out of the sample after 6 months, so only the most recently formed job is observed. If regional labor market conditions have been favorable for quite some time, then it is possible that a large share of overqualified workers from the previous downturn have switched into more suitable jobs since. In this case their overqualification is missed. This is particularly true for any job formed between 1987-1996, where workers are not observed.

[18]Although it is possible to achieve identification from the functional form, in the case where a majority of the covariates are near the mean value the probit model is approximately linear and collinearity problems may arise in the absence of an exclusion restriction (Bushway, Johnson, and Slocum, 2007).

[19]Job match quality is determined at the time of hire. Even though these workers are from the same cohort, the date of hire at the most recent job varies widely suggesting that the current peer group is not the same as the peer group at the time of hire.

[20]Because the conditional logit does not estimate a constant term additional assumptions must be imposed in order to calculate marginal effects.

window.

Consistent with estimates of job match quality from the US (Bowlus, 1995; Hagedorn and Manovskii, 2013), results in the left panel of Tables 5-7 show that overqualification varies across the economic cycle in Canada. The estimates from the O*NET and median measures suggest that an increase in regional unemployment rates from 5% to 9% coincides with an average increase in the probability of being overqualified of approximately half a percentage point. In the context of the Canadian population, a downturn of this magnitude would result in the population of Kingston becoming overqualified. In the US population, a comparable change would overqualify the population of Phoenix or Philadelphia. Small impacts of past labor market conditions on wages are common in the literature. Oreopoulos, von Wachter, and Heisz (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%. One reason for coefficients to be small is that the fraction of employed who begin a new job in any given year is low (1.6 - 2.4% in this sample). Another reason is the sample choice which excludes workers that may be less mobile and or less willing to seek out better job match quality. Despite the small magnitude of these impacts, in aggregate they may account for significant productivity losses from idle skill. Estimates of the impact using the GH measure, however, are much larger in magnitude at 3%. Larger impacts for this measure might be expected if employers decrease wages during downturns, but are still able to attract highly skilled individuals because there are few vacancies available. If this is true, then the GH measure could pick up two effects, the migration of high-skilled workers to jobs which require less education and a decrease in the likelihood that jobs pay substantial education premiums.

The importance of changing job tasks can be seen by comparing the estimates in the left and right panel of tables 5-7. Corresponding results in the right panels of Tables 5-7 are also conditioned on S from the O*NET.[21] The impact of past unemployment rates on the probability of overqualification is reduced and becomes insignificant when conditioned on the tasks of the job. It is evident that tasks displace the predictive power of past labor market conditions, in some cases entirely. Instead, the coefficients on the tasks themselves indicate that having accepted a job with lower cognitive and higher manual tasks increases

[21] Other dimensions, such as geography or individual preferences, may be important in fully characterizing the match between a worker and their job, however, Green and McIntosh (2009) find that overqualification “on paper” coincides with unused skill in practice for 47% of workers. Prior measures of match quality using Canadian data include 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. Uppal and LaRochelle-Côté (2014) use measures of education requirements from ESDC (Employment and Social Development Canada) to define one digit occupation groups which are suitable for various education levels This approach is most similar to the current paper, although it finds fewer workers to be overqualified (17% of men in 2011).

the likelihood that a worker is overqualified. I interpret this as evidence of the second model prediction that the cyclicality of job match quality is due to changes in the type of job. The marginal effects of the task measures themselves are informative because tasks are measured in standard deviations. In Table 5, then, a single standard deviation increase in the cognitive tasks of jobs decreases the probability that a worker is overqualified by up to 17%. An increase in the likelihood of overqualification from a standard deviation in manual tasks ranges from 5%-12%.

The results are robust to alternative specifications. Increased overqualification could be partially due to temporary work arrangements (McKenna, 1996), or credential recognition issues specific to immigrants (Piracha, Tani, and Vadean, 2012). Appendix Tables B.2 and B.3 provide results for the O*NET and median measures which include these covariates. Unfortunately, immigration information was not available prior to 2006 and so the resulting sample is limited to the time period covered by the great recession. Coefficients from this subsample are much larger, and are likely biased upwards because the time period is one where the Canadian economy experience more fluctuation.[22]

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 unemployment rates at the time of hire. Estimation shows that cognitive and manual job tasks hold predictive power for the probability of overqualification. This finding suggests that job tasks are an important transmission mechanism by which economic conditions affect overqualification rates. The empirical findings support general equilibrium evidence from a job search model. The model shows that firms may exploit their relatively favorable position in the labor market to attract high-skill workers into lower paying, manual task, jobs. One result of this change is an increase in overqualification. These predictions are new to the literature and arise from the model because of alternative assumptions that I argue are more consistent with the empirical evidence.

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 high 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

[22]Unlike the US, Canada did not officially experience a recession in the early 2000s.

Table 5: Task Measures and The Cyclicality of Overqualification: O*NET Measure

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Urate at	0.071**	0.049	1.995**	-0.016	-0.016	1.038
Hire $\times$ 100	(0.036)	(0.034)	(0.858)	(0.032)	(0.030)	(1.635)
S_1				-0.174***	-0.152***	-3.591***
(COG)				(0.005)	(0.004)	(0.057)
S_2				0.052***	0.046***	1.152***
(COG)				(0.005)	(0.004)	(0.034)
S_3				0.074***	0.063***	1.545***
(COG)				(0.002)	(0.002)	(0.035)
S_4				-0.002***	-0.001	-0.080***
(COG)				(0.003)	(0.003)	(0.028)
S_5				-0.027***	-0.024***	-0.565***
(COG)				(0.002)	(0.002)	(0.029)
Region FE	✓	✓		✓	✓	
Month FE	✓	✓		✓	✓	
Person FE			✓			✓
Year FE			✓			✓
Dem. Controls	✓	✓	✓	✓	✓	✓
Selection						
Fraction of		1.252***			1.252***	
Peers Stay		(0.055)			(0.055)	
N	1450984	1372347	99102	1450984	1372347	99102
R^2	0.025			0.445		
χ^2		0.16			6.02**	

Urate estimates are the effect of increases in regional unemployment rates ($\times$100) on the probability of overqualification. Column 1 presents probit marginal effects at the mean. Column 2 presents probit marginal effects corrected for sample selection bias. Sample selection indicates whether workers selected out of their current job. The selection equation is identified using an exclusion restriction for the selection decisions of peers. Column 3 presents conditional logit coefficients. O*NET overqualification measure is based on expert ratings of required education. 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 unemployment rate. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are tasks generated from factor analysis of occupations. Tasks 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

Table 6: Task Measures and The Cyclicality of Overqualification: Median Measure

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Urate at	0.035	0.096**	2.541***	0.018	0.024	3.276**
Hire $\times$ 100	(0.049)	(0.044)	(0.767)	(0.052)	(0.043)	(1.311)
S_1				0.002	-0.128***	-2.744***
(COG)				(0.004)	(0.003)	(0.039)
S_2				-0.002	0.074***	1.534***
(COG)				(0.002)	(0.001)	(0.029)
S_3				-0.009***	0.058***	1.380***
(COG)				(0.002)	(0.001)	(0.028)
S_4				-0.015*	-0.034***	-0.458***
(COG)				(0.008)	(0.007)	(0.023)
S_5				-0.024***	-0.017***	-0.181***
(COG)				(0.003)	(0.003)	(0.021)
Region FE	✓	✓		✓	✓	
Month FE	✓	✓		✓	✓	
Person FE			✓			✓
Year FE			✓			✓
Dem. Controls	✓	✓	✓	✓	✓	✓
Selection						
Fraction of		1.207***			1.207***	
Peers Stay		(0.052)			(0.052)	
N	1744784	1338530	51487	1744784	1338530	51487
R^2	0.139			0.1417		
χ^2		0.56			11.19***	

Urate estimates are the effect of increases in regional unemployment rates ($\times$100) on the probability of overqualification. Column 1 presents probit marginal effects at the mean. Column 2 presents probit marginal effects corrected for sample selection bias. Sample selection indicates whether workers selected out of their current job. The selection equation is identified using an exclusion restriction for the selection decisions of peers. Column 3 presents conditional logit coefficients. Median overqualification measure is based on the distribution of observed education within an occupation. 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 unemployment rate. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are tasks generated from factor analysis of occupations. Tasks 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

Table 7: Task Measures and The Cyclicality of Overqualification: GH Measure

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Urate at	0.296***	0.312***	2.306***	0.164	0.024	1.930**
Hire $\times$ 100	(0.099)	(0.117)	(0.685)	(0.104)	(0.043)	(0.853)
S_1				-0.191***	-0.190***	-1.433***
(COG)				(0.002)	(0.002)	(0.021)
S_2				0.097***	0.096***	0.713***
(COG)				(0.004)	(0.004)	(0.018)
S_3				0.066***	-0.065***	0.406***
(COG)				(0.002)	(0.002)	(0.018)
S_4				-0.174***	-0.174***	-1.242***
(COG)				(0.002)	(0.002)	(0.022)
S_5				0.002	-0.001	0.157***
(COG)				(0.005)	(0.005)	(0.019)
Region FE	✓	✓		✓	✓	
Month FE	✓	✓		✓	✓	
Person FE			✓			✓
Year FE			✓			✓
Dem. Controls	✓	✓	✓	✓	✓	✓
Selection						
Fraction of		1.262***			1.262***	
Peers Stay		(0.059)			(0.059)	
N	1007150	827630	115820	1007150	827630	115820
R^2	0.044			0.259		
χ^2		4.09**			0.10	

Urate estimates are the effect of increases in regional unemployment rates ($\times$100) on the probability of overqualification. Column 1 presents probit marginal effects at the mean. Column 2 presents probit marginal effects corrected for sample selection bias. Sample selection indicates whether workers selected out of their current job. The selection equation is identified using an exclusion restriction for the selection decisions of peers. Column 3 presents conditional logit coefficients. The GH overqualification measure is based on the education premium for HS graduates in a given occupation and year, similar to the measure defined in Gottschalk and Hansen (2003). 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 unemployment rate. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are tasks generated from factor analysis of occupations. Tasks 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

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, to the extent that overqualification represents an alternative to unemployment, it may be considered a relatively beneficial option. Reduced overqualification at the expense of employment may not be a desirable outcome for workers or policymakers. 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. Third, overqualification is shown to arise partially due to the equilibrium response of firms in a downturn. This suggests that the reductions in overqualification might arise from the greater effort to dampen business cycle fluctuations. It is also true that the jobs formed in the recovery phase would decrease the overqualification rate with time.

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 the foregone productivity. However, field of study or the quality of educational institutions where degrees have been obtained may also affect job match quality. The empirical results in this paper focus on filled job vacancies because the analysis of unfilled vacancies is beyond the scope of the 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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A Model Solutions Appendix

A.1 Wages

Solving the value functions, it is first assumed 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:

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

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

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

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

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 value of unemployment. Substituting (A.4) into (1) gives an expression for the asset value of an unemployed worker 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 (6):

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

A.2 Equilibrium Conditions

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

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

A similar solution is found for cognitive vacancies. Because both free entry conditions equate to zero, these two solutions can also be equated and solved for the share of manual vacancies the firm will post, ϕ.

$$\begin{aligned}\phi =& \frac{r\left[k_C(r+\sigma_C)-k_M(r+\sigma_M)\right]\left(b+F_C\frac{z\beta m(\theta)}{r+\sigma_C}\right)}{D}\\ &-zr\frac{\left(1+\frac{\beta m(\theta)}{r+\sigma_C}\right)\left[F_M k_C(r+\sigma_C)-F_C k_M(r+\sigma_M)\right]}{D}\end{aligned} \tag{A.11}$$

where

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

$$\begin{aligned}D =& zr\beta m(\theta)\left\langle \frac{1}{r+\sigma_M} - \frac{1}{r+\sigma_C}\right\rangle \Big[F_M k_C(r+\sigma_C) - F_C k_M(r+\sigma_M)\Big]\\ &-zr\beta m(\theta)\Big[k_C(r+\sigma_C)-k_M(r+\sigma_M)\Big]\left(\frac{F_M}{r+\sigma_M}-\frac{F_C}{r+\sigma_C}\right).\end{aligned}$$

Because D simplifies to $zr\beta m(\theta)[F_M - F_C](k_M - k_C)$, the expression (A.11) above may also be written as

$$\begin{aligned}\phi =& \frac{r\left[k_C(r+\sigma_C)-k_M(r+\sigma_M)\right]\left(b+F_C\frac{z\beta m(\theta)}{r+\sigma_C}\right)}{zr\beta m(\theta)[F_M-F_C](k_M-k_C)}\\ &-zr\frac{\left(1+\frac{\beta m(\theta)}{r+\sigma_C}\right)\left[F_M k_C(r+\sigma_C)-F_C k_M(r+\sigma_M)\right]}{zr\beta m(\theta)[F_M-F_C](k_M-k_C)}\end{aligned}$$

Combining over the common denominator, the numerator reduces to

$$k_C(r+\sigma_C)[b-zrF_M] - k_M(r+\sigma_M)[b-zrF_C] + zr\beta m(\theta)k_C[F_M-F_C]$$

Therefore,

$$\phi = \frac{k_C(r+\sigma_C)[b-zrF_M]-k_M(r+\sigma_M)[b-zrF_C]}{zr\beta m(\theta)[F_M-F_C](k_M-k_C)} + \frac{k_C}{k_M-k_C} \tag{A.12}$$

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

$$\theta = \frac{m(\theta)(1-\beta)z(F_M-F_C)}{(r+\sigma_M)k_M-(r+\sigma_C)k_C} \tag{A.13}$$

A.3 Proofs of Existence

The mixing equilibrium exists provided that two conditions hold. This section details the proofs, which follow closely to the proofs in Wong (2003). For mixing, a high-skill worker must be willing to accept a manual skill job. This will occur only if there is a non-negative surplus to be split between the firm and the worker:

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

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

$$zf(x_H, s_M) - b \geq \frac{z\beta m(\theta)(1-\phi)}{r+\sigma_C}\Big[f(x_H, s_C) - f(x_H, s_M)\Big]. \tag{A.14}$$

This result shows that in order to support a mixing equilibrium, it is necessary for the marginal cost of a high-skill worker rejecting a manual job offer to exceed the marginal benefit of waiting for a cognitive offer to arrive.

The mixing equilibrium also requires firms that post cognitive vacancies to be willing to accept a low-skill worker. If this is true, the expected surplus of filling the vacancy with a low-skill worker must not be 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

$$\frac{zf(x_L, s_C) - rU(x_L)}{r+\sigma_C} \geq \frac{zf(x_H, s_C) - rU(x_H)}{r+\sigma_C} \tag{A.15}$$

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

$$[f(x_H, s_C) - f(x_L, s_C)] \leq \frac{\beta m(\theta)\phi}{r+\sigma_M}\Big\langle [f(x_H, s_M) - f(x_L, s_M)] - [f(x_H, s_C) - f(x_L, s_C)]\Big\rangle \tag{A.16}$$

This relation is true when the output loss from employing a low-skill worker in a cognitive job is low enough. 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.

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

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

Finally, substituting equation (A.17) into (9) and simplifying:

$$\phi = \frac{k_C}{(k_C - k_M)} + \frac{k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]}{z\beta(k_C - k_M)(F_C - F_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi}} \tag{A.18}$$

Substituting the above two expressions into equation (9) gives

$$\begin{aligned} v = \Bigg[& \left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{1/\xi} \\ & \times \Bigg(z\beta(F_C - F_M)(k_M\sigma_C - k_C\sigma_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi} \\ & + k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]\Bigg)\Bigg] \Bigg/ \\ & \Bigg[z\beta(k_M - k_C)(F_C - F_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{2(1-\xi)/\xi} \\ & + z\beta(F_C - F_M)(k_M\sigma_C - k_C\sigma_M)\left(\frac{(1-\beta)z(F_C - F_M)}{k_C(r+\sigma_C) - k_M(r+\sigma_M)}\right)^{(1-\xi)/\xi} \\ & + k_M(r+\sigma_M)[zF_C - b] - k_C(r+\sigma_C)[zF_M - b]\Bigg] \end{aligned} \tag{A.19}$$

B Figures and Tables Appendix

Figure B.1: Small Changes in Productivity

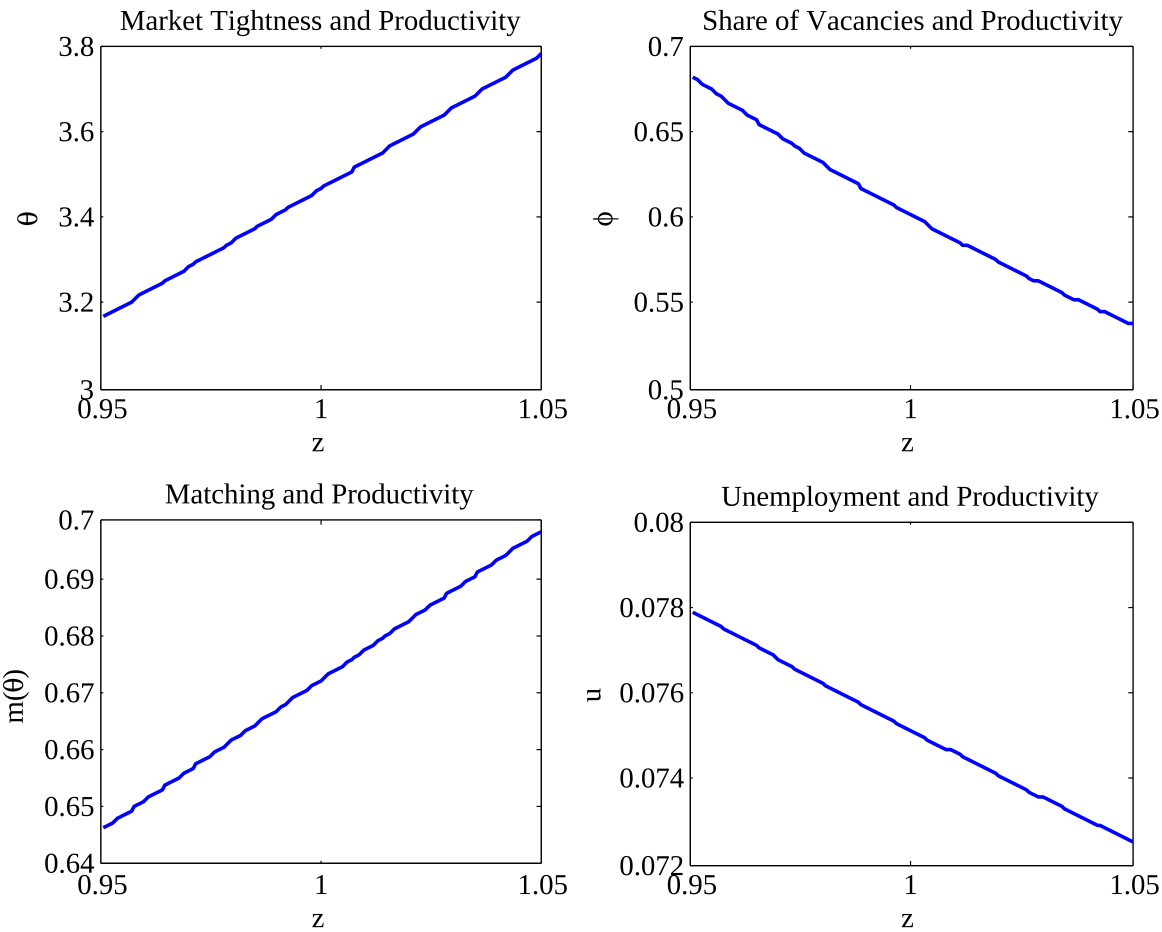


Table B.1: Calibration Results

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 B.2: Task Measures and The Cyclicality of Overqualification: O*NET Measure with Immigrant Subsample

	(1)	(2)	(3)	(4)
Outcome	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Urate at	0.138***	0.051*	-0.057	-0.005
Hire $\times$ 100	(0.066)	(0.027)	(0.077)	(0.020)
S_1			-0.205***	-0.053***
(COG)			(0.005)	(0.002)
S_2			0.061***	0.016***
(COG)			(0.005)	(0.001)
S_3			0.092***	0.023***
(COG)			(0.003)	(0.001)
S_4			-0.001	-0.000
(COG)			(0.004)	(0.001)
S_5			-0.035***	-0.009***
(COG)			(0.003)	(0.001)
Prov FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Dem. Controls	✓	✓	✓	✓
Selection				
Fraction of		0.998***		0.998***
Peers Stay		(0.026)		(0.026)
N	504915	572263	504915	572263
R^2	0.268		0.457	
χ^2		1.24		0.37

Urate coefficients are the effect of increases in regional unemployment rates ($\times 100$) on measures of overqualification, corrected for sample selection bias. Sample selection indicates whether workers selected out of their current job. The selection equation is identified using an exclusion restriction for the selection decisions of peers. Coefficients reported are marginal effects from probit estimates of the probability of overqualification. O*NET overqualification measure is based on expert ratings of required education. 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 unemployment rate. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are tasks generated from factor analysis of occupations. Tasks 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

Table B.3: Task Measures and The Cyclicality of Overqualification: Median Measure with Immigrant Subsample

	(1)	(2)	(3)	(4)
Outcome	Pr(OQ)	Pr(OQ)	Pr(OQ)	Pr(OQ)
Urate at	0.157**	0.142***	0.025	0.022
Hire $\times$ 100	(0.042)	(0.038)	(0.051)	(0.050)
S_1			-0.127***	-0.127***
(COG)			(0.003)	(0.003)
S_2			0.074***	0.074***
(COG)			(0.001)	(0.001)
S_3			0.060***	0.058***
(COG)			(0.001)	(0.001)
S_4			-0.034***	-0.034***
(COG)			(0.007)	(0.007)
S_5			-0.017***	-0.018***
(COG)			(0.034)	(0.003)
Prov FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Dem. Controls	✓	✓	✓	✓
Selection				
Fraction of		1.155***		1.19032
Peers Stay		(0.038)		(0.042)
N	2082638	1596323	1656874	1302349
R^2	0.331		0.433	
χ^2		7.09****		11.13***

Urate coefficients are the effect of increases in regional unemployment rates ($\times$100) on measures of overqualification, corrected for sample selection bias. Sample selection indicates whether workers selected out of their current job. The selection equation is identified using an exclusion restriction for the selection decisions of peers. Coefficients reported are marginal effects from probit estimates of the probability of overqualification. O*NET overqualification measure is based on expert ratings of required education. 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 unemployment rate. Standard errors in parentheses clustered at the economic region. Results weighted with LFS final weights. S_r are tasks generated from factor analysis of occupations. Tasks 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

C Data Appendix

C.1 The O*NET

The O*NET database, which is the successor to the Dictionary of Occupational Titles (DOT), 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 SOC coding system. The purpose of the O*NET is to attribute characteristics to each occupation, which 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."

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.[23] After collapsing to the SOC level and merging with the LFS, the sample contains workers in 327 different occupations.

C.1.1 The O*NET Overqualification Measure

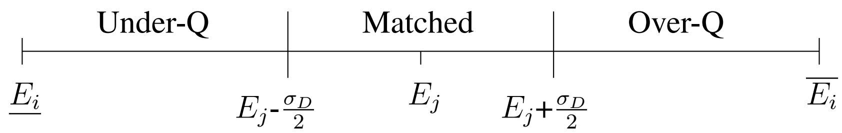
This paper uses education requirements to generate one measure of overqualification. In recent versions of the O*NET, education requirements are assessed by a group of occupational experts. An occupational expert is a worker in the occupation who is deemed, due to rank or experience, to have expert knowledge about the occupation. Education requirement rankings, using discrete education milestones, are reported for each surveyed expert (See Figure C.3 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 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

[23] 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 through 2010 versions are limited to 8 occupations. The final concordance between the US SOC 2000 codes and the Canadian NOCS06 codes was provided by Statistics Canada. At the time this paper was written it had been verified by the custodians of the NOCS06, but not the SOC.

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.[24] Appendix Figure C.2 gives a visual representation of these measures from the O*NET.

Figure C.2: A Binary Measure for Assessing Mismatch



C.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.[25] An important way the task measures in this paper differ from those in the polarization literature (Autor, Levy, and Murnane, 2003; Firpo, Fortin, and Lemieux, 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.[26] Performing factor analysis on the 52 abilities in the O*NET, occupation

[24] $\sigma_D \approx 1.9$ years of education. Sensitivity reveals that results are robust to a range 0.5-1.5 years of schooling. This measure classifies 25% of the workers in the sample as overqualified, and approximately 30% as underqualified. Standard deviation measures of match quality are common in the literature, however, these typically compare workers to the reported education of other workers within occupation, rather than comparing workers to measures deemed education requirements.

[25] Because overqualification measures are constructed using worker education and occupation education requirements, it is not possible to control for education requirements in empirical analysis. The task approach not only provides a richer understanding of the nature of certain jobs, but it also provides job characteristics which are not collinear.

[26] The choice of the ability category is admittedly subjective. In contrast to the approach of this paper, papers in the polarization literature pick particular elements from various categories of the O*NET, or its predecessor the Dictionary of Occupational Titles (DOT), which may be well suited to illustrate job characteristics which are routine or manual in nature. These elements might best be chosen individually because they relate to the possibility that jobs are off-shored or replaced by new technology.

codes are replaced by a vector of 5 orthogonal tasks, S. The procedure follows closely to Poletaev and Robinson (2008).

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 $a_{jk} = I_{jk}^{a} \times C_{jk}^{1-a}$.[27] The common factor model estimation procedure identifies the relevant underlying factors from the 52 different abilities.

C.2.1 Factor Analysis

To extract the relevant information about occupation specific skill, summary measures of tasks $S_{rj}, r = 1, \ldots, 5$ 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 of the propensity for duplicate information in the O*NET, it is likely that much of the unique variation is attributable to noise. In addition, factor analysis is more suitable for orthogonal rotation. This rotation 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:

$$A = S\mathbf{\Lambda}' + e, \tag{C.20}$$

where A is the vector of ability ratings and S is the resulting vector of factors. The matrix $\mathbf{\Lambda}$, 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;

$$\boldsymbol{R} = \mathbf{\Lambda} \boldsymbol{I} \mathbf{\Lambda}' + \mathbf{\Psi}, \tag{C.21}$$

[27] 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 C.4. Results reported in this paper use a=1/2, but results are robust to variation in this parameter.

and that $\mathbf{\Psi}$ represents the uniqueness element in the ability measures which will not be attributed to common factors. The model estimates $\mathbf{\Psi}$ first, then computes each column of the factor loading matrix $\mathbf{\Lambda}$ 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.

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 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 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 C.6) 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 C.4.[28] The scale of the tasks 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 task in the distribution of occupations in the Canadian economy.[29] Table C.5 presents the five occupations scoring highest for each

[28]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.

[29]Although this scaling ambiguity diminishes the possibility to make cardinal comparisons between the tasks of individual jobs, each task has an ordinal meaning and the variation in the scale of the tasks contains information. For example, a higher minimum level for one task than another indicates that the baseline re-

of the two leading factor scores.

Table C.4: 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.

Table C.5: 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

quirement for all jobs in the economy is higher in this first skill. Because this paper does not make any claims about the magnitudes of any individual job's tasks, further manipulation of the factors is avoided.

Table C.6: 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 C.3: 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 C.4: 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 [X] 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*?

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