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Labor Market Conditions, Skill Requirements and Education Mismatch

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Labor Market Conditions, Skill Requirements and Education Mismatch*

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Abstract

This paper shows that changes in the skill requirements of jobs are one way by which economic downturns affect job match quality. In doing so this paper makes two contributions to the literature. The first contribution is to document a stylized fact about the cyclicality of skill requirements (tasks) for newly formed jobs. Relating local unemployment rates in Canadian data, to skill requirements generated from the Occupational Information Network (O*NET) database, I show that the demand for manual skill requirements is countercyclical. This stylized fact shown to be consistent with the predictions of a job search models with heterogeneous workers and vacancies. In this framework, firms increase the share manual job vacancies during downturns because they are less costly to post and fill. The second contribution is to show that the cyclicality of skill requirements, rather than economic conditions themselves, contribute to the incidence of overqualification. Estimates using various measures of overqualification confirm that changes in the skill requirements of newly formed jobs can account for much of the relationship between labor market conditions and job match quality. This empirical finding is also consistent with the model, where the share of overqualified workers varies with economic conditions partially because of corresponding changes in the type of job vacancies.

Keywords: Mismatch, Job Search, Overeducation, Skill Demand, Business Cycles

JEL Codes: E24; E32; J24; J63; J64

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1 Introduction

Although firms often post explicit requirements in job ads, many workers are found in employment situations where they appear overqualified. Some examples include a clerical worker with a bachelor's degree, or a manager with high school education. These mismatched arrangements can been costly for workers in terms of wage penalties (McGuinness, 2006; Rubb, 2003; Sloane, 2003; Groot and Maassen van den Brink, 2000), and in terms of lower job satisfaction (Peiró, Agut, and Grau, 2010).[1] Overqualified workers also have higher job mobility (Sicherman, 1991), implying that poor job matches also impose additional turnover costs on firms. In addition to these costs, overqualification implies idle skill and may ultimately result in foregone economic output. Recent estimates suggesting that 37 percent of North American workers are overqualified (Leuven and Oosterbeek, 2011), mean that these losses are likely substantial.[2]

One reason that workers are found in jobs for which they are overqualified is the state of the labor market. Evidence regarding the cyclicality of job match quality has been found using various indicators of mismatch including job duration (Bowlus, 1995), job mobility (Moscarini and Vella, 2008), and more specifically occupation (Devereux, 2002) and industry (Liu, Salvanes, and Sørensen, 2012) mobility. In aggregate measures, Lazear and Spletzer (2012) also observe that mismatch in the US was countercyclical through the 2008 recession and the ongoing recovery. This cyclical relationship is typically modeled with a heterogeneous agent job search framework. During a downturn, search frictions can lead more workers to accept mismatched jobs, rather than unemployment (Chassamboulli, 2011). Similar models have also been used to establish that unemployment benefits (Marimon and Zilibotti, 1999), on-the-job search (Barlevy, 2002; Krause and Lubik, 2006; Gautier, Teulings, and Van Vuuren, 2010), and productivity risk (Moscarini, 2005) also contribute to the extent of mismatch.

[1] The analysis of mismatch in this paper focuses on overqualification because it has received the most attention in the literature, and because the evidence for a cyclicality of underqualification is weak. In this paper the word "mismatch" is used to describe how individual worker credentials compare to job requirements, and should not be confused with alternative uses such as Shimer (2007) where mismatch reflects the difference between job vacancies and job seekers in a given market.

[2] These results are from a meta-analysis which suggest that approximately 37% of workers in the US and Canada are overeducated and 16% are undereducated.

Another cyclical phenomenon, which this paper establishes as a contributor to job match quality, is the assignment of workers to tasks across the business cycle. Facing less-favorable economic conditions, firms assign well educated workers to tasks or occupations normally filled with low skilled workers. I propose that this patter, documented by Devereux (2000), has not received enough attention in the literature. In the current analysis I highlight the importance of the this heterogeneous demand for skill by showing that similar strategies across measures of cognitive and manual tasks (or skill requirements) may apply to the hiring of new workers.[3] The intuition behind decreased (increased) relative demand for cognitive (manual) skill in a downturn includes the possibility that investment in R&D is procyclical (Barlevy, 2004, 2007). Reacting strategically to the scarcity of jobs, firms could also stand to gain from positive externalities if they are able to fill a low-wage, low-skill job with a well educated worker. Moreover, infrastructure stimulus spending, such as recent "shovel-ready" projects during the great recession, may also increase the relative demand for manual skills.

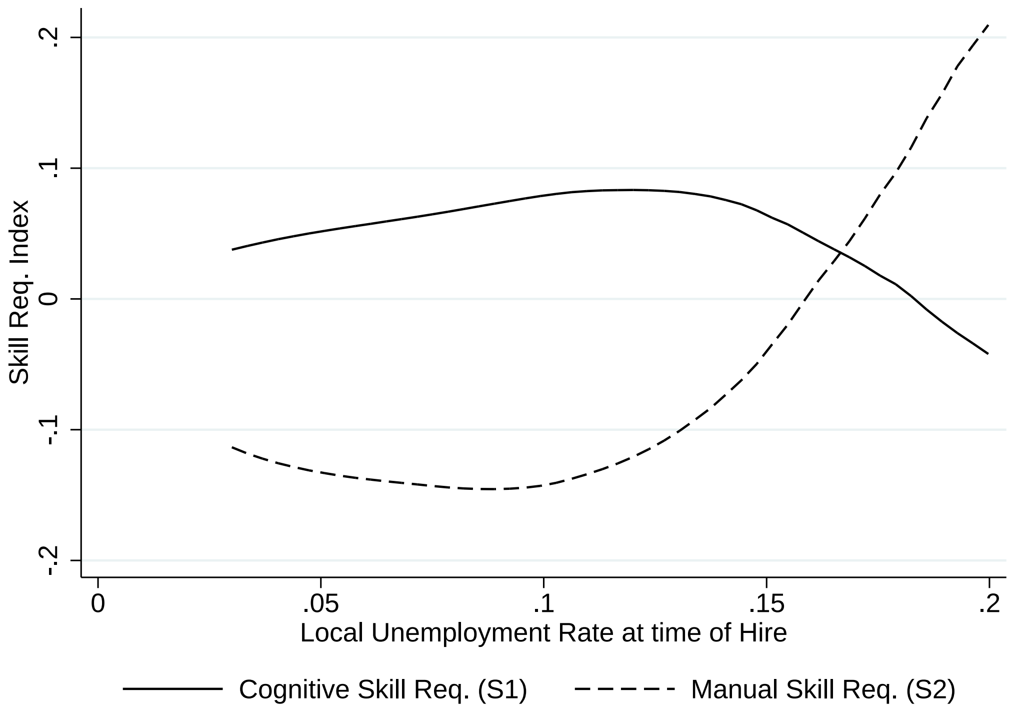
The first contribution of this paper is to document this stylized fact, complementary to Devereux (2000): the relative share of manual skill requirements among newly formed jobs is countercyclical. Using measures of occupational skill requirements (or tasks), I show that the share of manual skill requirements in newly formed jobs is positively correlated with local unemployment rates in Canada.[4] Because newly filled job vacancies do not represent the full extend of the demand for skill, I also consider empty job vacancies. Mapping the skill requirement measures into the Minnesota Job Vacancy Survey data, I find that similar cyclical patterns exist for unfilled vacancies.[5] Figures 1 and 2 use local moving averages to illustrate changes in these skill requirements, which are detailed later in the paper,

[3]The reader may also wonder about firing strategies. One popular stylized fact about the US labor market is a suggestion that less educated workers may be more likely to become unemployed during downturns (Hoynes, 1999; Kydland, 1984), although some evidence suggests this is highly dependent on industry Prasad and Keane (1993). This papers findings account for education differences among matched and mismatched workers. In addition, while I do find evidence suggesting less that more educated workers are less likely to enter unemployment, this pattern does not appear to change over the business cycle.

[4]Although the focus of this paper is cyclicality, rather than the overall trend in the economy, the relative shift towards manual skill jobs is consistent with a decrease in demand for cognitive skills following the 2000 recession in the United States, documented in current work (Beaudry, Green, and Sand, 2013).

[5]This procedure requires job vacancy data encoded by detailed occupation. No such data is currently available for Canada, and I am unaware of any american data beyond the Minnesota Job Vacancy Survey to provide this information.

Figure 1: Cyclical Skill Requirements in Newly Formed Jobs



Plot is a local moving average smooth of the cognitive and manual skill requirements of filled jobs in Canada (on the Y axis) against the local unemployment rates at the time these jobs were formed (on the X axis). Smoother uses Epanechnikov kernel with bandwidth of 0.015. The skill requirements are leading factors, each with mean zero, from the O*NET data. A single standard deviation represents the population standard deviation of that particular skill requirement. Local unemployment rates and occupation information are from the Canadian Labour Force Survey for jobs formed over the period 1987-2012, and are measured monthly at the economic region level. Results are trimmed to the range (3%,20%).

across local economic conditions.[6]

The second contribution of the paper is to link the cyclicality of job match quality to the observed cyclicality in the demand for skill. I show that overqualification arises partially from corresponding changes in the demand for skill.[7] Examining the demand for skill may be especially helpful for explaining cyclical changes in job match quality. This is true because changes in the skill supply of the

[6]Because of the confidential nature of the data, this smoothing process minimizes the disclosure risk in place of summary statistics. The local moving average smoother uses Epanechnikov kernel weighting, incorporating neighboring observations with a bandwidth of 0.015.

[7]Although skill demand has been suggested as an important contributor to mismatch across countries (Desjardins and Rubenson, 2011), to the best of my knowledge, I provide the first evidence explicitly linking to job match quality to the cyclical changes of skill requirements.

workforce, following from cyclical immigration or education patterns, are likely slow by comparison.[8]

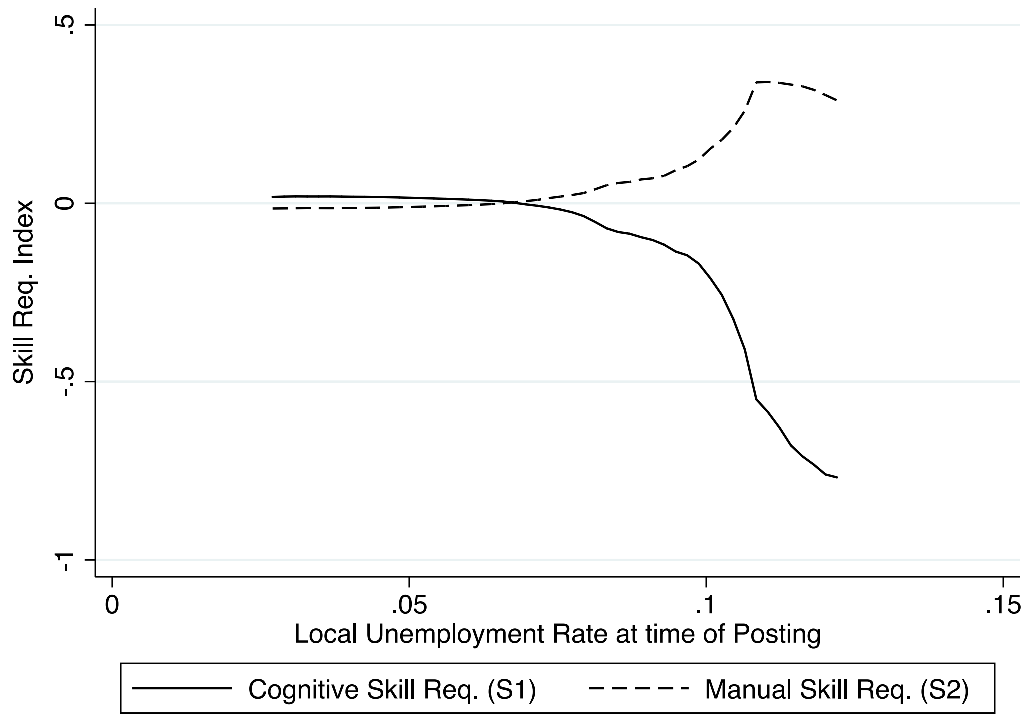
Using a job search model with heterogeneous workers and vacancies, this paper shows that changes in the type of available job vacancies result in corresponding fluctuations in job match quality for newly formed jobs which are consistent with the data. Firms not only reduce the number of vacancies during a downturn, but they also shift the type of jobs they post in favor of manual skill jobs. These jobs are less expensive to post, and pay lower wages. Because of the congestion externalities in the model, not only is there a reduction in the overall number of job matches, but also there is a reduction in the share of "suitable" job matches.

Reduced-form empirical results support this result of the model. Using Canadian data, I first show that downturns increase the incidence of overqualification, conditional on worker characteristics. Conditioning on skill requirements, I then show that the variation relevant to overqualification comes from changes in job characteristics rather than labor market conditions themselves. These second estimates suggest that economic conditions may affect mismatch indirectly, through their influence on the type of jobs formed over the business cycle. This finding is quite robust to specification changes, various definitions of overqualification, and does not appear to be the result of sample selection bias or unobserved characteristics among workers.

Previous empirical work on overqualification, or overeducation as it is often referred, documents the implications of, rather than the causes of, overqualification. The literature builds on the identification of wage penalties for mismatched workers from Duncan and Hoffman (1981); Verdugo and Verdugo (1989), and cross sectional evidence suggest that overqualified workers earn 8% (per year of excess education) less than similar well matched workers in the US and Canada. Whereas this literature has primarily attributed overqualification to worker heterogeneity, including specific skills such as literacy (Boothby, 2002) and unobserved characteristics (Sicherman, 1991; Bauer, 2002; Frenette,

[8] Betts and McFarland (1995); Dellas and Koubi (2003); Dellas and Sakellaris (2003); Méndez and Sepúlveda (2012) show that education enrollment is countercyclical in American Data. Despite this, it is unlikely that workers can upgrade their education credentials in time with the business cycle. For example, a high school educated worker returning to community college would require at least 2 years of study to receive a recognized diploma. Furthermore, Canadian evidence (King and Sweetman, 2002) shows that workers return to school in a procyclical pattern, meaning that increased overqualification in downturns is unlikely due to an increase in skill supply.

Figure 2: Cyclical Skill Requirements in Posted Job Vacancies



Plot is a local moving average smooth of the cognitive and manual skill requirements of posted job vacancies in Minnesota (on the Y axis) against the local unemployment rates (on the X axis). Smoother uses an Epanechnikov kernel with a bandwidth of 0.15. The skill requirements are leading factors, each with mean zero, from the O*NET 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.

2004; Tsai, 2010), my innovation is to show that the cyclical demand for skill is also an important contributor to the incidence of overqualification, conditional on worker characteristics. Supplementary findings of this paper, which replicate similar wage penalties for overqualified workers, also suggest that a substantial component of the wage penalty for overqualified workers follows from employment in lower paying, manual skill, jobs.

This paper also offers insights for the literature on the wage impacts of past labor market conditions. Poor labor market conditions at graduation (Oreopoulos, von Wachter, and Heisz, 2012; Kahn, 2010; Bowlus and Liu, 2003) and during past job spells (Beaudry and DiNardo, 1991; McDonald and Worswick, 1999; Grant, 2003; Devereux and Hart, 2007) have been shown to reduce worker wages.

Current research by Hagedorn and Manovskii (2010) summarizes these findings, demonstrating that job match quality could be the link between past labor market conditions and current wages. My results provide complementary evidence based on observable measures of match quality. In addition my results show that the type of jobs formed during past business cycles may affect the current wages of workers, because pay varies with the skill requirements of the job.

The rest of the paper proceeds as follows: Section 2 outlines the Data, Canada's Labour Force Survey (LFS) and the O*NET database from which I draw information on jobs, and discuss various empirical measures of skill requirements and education mismatch. In Section 3, I use a model of job search to show that firms may vary the share of cognitive and manual job vacancies with labor market conditions. Section 4 provides empirical evidence that the cyclicality of mismatch is due to changes in the skill composition of new jobs. Section 5 relates my findings to the wage penalty literature, and Section 6 concludes.

2 Data

In order to assess the match between a worker and their job, it is necessary to observe the characteristics of both. Using occupation codes as a link, this paper combines information on workers from the LFS with occupation characteristics from the O*NET. The resulting dataset has rich information on workers, their jobs and local labor market conditions. Details of the O*NET data and linking procedure are available in the Appendix section A.

2.1 The Labour Force Survey

Worker data are from the monthly confidential rounds of Canada's LFS for the period 1997-2012.[9] The LFS is a large representative sample of Canada's working population, from which I draw 1.7 million observations of employed males age 16-65. The sub-sample excludes unionized, part-time, and self-employed workers because these individuals may be mismatched due solely to the nature of

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

their work contracts. The sample is also restricted to workers reporting an occupation to allow job characteristics to be linked from the O*NET data. Occupations in the sample are classified according to the 2001 National Occupational Classification System (NOCS-01) occupation codes, providing a substantial level of detail about occupational differences and a consistent mapping across the sample.[10]

Several measures of human capital are constructed from the LFS. Binary variables for education milestones are created, including Less than High School (LHS), High School (HS), Post-Secondary non-degree (PS), Bachelor's degree (BA) and higher degrees (PG).[11] Potential years of experience are also calculated, and those with negative potential experience are excluded from the sample. Additional worker characteristics include dummy variables for marital status, various geographical indicators for residence, immigration status and indicators for the date of observation. Information about job characteristics, aside from the occupation codes, includes an indicator for job switchers, monthly job tenure, and a firm size index.[12]

Local economic conditions which will be used to measure the cyclicality of overqualification are identified from unemployment rates at the economic region (ER) level, a Census geographic division for analysis of economic activity. Because the LFS is the official source for Canadian unemployment rates, I calculate ER level unemployment rates 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.[13]

Using an extended sample of the LFS, I generate local labor market conditions for the years 1987-

[10]The consistency of the occupation codes is one advantage of using Canadian data instead of the Current Population Survey (CPS) for the US. Occupation codes in US data experience a structural break in 2003 as the Census occupation coding system was revised substantially. Because of the level of detail required in linking the microdata to the O*NET, splitting the sample would be undesirable as it would result in several occupations with few observations.

[11]For the LFS data, PS captures mainly community college graduates, the closest equivalent in the United States being the Associate's Degree. This category represents the majority of Canadians with education beyond high school. This education milestone approach allows for non-linearity in the impacts of schooling years and is common in the literature on the returns to education in Canada (Boudarbat, Lemieux, and Riddell, 2010). The results presented in this paper were also found to be robust to substitution of a yearly measure of education and it's quadratic.

[12]Firm size index groups firms as follows, 1: 1-20, 2: 20-99, 3: 100-500, 4: 500+

[13]Some ER's, such as those in the territories where representative sampling is prohibitive, are not sampled for the LFS.

2012. Linking these to worker observations using their monthly job tenure, I am able to capture the labor market conditions at the time of job formation for many workers who begin their job before being sampled. Because workers are only sampled for 6 months, this procedure allows me to observe labor market conditions for a large fraction of the sample, rather than just those who happen to start a new job during their survey cycle.[14] Although many other variables of interest are not available in the data prior to 1996, this extended period also allows me to include jobs formed around and during the1990 recession.[15] Consistent job tenure measures are a key feature of the LFS data, which is not available in other large representative data sets such as the CPS. Attributing labor market conditions at the time of hire to worker observations is central to this paper's analysis of cyclical changes in the nature of job creation, and is only possible with job duration information.

Although it is not widely advertised, the LFS is a rotating 6-month panel. It is therefore possible to obtain details of worker job histories up to 5 months prior to observation and identify job switchers as well as those who transition in and out of unemployment.[16] In order to address sample selection bias, I exploit the rotational panel feature of the LFS using a linkage methodology adopted from Brochu and Green (Forthcoming). This allows for the creation of job mobility indicators and make it possible to demonstrate the robustness of the results with respect to unobserved heterogeneity using worker fixed-effects, although such estimates limit the identifying variation to workers in my sample who are observed while switching jobs.

[14]This procedure is limited to 1987 because ER indicators underwent a major change in 1987, and the 2012 ER boundaries in the dataset are not encoded prior to 1987. An assumption is also made that workers do not re-locate outside of their current ER while staying with the current employer.

[15]Because Canada did not officially enter recession in 2000, capturing the 1990 recession helps to ensure that my analysis covers a large variation in economic conditions.

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

2.2 Overqualification

This paper assess overqualification based on years of education. Although overqualification may be measured in other ways, education is a common choice because it is observable. Because formal education represents the most significant human capital investment for many workers, education mismatch may also be the most important type of mismatch to understand.[17] It is also advantageous to a general measure of mismatch itself, rather than identifying mismatch based on a proxy such as mobility across occupation or industry, because not all workers switching jobs may be mismatched.[18] Other dimensions, such as geography or individual preferences, may be important in fully characterizing the match between a worker and their job, however, my focus is overqualification in terms of formal education. This paper does not explicitly address underqualification for the same reason as much of the prior empirical literature: undereducated workers may not be true cases of "mismatch" (Sicherman, 1991).[19]

To ensure that the findings of this paper are not an artifact of one particular definition of overqualification, I use four different education-based measures.[20] Two of the measures are observed by comparing a worker's reported education E_i to the required education levels from the O*NET database E_j. From this information I generate a linear distance $D_{ij} = E_j - E_i$, reporting the years of education by which job requirements exceed worker achievement.[21] The continuity of D_{ij} allows for both

[17] Education mismatch has important implications because education can be costly in terms of tuition, foregone earnings, and subsidy costs where governments intervene.

[18] Consider these examples of mobility which would not necessarily lead to mismatch: A secretary moving from a construction company to a transportation company, or a construction worker becoming an assembly line worker.

[19] It is plausible that the mechanisms generating over and underqualification could differ. Much of the underqualification is likely the result of changes in the job requirements over time, where workers have received training on the job to adapt to a changing work environment. The current paper also focuses on overqualification (or overeducation), because underqualification does not exhibit consistent cyclical patterns. Appendix Table 8 shows that while overqualification is correlated with labor market conditions, underqualification does not. In addition, estimates which allow for both over and underqualification suggest that overqualification is the relevant measure of mismatch across the cycle.

[20] Prior measures of mismatch 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 levels of education. This approach is most similar to mine, although it finds fewer workers to be overqualified (17% of men in 2011).

[21] Both the LFS and O*NET data report education in binary groups. I convert these to yearly equivalents to make categories comparable and to average across the sample of expert ratings in the O*NET.

over and underqualification. I also use a binary measure OQ, that labels a worker as overqualified when D_{ij} exceeds a threshold of $\alpha\sigma_E$, a weighted standard deviation of the distance D.[22] The results reported in Section 4 are for the case where $\alpha = 1$, which implies that 25% of the workers in the sample are overqualified and approximately 30% are underqualified. Appendix Figure 6 gives a visual representation of these measures from the O*NET.

The third and fourth measures of overqualification, which are also binary, are based on the contribution of Gottschalk and Hansen (2003) and are a complete departure from the previous two. These "GH" measures define overqualification using the market return to education, rather than (expert) categorization of occupations. For the first measure, GH-PS, occupations are classified as "post-secondary jobs" only when they pay a certain premium for college or university education. Overqualified workers then, are post-secondary educated individuals who are found in occupations which, on average, do not reward their education.[23] Similarly, GH-HS assesses whether workers that have at least high school education are in occupations that pay them a premium above LHS workers. These measures illustrate that the results in this paper do not follow from particular judgements about the appropriate amount of education for any given occupation.

2.3 Skill Requirements

In addition to characterizing occupations in terms of education requirements, I also generate skill requirement (task) measures using the O*NET data. These measures provide additional characteristics about jobs, and are much more informative that occupational dummy variables.[24] An important difference between the skill requirement measures generated in this paper and those from the polar-

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

[23] GH defined this measure for the US using "college" and "non-college" jobs, using a premium threshold of 10%. I use a threshold wage premium of 10 log points ($\approx 6\%$) to define a suitable wage premium for a given job in a given year and economic region. It is also important to note that this measure is only defined for workers with education $\geq$ PS.

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

ization literature, (Autor, Levy, and Murnane, 2003; Firpo, Fortin, and Lemieux, 2011), is the choice of what subset of the O*NET data to use.[25] In this paper I remain agnostic about which O*NET elements would best identify various skills and draw information from the entire "ability" category, an approach taken in Peri and Sparber (2009).

A set of 5 orthogonal skill requirements are generated from the 52 ability measures using factor analysis. The approach follows closely to Poletaev and Robinson (2008), and details of this procedure are in the Appendix section A.1. By examining how each ability contributes to a factor in Appendix Table 17 it is possible to interpret the skill requirements as demonstrated by Ingram and Neumann (2006). For example, the leading factor S_{1j} is highly correlated with many cognitive and communication abilities such as "deductive reasoning" and "written expression," while being uncorrelated with abilities such as "finger dexterity". Therefore this factor appears to represent reasoning and communication skill, and could be classified as a cognitive measure. By contrast, S_{2j} correlates positively with manual abilities including aspects of visual perception, "reaction time" and the "speed of limb movement". Similar interpretations are developed for the remaining factors, leading to the skill requirements presented in Table 1.[26] The scale of the skill requirements is set by weighting during the factor analysis procedure, and affects the cardinal interpretation. A single standard deviation in each factor represents a standard deviation of that skill requirement in the distribution of filled vacancies in the Canadian economy.[27]

One contribution of this paper, illustrated previously Figures 1 and 2, is to document the cyclical

[25]The polarization literature picks particular elements from 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, as these elements relate to the possibility of jobs to be off-shored or replaced by new technology.

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

[27]Although this scaling ambiguity diminishes the possibility to make cardinal comparisons between the skill requirements of individual jobs, each skill requirement has an ordinal meaning and the variation in the scale of the skill requirements contains information itself. For example, a higher minimum level of one skill requirement than another indicates that the baseline requirement for all jobs in the economy is higher in this first skill. Because this paper does not make any claims about the magnitudes of any individual job's skill requirements, I avoid further manipulation of the factors such as standardization.

Table 1: Factor Analysis Output

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

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

properties of skill requirements. Several papers discuss the cyclicality of worker skill supply (Chassamboulli, 2011; Barlevy, 2001; Devereux, 2002, 2004) but little is known about the behavior of the firm and the resulting skill requirements of jobs. To provide additional evidence that these skill requirements change with the economic cycle, Table 2 shows the impact of local unemployment rates at the time of job formation on the average skill requirements of jobs.[28] These impacts are conditioned on time and ER fixed-effects, and show a particularly significant response of manual skill job formation to poor economic conditions.

Table 2: The Relationship between Local Unemployment Rates and Job Skill Requirements

	S_1 (COG)	S_2 (MAN)	S_1 (COG)	S_2 (MAN)
Urate at	**-1.939*** **	**0.912*** **	-0.269	**0.975** **
Hire	(0.252)	(0.327)	(0.531)	(0.393)
ER FE	✓	✓	✓	✓
Time FE			✓	✓
R^2	0.643	0.683	0.807	0.813

OLS estimates of the skill requirement index for the leading cognitive and manual skill requirements from the O*NET data. Coefficients show the effect of local unemployment rates at the time of job formation on skill demands at the ER level. LFS data collapsed to mean values by economic region and month. N=14010.

[28]Impacts are calculated on data collapsed at the mean for each ER and month.

These observed patterns in job characteristics across economic conditions are central to the argument of the paper. Because overqualification has a cyclical component, and because job characteristics exhibit cyclicality, there is reason to believe that skill requirements are important to the incidence of overqualification. One explanation consistent with the data is that firms respond to a downturn, not only by posting fewer job vacancies, but also by posting a greater share of vacancies that require manual skills. There are several potential reasons for this relationship including reluctance to fill more crucial positions or invest in research and development when economic conditions are unfavorable, and the increase in construction-based infrastructure spending by government.[29]

3 A Model of Job Search and Mismatch

This section outlines a job search framework with heterogeneous workers and vacancies, that further motivates the empirical analysis of the labor market. The model shows that economic conditions lead to mismatch and overqualification through changes in the type of new jobs; during downturns, which I characterize using a decrease in productivity, firms respond by posting fewer total vacancies but relatively more manual skill (or low skill) vacancies. Because meeting is random in the model, a greater share of highly educated workers are therefore meet manual skill vacancies when unemployment is high (and productivity is low). The model presented in this section is an extension of Wong (2003) and Albrecht and Vroman (2002) with a more general production process that permits both over and underqualification.[30] The share of cognitive and manual vacancies, the incidence of overqualification and unemployment are endogenously determined in an equilibrium with search frictions.

3.1 Environment

Consider an economy with two types of workers indexed by their level of education $x \in \{x_L, x_H\}$ and two types of firms indexed by the skill requirement (or task) $y \in \{y_C, y_M\}$. Manual jobs y_M are

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

[30]My model allows for underqualification because its incidence in the data is equally prevalent to overqualification. Assuming that low skill workers produce nothing in a high skill (cognitive) job may therefore be too strong. Allowing for both over and undereducation is akin to assuming $\pi_{ij} = 1 \; \forall \; \{i, j\}$ in Wong (2003).

less productive than cognitive jobs, and the share of these less productive vacancies is given by ϕ. Workers can chose whether or not to accept wage offers arriving from a firm, and firms chose to enter the market and which type of vacancy to post. All workers who are unemployed, regardless of type, meet vacancies of measure v according to the standard meeting function

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

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 $m(\theta)/\theta$. 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 strictly positive.

In this model a filled job dissolves according to a common exogenous probability σ. In Appendix Section B.4, I discuss an extension to the model that allows for heterogeneity in job destruction by vacancy type. In this model I do not address on-the-job search because it introduces additional complication to the model and job mobility does not appear to be empirically important to the main issue in the paper. Table 4 in Section 4.2 demonstrates that matched and mismatched workers exhibit similar patterns with respect to job mobility and Table 5 shows that workers of varying levels of education have similar likelihoods of being laid off as economic conditions vary.

Workers

In this economy there are a continuum of risk-neutral and infinitely lived workers of mass 1, ψ of which are exogenously assigned type x_L. Workers can be either employed or unemployed, where γ determines the share of unemployed who are endowed with a low level of education.[31] In a given period, an unemployed worker receives a present value return of

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

[31] 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.[32] The present value return to employment for a worker of x in a job of type y, which depends on the wage $w(x, y)$ is given by

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

Firms

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

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

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

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

A filled vacancy produces according to the production function $f(x, y)$ where output is increasing in x and y.[33] Despite the fact that a x_H worker is at least as productive in a y_M job than a x_L worker, such a worker may be considered overqualified because they would be even more productive and earn a higher wage in a y_C job.

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

[33] It is reasonable to assume that more educated workers are at least as productive as less educated workers. 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 importance of this general production function is that it permits workers with either high or low education to be productive in a cognitive skill job, a departure from models such as Albrecht and Vroman (2002) where any (x_L, y_C) partnerships are not productive by assumption.

Wage Determination

Wages are determined by Nash bargaining, where the parameter β represents the worker's share of the total surplus in the economy.[34]

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

Substitution of the value functions, following the steps outlined in Appendix section B.1, leads to an expression for the wage of worker type x in vacancy type y as a function of exogenous parameters:

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

3.2 Equilibrium

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

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

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

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

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

$$\gamma = \psi$$

[34]Each meeting pair therefore solves

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

giving rise to the wage sharing condition (5).

In the absence of constraints on which workers may match with which jobs, the share of unemployed x_L workers is equal to the share of x_L workers in the population. This follows from the common pool of unemployment, and the fact that all workers the same job finding probability regardless of their type. Using the expression for u and the free entry conditions, $V(y_M) = 0$ and $V(y_C) = 0$ one can solve (9), (10) and (11) for the equilibrium triplet $\{u, \theta, \phi\}$ following steps from Appendix Section B.2. To be as general as possible, I do not parameterize the matching technology, and therefore depict equilibrium graphically in Figure 3 .

$$\phi = \frac{[r + \sigma + \beta m(\theta)][F_C k(y_M) - F_M k(y_C)]}{(F_M - F_C)\beta m(\theta)(k(y_M) - k(y_C))} - \frac{b(r + \sigma)}{\beta m(\theta) z(F_M - F_C)} - \frac{F_C}{F_M - F_C} \tag{10}$$

$$\theta = \frac{m(\theta)(1 - \beta) z(F_M - F_C)}{(r + \sigma)[k(y_M) - k(y_C)]} \tag{11}$$

3.3 Market Conditions

Economic conditions in the model are driven by the productivity parameter, z. Provided that $F_M < F_C$ and $k(y_M) < k(y_C)$, equation (11) shows that a downturn will lead to fewer vacancies relative to the unemployment rate.[35] Since $m(\theta)$ is increasing in theta, and is in the denominator of the Beveridge curve condition, (9), unemployment rates rise in response to the change of state.[36]

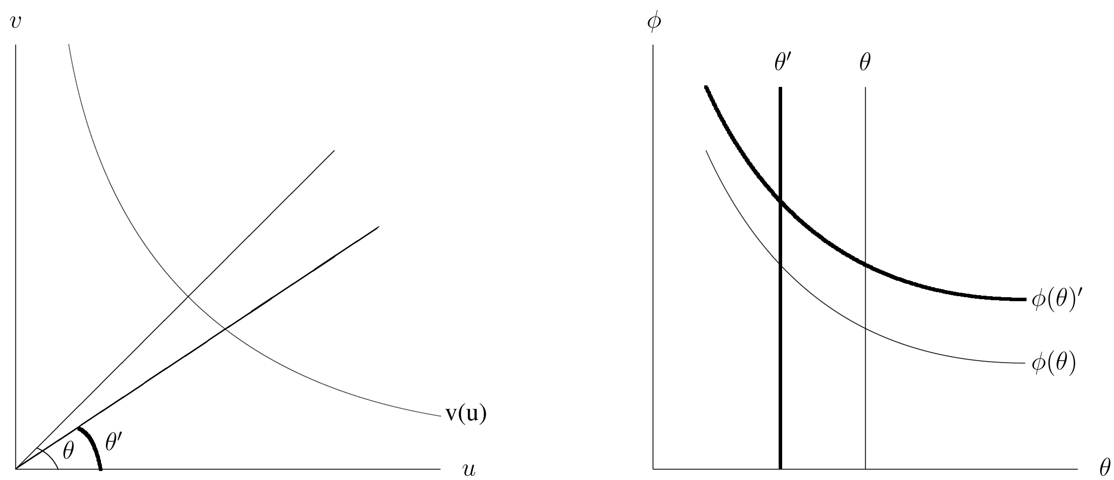
Whether or not this productivity change also increases the share of manual vacancies depends on the relative change of θ and ϕ. The sign is not obvious because job creation in general will lead to more of both types of jobs. Figure 3 depicts the case where z falls to z' leading to more unemployment θ' and relatively more manual skill jobs ϕ'. Partial differentiation of (36) shows that following a downturn, the share of manual vacancies will increase as long as

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

[35] The first assumption follows from the production function. The second is based on the logic that hiring a manager or executive usually involves several rounds of interviews and advertisement in professional magazines, while hiring a laborer might involve a single interview and advertisement in the local newspaper.

[36] This supports the use of rising unemployment rates as an indicator of a downturn in the empirical component of this paper.

Figure 3: Equilibrium in High and Low Economic States



This inequality is satisfied as long as $[F_M - F_C] < 0$: highly educated workers more productive than less educated workers in cognitive jobs, and no less productive than less educated workers in manual jobs.[37] The intuition behind this shift is as follows: When productivity falls, the firm will post fewer vacancies in total. As long as it is more expensive in present value terms to post and fill a cognitive type vacancy, however, the firm will also shift the remaining jobs in favor of less expensive manual skill jobs. Examples of this behavior could include hiring production rather than research and design staff during poor economic times, or opting for a production process which requires pairing a more physical labor with equipment that is less expensive to operate. It is also possible that the firm may attempt to exploit the larger employment pool, which increases the possibility of meeting a highly educated worker who will be at least as productive as a less educated worker.

This shift in favor of manual skill jobs leads to an increase in overqualification. Overqualification in the model is represented by the share of x_H workers in y_M jobs, referred to in the literature as "cross-skill matching", and is given by the expression

$$[1 - \psi - (1 - \gamma)u]\phi. \tag{12}$$

[37]This is true because the production function is increasing in both arguments.

This expression motivates the estimation specification in the next section of the paper, and shows that overqualification is a function of worker types, ψ unemployment rates, u, and the skill requirements of vacancies, ϕ. Because this expression is increasing in ϕ the model generates more overqualification as the share of manual vacancies increases in equilibrium. Search frictions are central to this result, because highly educated workers arrive to all vacancies at rate $m(\theta)(1-\gamma)$. Although the firm may not choosing which worker in will have the opportunity to hire, it does have control over which market to enter and post a vacancy.

This class of models is therefore able to generate the following equilibrium result: overqualification increases in downturns because firms change the type of vacancies they post, therefore affecting the skill requirements of jobs. In the following section I provide empirical evidence supporting this result. This behavior is consistent with the positive relationship between the unemployment rate, at the time of job formation, and the share of manual skill requirements in new employment relationships documented in Section 2.3.

4 Estimates of Mismatch

To provide evidence that changing skill requirements affect overqualification, I estimate the reduced form equation (13) which is motivated by the expression for overqualification from the job search model.[38] Overqualification is specified empirically as a function of the following model elements: worker characteristics, x, labor market conditions, u, and job skill requirements, ϕ. Worker characteristics, $\boldsymbol{x}$, include dummies for education levels, experience and its quadratic, job tenure and marital status, while the vector $\boldsymbol{u}$ contains the various measure of the local unemployment rate to capture labor market conditions at the economic region (ℓ) level. Skill requirements are given by the O*NET

[38]Although both over and underqualification are important sources of mismatch, they are separate issues. As evidence that measures of over and underqualification deserve separate treatment, comparative results presented in Appendix Table 8 demonstrate that underqualification does not exhibit a cyclicality. It is possible that underqualification is the result of workers who have gained sufficient work experience to mitigate the observable mismatch documented in this paper. These workers therefore, while appearing mismatched, may in fact be in suitable jobs. In addition, it is possible that job requirements have changed over time leading workers with longer tenure to appear undereducated.

factors $\boldsymbol{s}$, and $\boldsymbol{\delta}$ and $\boldsymbol{\tau}$ represent economic region and time fixed-effects.

$$D_{ijt} = \boldsymbol{u}'_{\ell t}\boldsymbol{\mu} + \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + \boldsymbol{s}'_{jt}\boldsymbol{\kappa} + \boldsymbol{\delta}_{\ell t} + \boldsymbol{\tau}_t + \epsilon_{ijt}. \tag{13}$$

Estimates are given for all four measures of overqualification. The first measure, $Pr(OQ)$ from the O*NET, is a binary indicator based on the distance between the suggested education requirements and the worker's reported education in years, $E_j - E_i$. The second and third measures, GH-PS and GH-HS, are the binary measure based on the education premium within an occupation for college and high school workers respectively, adapted from Gottschalk and Hansen (2003). Estimates on these measures are performed using the probit model, and the marginal effects are interpreted in terms of the probability of being overqualified.[39] The fourth measure is simply the continuous measure from the O*NET, $D_{ij} = E_j - E_i$, estimated with OLS.[40]

Identification is based on the assumptions that local unemployment rates are due to exogenous sources of variation in the economy and that workers do not explicitly chose the skill requirements of their jobs. Regarding the former, the ER level fixed-effects specifications shut down all other variation at ER level which may correlate with the local unemployment rates, and time-fixed effects ensure that any common source of time variation is accounted for. Therefore the effect of labor market conditions on overqualification is identified from time-series changes in the unemployment rate within each ER. Regarding the latter, the theoretical framework motivating the specification suggests that workers do not search for any specific type of job, but meet jobs of various types at random. While this simplification may not be entirely satisfactory, it does represent the external input of firms in the hiring process $-$ a worker may not be hired for the occupation they would choose. Although it is possible that some workers may be able to choose their occupation, it is reasonable to assume that

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

[40] Because the data is a rotating panel, observations may not be truly independent. The implication for the OLS and probit estimators is inefficiency. While it may be possible to improve the standard errors by adopting a GLS framework, an underlying assumption of the error correlation structure would be necessary. In addition, efficiency gains may not be realized due to the clustering of standard errors. Since the source of identifying variation in labor market conditions is at the ER level, standard errors are penalized accordingly. Moulton (1990) provides a good explanation of why this is necessary.

they are not perfectly informed about the skill requirements in their occupation.[41] These are chosen by the firm in the model and empirically are derived from the O*NET data.

Because I intend to demonstrate the effect of local economic conditions with and without adjusting for job characteristics, rather than identifying the causal impact of unemployment rates or particular cardinal changes in the skill requirements of jobs, I also present estimates conditioned on province and year fixed-effects.[42] These results provide a suitable robustness check for the primary specification, and also allow for important sources of identifying variation in labor market conditions that are ruled out by the more restrictive model. Because of the Canadian climate, there are important monthly and seasonal variations in economic output and employment. Monthly fixed-effects will therefore suppress variation that is common across ER's that could be an important contributor to mismatch.[43] Similarly, province level fixed-effects continue to control for important cultural, political and regulatory differences across geographic regions, while allowing for the possibility that sectoral differences which may dis-proportionately affect certain ER's throughout the sample, can provide identifying variation.[44] Any bias in this specification is likely to be minimal because It is unlikely that mismatch, which is measured at the individual level, could have a meaningful impact on ER level unemployment rates.

A summary of the marginal effects for both of the specifications are presented in the left four columns of Table 3, while full sets of estimates are left to Appendix Tables 9-10. Consistent with US estimates (Bowlus, 1995; Hagedorn and Manovskii, 2010), these coefficients show that overqualification (or job match quality) varies across the economic cycle in Canada. Positive coefficients for

[41]In fact, if a worker applies to a job, it must be true that they consider themselves qualified and able to perform the required tasks. Because many workers appear mismatched, I conjecture than many workers do not in fact know or consider the various skill requirements when choosing an occupation.

[42]In fact, the magnitude of coefficients on skill requirement measures are of limited meaning due to factor analysis. These coefficients represent the change in mismatch measures from a change in the skill requirement which is the size of a single standard deviation of the skill requirement in the Canadian male labor force for the period 1997-2012.

[43]Because Canada's GDP relies heavily on exports to the US, shutting down this national level variation likely masks important contributors to mismatch.

[44]Important provincial differences in Canada include minimum wage laws, taxes, education systems, first languages, unemployment benefit regulations and account for some important and persistent differences in economic conditions. Certain industries in Canada have concentrations in few ER's, including oil in northern Alberta and Finance and banking in Toronto.

the relationship between local unemployment rates at the time of hire and the binary OQ indicators in specifications 1 - 3 suggest that an increase in local 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, this is akin to the population of a city such as Kingston becoming overqualified, and in the US population akin to the overqualification of Phoenix or Philadelphia.[45] The coefficients relating local unemployment to the linear mismatch indicator suggests that an increase in the local unemployment rate from 5% to 9% would coincide with an average increase in overqualification of 0.2 to 0.3 years of schooling in the specification with province and year fixed-effects, however this impact is insignificant with the main specification.

Additional results, which includes indicators for temporary job and immigrant status as well as specifications with worker fixed-effects are also provided in the Appendix Tables 11-12. Immigration information was not available prior to 2006 and so the resulting sample with these conditioning variables is limited to the time period covered by the great recession. Estimates from this subsample are much larger, and are likely biased upwards. Worker fixed-effects regressions are also problematic because they must either be computed with the linear probability model, or the conditional logit model. The former is an unsatisfactory way to model a discrete relationship because the non-normality of the error term compromises inference. The latter leads to significant sample attrition, because the conditional logit identifies impacts based on the discrete change of overqualification within observations of each individual, and each worker is observed for at most 6 months. In the context of this paper, a change in overqualification could only identify the impact of unemployment on overqualification for workers who switch jobs in the sample.

[45] These estimates range between 0.035 and 0.2% for each 1% increase in the unemployment rate. Other studies also find small impacts of past labor market conditions on wages, including Oreopoulos, von Wachter, and Heisz (2012) who find that a single percentage point increase in local unemployment rates at graduation induce job mobility at a rate of 0.003%, and affect starting wages by 0.01-0.02%.

4.1 Skill Requirements and Mismatch

As a response to an economic downturn, the model presented in Section 3 shows that firms may choose to create more manual skill vacancies. Complementary evidence that the share of manual skill jobs are procyclical was also presented in Figure 2 using job vacancy data from the state of Minnesota for the years 2005-2013, and Figure 1 for filled jobs in Canada's LFS. Reasons for firms to change their hiring behavior in a downturn might include stimulus packages which promote labor intensive manual skill jobs, or the assignment of greater responsibilities to lesser paying occupations (for example a "supervisor" hired in a downturn may have similar job tasks to a "manager" hired in a boom period), or an unwillingness to fill high paying cognitive skill jobs during periods of economic uncertainty. Because overqualification depends on skill supply and skill demand, in this section of the paper I expand my estimates of overqualification to also account for changes in the type of job.

To show the relative importance of skill requirements, the right four columns in Table 3 include estimates from corresponding specifications that are augmented to include skill requirement controls, s, from the O*NET data. The skill requirements are the result of factor analysis and include two cognitive and three manual measures. If the cyclicality of mismatch is due to changes in the type of job, skill requirements rather than labor market conditions should contribute to the incidence of overqualification.

A comparison of specifications on the right and left (1 and 5, or 2 and 6, for example) shows that the impact of past unemployment rates on the probability of overqualification is significantly reduced when conditioned on the skill requirements of the job, and may be statistically indifferent from zero. Instead, the coefficients on the skill requirements themselves show that having accepted a job with lower cognitive and higher manual skill requirements increases the likelihood that a worker is overeducated. I interpret this as evidence that changes in the demand for skill are an important contributor to mismatch. Workers may have a higher probability of being overqualified during a downturn because they are more likely to obtain a manual skill job at this time. A similar reduction

Table 3: The Impact of Unemployment Rates at Hire on Overqualification

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Time & ER FE	**0.071****	0.135	**0.097****	-0.190	-0.016	0.067	0.054	0.093
	(0.036)	(0.174)	(0.047)	(0.169)	(0.032)	(0.151)	(0.043)	(0.126)
Year & Prov FE	**0.095****	**0.198***	**0.098****	**-0.476***	-0.053	0.063	0.018	0.225
	(0.041)	(0.117)	(0.046)	(0.204)	(0.056)	(0.135)	(0.035)	(0.214)
Skill Req					✓	✓	✓	✓

Impacts are the effect of increases in local unemployment rates ($\times 100$) on measures of overqualification. Specifications 1-3,5-7 are average marginal effects from probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and various fixed-effects. Specifications 4 and 8 are OLS regressions on the linear distance measure with the same controls. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses. Skill Req indicates whether the specification also controlled for the skill requirements of a job.

of the relationship between labor market conditions and overall mismatch is found in a comparison of the two linear distance specifications 4 and 8.

These results are quite robust and hold for a number of specification changes including the replacement of quadratic and linear measures of tenure and experience with dummies, controls for temporary jobs or firm size, various combinations of the five skill requirements, worker fixed effects, and different overeducation threshold values on the O*NET binary measures (α).[46]

4.2 Sample Selection

One additional challenge to identification stems from potential bias in the sample because of changes in the pools of matched and mismatched workers. Both the mobility decisions of workers and the firing decisions of firms may therefore contribute to a sample which is not representative of the labor force as a whole.

The first mechanism which may alter the sample is job mobility. Several studies have documented differences in the job duration (Bowlus, 1995) and mobility patters (Sicherman, 1991) of workers

[46]Estimates were also performed on a reduced sample containing only a single observation per individual, leading to similar results. A reasonable threshold for the standard-deviation based measure, $\alpha\sigma_D$ ranges from approximately one year of education to four years of education.

who are mismatched. Workers who have excess education may be more likely to switch to "better jobs" where the return to their skill is higher (Robst, 1995). In other words, overqualified workers are less likely to remain in their jobs and because of this, job mobility itself has been used as a measure of mismatch (Moscarini and Vella, 2008). If overqualified workers are more likely to switch out of their jobs, then the share of mismatched workers in the sample is too small. This concern is particularly salient because I link of labor market conditions at the time of hire to currently observed workers, meaning that my sample will only contain the share of mismatched workers hired before 1997 who did not switch jobs.

The second mechanism which may alter the sample is unemployment volatility. A popular stylized fact of the US economy is that low skill workers exhibit higher volatility Hoynes (1999); Kydland (1984), leading to the suspicion that less educated workers are more likely to be dismissed. Although these results may have more to do with age than education, and are sensitive to industry choice Prasad and Keane (1993), the potential for firms to hoard higher skilled workers in a downturn could mean the sample of less-educated workers is too small.

Because of these potential differences, estimates may be subject to sample selection bias and these factors related to the endogenous destruction of jobs may confound the importance of skill requirements as an explanation for the cyclicality of overqualification. Although worker fixed-effects estimates presented in the Appendix Table 12 account for unobservable worker characteristics, fixed-effects regressions are based on within-individual estimation and therefore do not provide estimates which generalize to the population. Overqualification is only observed only when workers remain in the sample (do not select out of the sample), denoted by $h_i = 1$. The correct model simultaneously accounts for the likelihood a worker will remain in the sample, given by equation (15) when estimating

Table 4: Mismatch and Job Separations

	O*NET		GH-PS		GH-HS	
	OverQ$_t$	Matched$_t$	OverQ$_t$	Matched$_t$	OverQ$_t$	Matched$_t$
Switch$_{t+1}$	0.043	0.047	0.044	0.035	0.045	0.047
Tenure$_t$	71.4	82.9	74.1	79.8	75.2	83.9

Sample means from the LFS for the period 1997-2012. Job tenure measured in months.

the outcome equation (15).[47]

$$y_i = \begin{cases} \tilde{\boldsymbol{x}}_i'\tilde{\boldsymbol{\beta}} + e_{1i} & \text{if } h_i = 1 \\ \\ missing & \text{if } h_i = 0 \end{cases} \tag{14}$$

$$Pr(h_i = 1|\boldsymbol{z}) = \boldsymbol{z}'\boldsymbol{\gamma} + e_{2i} \tag{15}$$

A key assumption in selection the model is give by the relationship $e_{2i} = \rho e_{1i} + \eta_i$. If selection into the sample is random, because endogenous job destruction is not disproportionately affecting certain groups in the sample, then $\rho = 0$ and the independent estimates of (14) from the prior section do not suffer from sample selection bias. Evidence of endogenous job destruction from the data is mixed. Table 4 suggests that, despite shorter job tenures, the difference in the number of workers switching jobs is less that 1% across all definitions of overqualification. With respect to the propensity for less educated workers to be laid off during a recession, this trend is not observed in the Canadian data conditional on experience and job tenure. Table 5 shows coefficients for interaction terms between local unemployment rates and education levels in a probit regression for the probability of being laid off. It appears that only PS graduates, are more likely to be laid off due to market conditions, and this coefficient is marginally significant. Evidence of sample selection may also be found by performing a likelihood ratio test for independence of the two equations, and by comparing prior estimates to those from the bivariate selection. This procedure is meaningful only under the assumption that the selection equation will be correctly identified, which is itself untestable.

I model the selection mechanism as the likelihood of remaining in the job, so that identification will hinge on a single parameter. I include an exclusion restriction based on the likelihood that peers

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

Table 5: Education and Worker Displacement

	LHS	HS	PS	BA
$\times$ Urate	0.636	0.306	0.832*	-0.060
	(0.422)	(0.474)	(0.466)	(0.522)

Coefficients from interaction terms of education milestones with local unemployment rates in a probit regression for the probability of being laid off due to economic conditions. Omitted category is PG

remain in their jobs.[48] The selection equation is given by (16)

$$z_{ijt} = \zeta \bar{h}_{\ell-it+1} + \boldsymbol{u}'_{\ell t}\boldsymbol{\mu} + \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + e_{2ijt} \tag{16}$$

where h_{ijt+1} is the probability a worker stays in their job in the following month and the exclusion restriction, $\bar{h}$, is the probability that a worker's peers also stay in their jobs. The instrument $\bar{h}$ represents the (negative) selection decisions of peers, calculated as the average of h for all other workers of the same age in the same ER and month. This is a relevant exclusion restriction because the probability of observed peers remaining is correlated to the individual's current mobility decision. I also believe it is exogenous to the outcome, because I can think of no reason why the mobility decisions of a current peer should be related to the mismatch of a worker and their job, which was determined in the past, at the time of hire.[49]

I estimate this selection model using Full Information Maximum Likelihood (FIML).[50] The selection model outlined above assumes OLS estimation of the outcome equation as in Heckman (1979), which is suitable for estimates of the simple linear distance measure D_{ij}. For the binary measures of

[48] 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)

[49] 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 groups is not the same as the peer group at the time of hire.

[50] The FIML estimator is given by:

$$\ln L_i = \begin{cases} w_i \ln \Phi \left\{ \frac{\boldsymbol{z}_i\boldsymbol{\gamma} + (y_i - \tilde{\boldsymbol{x}}_i\tilde{\boldsymbol{\beta}})\rho/\sigma}{\sqrt{1-\rho^2}} \right\} - \frac{w_i}{2}\left(\frac{y_i - \tilde{\boldsymbol{x}}_i\tilde{\boldsymbol{\beta}}}{\sigma}\right)^2 - w_i \ln \sqrt{2\pi\sigma} & \text{if } h_i = 1 \\ w_i \ln \Phi(-\boldsymbol{z}_i\boldsymbol{\gamma}) & \text{if } h_i = 0 \end{cases} \tag{17}$$

where w_i represent LFS final population weights. Maximum Likelihood estimation is preferable to the simpler two-step estimator, as shown in Puhani (2000).

Table 6: Selection Corrected Impacts of Unemployment Rates at Hire on Overqualification

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Time & ER FE	0.049	–	**0.133*** **	-0.134	-0.016	–	0.084	**0.427****
	(0.034)	–	(0.047)	(0.177)	(0.030)	–	(0.051)	(0.179)
Year & Prov FE	**0.080****	**0.306*** **	**0.106****	**-0.399***	0.312	-0.027	0.034	**0.412***
	(0.036)	(0.115)	(0.069)	(0.216)	(0.387)	(0.049)	(0.041)	(0.236)
Skill Req					✓	✓	✓	✓

Impacts are the effect of increases in local 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. Specifications 1-3,5-7 are average marginal effects from probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and various fixed-effects. Specifications 4 and 8 are OLS regressions on the linear distance measure with the same controls. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses. Skill Req indicates whether the specification also controlled for the skill requirements of a job.

overqualification, a selection estimator developed by Van de Ven and Van Praag (1981) provides a similar selection correction where the outcome equation is also estimated with the probit model.

Table 6 provides estimates accounting for sample selection bias that are comparable to the estimates in Table 3. Controlling for selection bias, does not appear to change the main results of this paper: unemployment rates at the time of hire correlate with overqualification, and this relationship appears to be the result of changes in the nature of job creation with respect to skills. In the case of the GH-PS measure with time and ER fixed-effects, the likelihood function does not converge and so estimates are unavailable. A full set of these results are available in the Appendix Tables 13-14.[51] Compared to Table 3, estimates of the contribution of skill requirements to mismatch differ in magnitude. For O*NET measures, the estimates are slightly lower, suggesting that any sample selection bias was positive but minimal. For the GH measures, a larger negative bias may have resulted from the fact that workers are identified as overqualified based on wage differences. In better economic times, the mobility of workers to better paying jobs would therefore have a larger effect on this measure than

[51]Because the χ^2 statistic is small the null hypothesis, that the error terms are independent in the first and second stage regressions, cannot be rejected for some specifications. In other words, selection bias is not likely in the outcome regression if performed independently.

the O*NET measure where overqualification does not necessarily imply a wage difference.

5 Wage Outcomes

This section attempts to connect my findings about the incidence of mismatch to the literature on the implications (wage impacts) of education mismatch for workers. If overqualification is partly the result of increased manual skill jobs, then controlling for skill requirements in wage estimates should reduce the wage penalties for overqualification.

To test this hypotheses I estimate (18), a specification similar to that found in Verdugo and Verdugo (1989). This equation resembles a Mincer wage regression, conditional on the vector $\boldsymbol{m}$ containing binary measures for under (UQ) and overeducation, (OQ).[52] The binary measures used are those from the O*NET, rather than the GH measures, for two reasons. First, the GH measures have no undereducation counterpart, making it difficult to replicate the specification. Secondly, the GH measures themselves are a product of relative wages and so using these as controls in a wage equation could be problematic.

$$\ln w_{ijt} = \boldsymbol{m}'\boldsymbol{\phi} + \boldsymbol{u}'_{\ell t}\boldsymbol{\mu} + \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + \boldsymbol{s}'_{jt}\boldsymbol{\kappa} + \boldsymbol{\delta}_{pT} + \epsilon_{ijt} \tag{18}$$

Wage estimates are reported in Table 7. The first specification suggests significant wage penalties(bonuses) for over(under)qualification, as measured by the binary O*NET indicators. These results indicate a wage penalty, conditional on worker characteristics, of approximately 19%.[53] Conditional on skill requirements, however, the wage penalty is reduced by approximately 50%. Because manual skill jobs pay less than cognitive skill jobs on average, and because overeducated workers are found in jobs with proportionally more manual skill requirements, this finding is consistent with the possibility that up to half of the overeducation wage penalty reflects lower returns to manual tasks.

[52] Similar to concerns raised in the previous section about the conditional logit model, the use of the fixed-effects model in this case will eliminate the mismatch variables in all cases of job-stayers, meaning that the impact will be measured only for job-switchers, which are a specific and likely non-standard sample of job holders.

[53] The log wage penalty in the LFS data appears larger, at 0.18 than the penalty from Verdugo and Verdugo (1989) at 0.13%.

Specifications 3 and 4 control for the linear distance D_{ij} and its quadratic rather than binary mismatch measures, and also show diminished a wage penalty, although to a lesser extent.[54] A similar mechanism may help to explain a portion of why labor market entry during periods of high unemployment, affect future wages of workers (Oreopoulos, von Wachter, and Heisz, 2012), although testing this conjecture is beyond the scope of the LFS data because workers are only sampled for 6 months and graduation dates are not available.

6 Conclusion

This paper shows that overqualification, arises partially because of cyclical changes in the type of jobs available. Generating skill requirement (or task) measures from the O*NET data, I document a countercyclicality in the relative share of manual skill requirements among recently created jobs in Canada's LFS data, and vacant posts in Minnesota's job vacancy data. This apparent change in the demand for skill is consistent with job search theory. A model with search frictions and two sided heterogeneity illustrates that economic downturns may induce employers to post a different type of job vacancy than they otherwise might. An increase in the availability of manual skill jobs then results in overqualification as congestion externalities limit the ability of workers and firms to form "suitable" pairs. This appears to be one result from this class of models which has not received much attention.

Empirical evidence that this cyclicality in the demand for skill contributes to overqualification is provided through reduced form estimates using Canada's LFS. Increases in mismatch which had previously been linked directly to downturns, are found to be arise partly due to changes in job requirements, rather than economic conditions themselves. Estimates of mismatch show that skill requirements explain much of the relationship between local labor market conditions during job search and overqualification. This finding is robust to several different measures of overqualification and is the main contribution of the paper. Despite the possibility that worker mobility decisions affect the

[54]Because the dependent variable is measured $E_j - E_i$, the positive coefficients mean that a decrease in the extent of overqualification leads to higher wages.

Table 7: Wages and Labor Market Conditions

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

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

observation of matched and mismatched workers in the data, I find no evidence that the results are subject to sample selection bias. In addition, I show that the skill requirements themselves can explain a substantial component of the overqualification wage penalty, previously attributed to unobservable worker characteristics.

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Appendix

A The O*NET

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

To merge the LFS and the O*NET data, the O*NET job categories were collapsed to the SOC level. A concordance provided by the standards division of Statistics Canada allows the Standard Occupational Classification system (SOC) codes, and associated O*NET data, to be integrated into the LFS.[55] After merging with the LFS, the sample contains workers in 327 different occupations. Samples of the O*NET questionnaire are given below

In recent versions of the O*NET, education requirements are assessed by a group occupational experts. An occupational expert is a worker in the occupation who is deemed, due to rank or expe-

[55] 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.

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

Measures of skill requirements are derived from the O*NET category "Abilities". This category appears to have the most comprehensive and general set of elements, and I allow the common factor model estimation procedure to chose the relevant factors from the 52 different abilities, denoted by $k \in \{1, \ldots, 52\}$, for each O*NET occupation. Each ability, has a measure of "importance" I_k as well as a "level of complexity" C_k for a particular occupation. Both measures are standardized to a scale $\in (0, 10)$ and combined to generate a single measure $a_k j$ for each ability k in each occupation j, according to $a_{jk} = I_{jk}^a \times C_{jk}^{1-a}$.[56]

A.1 Factor Analysis

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

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

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

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

$$\boldsymbol{a} = \boldsymbol{s}\boldsymbol{\Lambda}' + \boldsymbol{e}, \tag{19}$$

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

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

and that $\boldsymbol{\Psi}$ represents the uniqueness element in the ability measures which will not be attributed to common factors. The model estimates $\boldsymbol{\Psi}$ first, then computes each column of the factor loading matrix $\boldsymbol{\Lambda}$ in succession for all factors, $1, \ldots, 52$. Because the common variation is attributed successively to the leading factors in order, not all of the resulting factors will be relevant. In this case, only the leading 5 factors appear to be meaningful, and are kept for analysis. The scree test borrowed from Cattell (1966) is used to select factors which have eigenvalues exceeding the mean, a popular rule of thumb in the literature. A plot of the scree test is shown in Figure 7.

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

Table 17 presents the rotated factor loadings for the 5 relevant skill measures. By examining how each of the 52 original abilities contribute to the resulting factors it is possible to interpret the factors. Factor 1 appears to represent cognitive skill requirements such as reasoning and communication. Factors 2 and 3 capture manual aspects of an occupation, and might be interpreted as sensory/coordination and strength/dexterity respectively. Finally, factors 4 and 5 differentiate within earlier factors. Factor 4 separates coordination and strength, while factor 5 isolates numerical skill from other cognitive traits.

B Model Solutions

B.1 Wages

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

$$N(x,y) = \frac{w(x,y) + \sigma U(x)}{r+\sigma} \tag{21}$$

$$J(x,y) = \frac{zf(x,y) - w(x,y)}{r+\sigma} \tag{22}$$

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

$$w(x,y) = \beta z f(x,y) + (1-\beta) r U(x) \tag{23}$$

It is also necessary to simplify the expression for the value of unemployment. Substituting (21) and (23) into (1) gives an expression for the asset value of an unemployed worker x.

$$U(x) = \frac{b(r+\sigma)}{r(r+\sigma+\beta m(\theta))} + \frac{\beta m(\theta) z}{r(r+\sigma+\beta m(\theta))} \times [\phi f(x, y_M) + (1-\phi) f(x, y_C)] \tag{24}$$

Combining (23) and (24) leads to (6) which can be expressed separately for each pair (x,y):

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

B.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:

$$k(y_M) = \frac{m(\theta)}{\theta}\left(\psi J(x_L, y_M) + (1-\psi)J(x_H, y_M)\right) \tag{25}$$

$$k(y_C) = \frac{m(\theta)}{\theta}\left(\psi J(x_L, y_C) + (1-\psi)J(x_H, y_C)\right) \tag{26}$$

Solving the free entry for manual vacancies gives

$$\theta = \frac{m(\theta)(1-\beta)}{k(y_M)}\left(zF_M - \frac{b(r+\sigma)}{r+\sigma+\beta m(\theta)} - \frac{\beta m(\theta) z}{r+\sigma+\beta m(\theta)}\left[\phi(F_M - F_C) + F_C\right]\right) \tag{27}$$

$$\begin{aligned} F_M &= \gamma f(x_L, y_M) + (1-\gamma) f(x_H, y_M) \\ F_C &= \gamma f(x_L, y_C) + (1-\gamma) f(x_H, y_C) \end{aligned} \tag{28}$$

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

$$\phi = \frac{[r+\sigma+\beta m(\theta)][F_C k(y_M) - F_M k(y_C)]}{(F_M - F_C)\beta m(\theta)(k(y_M) - k(y_C))} - \frac{b(r+\sigma)}{\beta m(\theta) z (F_M - F_C)} - \frac{F_C}{F_M - F_C} \tag{29}$$

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

$$\theta = \frac{m(\theta)(1-\beta) z (F_M - F_C)}{(r+\sigma)[k(y_M) - k(y_C)]} \tag{30}$$

B.3 The Relative Changes of ϕ and θ

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

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

This first order partial is positive for all increasing $m(\theta)$ as long as:

$$\frac{b - zF_C}{b - zF_M} < \frac{k(y_C)}{k(y_M)}.$$

This condition has an interpretation in terms of the profitability of various types of vacancies, which is most easily seen when $z = 1$. The left hand side is the ratio of differences between reservation wages and productivity, while the right hand side is the ratio of vacancy costs. Then this inequality holds, that the relative cost of posting a cognitive vacancy is greater than the expected relative profit (the difference between the expected output of that vacancy F and the payment to the worker reservation).

Under these same conditions, the second order partial

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

is positive for all matching functions with properties $m'(\theta) > 0$ and $m''(\theta) < 0$, which are satisfied by common matching functions such as the Cobb-Douglas.

B.4 Heterogeneous Job Destruction Rates

This section considers the case where exogenous job destruction rates might differ by the type of job. Consider the notion that high skill and cognitive type jobs are less easily destroyed. It is plausible that these jobs would withstand greater shocks than low skill jobs because they are more ingrained in the functioning of a business; it would be harder to replace a manager than a laborer, for example. This extension leads to the same equilibrium as long as $\sigma_C \geq \sigma_M$.

Equations 21 and 22 become:

$$N(x,y) = \frac{w(x,y) + \sigma_y U(x)}{r + \sigma_y} \tag{31}$$

$$J(x,y) = \frac{zf(x,y) - w(x,y)}{r + \sigma_y} \tag{32}$$

Equation 24 becomes:

$$U(x) = \frac{b}{A} + \frac{\beta m(\theta) z}{A} \times \left[\phi f(x, y_M) + (1-\phi) f(x, y_C)\right] \tag{33}$$

$$A = \frac{(r+\sigma_M)(r+\sigma_C) - m(\theta)\phi[\sigma_m + (1-\beta)r] - m(\theta)(1-\phi)[\sigma_C + (1-\beta)r]}{(r+\sigma_M)(r+\sigma_C)} \tag{34}$$

Although the free-entry conditions and the wage equation 23 do not change, the flow equations for unemployment lead to the following beveridge curve condition:

$$u = \frac{\phi\sigma_M + (1-\phi)\sigma_C}{m(\theta) + \phi\sigma_M + (1-\phi)\sigma_C}. \tag{35}$$

Solving the free entry conditions gives the following expression to replace 36:

$$\begin{aligned}\phi =& \frac{[F_C k_M (r+\sigma_M) - F_M k_C (r+\sigma_C)]A(r+\sigma_M)(r+\sigma_C)}{[k_M(r+\sigma_M) - k_C(r+\sigma_C)]\beta m(\theta) r [F_M(r+\sigma_C) - F_C(r+\sigma_M)]} \\ &- \frac{b(r+\sigma_M)(r+\sigma_C)}{\beta m(\theta) z [F_M(r+\sigma_C) - F_C(r+\sigma_M)]} - \frac{F_C(r+\sigma_M}{[F_M(r+\sigma_C) - F_C(r+\sigma_M)]}\end{aligned} \tag{36}$$

The new condition for ϕ to increase in a downturn requires that $F_M(r+\sigma_C) - F_C(r+\sigma_M) < 0$, which is satisfied as long as $\sigma_M > \sigma_C$, because $F_M < F_C$.

C Figures and Tables

Table 8: Estimates of Mismatch

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

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

Table 9: Estimates of Overqualification: Conditional on Time and ER Fixed-Effects

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Current Urate×100	-0.057	0.078	-0.097**	0.493*	-0.015	0.140	-0.091**	0.174
	(0.058)	(0.120)	(0.044)	(0.251)	(0.056)	(0.129)	(0.043)	(0.205)
Urate at Hire×100	0.071**	0.135	0.097**	-0.190	-0.016	0.067	0.054	0.093
	(0.036)	(0.147)	(0.047)	(0.169)	(0.032)	(0.151)	(0.043)	(0.126)
S_1 (COG)					-0.174***	-0.094***	-0.062***	1.016***
					(0.005)	(0.004)	(0.001)	(0.031)
S_2 (MAN)					0.052***	0.121***	0.054***	-0.401***
					(0.005)	(0.004)	(0.001)	(0.014)
S_3 (MAN)					0.074***	0.045***	0.030***	-0.439***
					(0.002)	(0.002)	(0.002)	(0.007)
S_4 (MAN)					-0.002***	-0.009**	0.004*	-0.128***
					(0.003)	(0.004)	(0.002)	(0.005)
S_5 (COG)					-0.027***	0.010***	-0.028***	0.184***
					(0.002)	(0.002)	(0.002)	(0.007)
LHS				4.870***				9.920***
				(0.057)				(0.086)
HS	-0.730***		0.225***	3.028***	-0.974***		0.110***	4.600***
	(0.008)		(0.008)	(0.051)	(0.009)		(0.009)	(0.068)
PS	-0.357***	0.106***	0.169***	2.070***	-0.574***	0.003	0.074***	3.392***
	(0.007)	(0.006)	(0.009)	(0.040)	(0.005)	(0.005)	(0.008)	(0.034)
BA	-0.260***	0.020***	0.046***	1.214***	-0.290***	-0.005	0.029***	1.508***
	(0.010)	(0.004)	(0.003)	(0.034)	(0.007)	(0.004)	(0.003)	(0.017)
Exp	-0.002**	-0.003***	0.001***	0.006*	-0.001	-0.002***	0.002***	-0.006***
	(0.000)	(0.001)	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.001)
Exp^2 × 100	0.002*	0.007***	-0.003***	0.012**	0.001	0.004***	-0.004**	0.035***
	(0.000)	(0.002)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)	(0.000)
Married	-0.017***	-0.008*	-0.002	0.102***	-0.002	-0.004	0.004*	0.010**
	(0.003)	(0.004)	(0.003)	(0.019)	(0.002)	(0.003)	(0.002)	(0.004)
Tenure	-0.0003***	-0.004***	-0.0001***	0.002***	0.0001***	-0.0002***	0.0003	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)
N	1450984	605743	1450984	1744784	1450984	605743	1450984	1744784
R^2	0.025	0.053	0.091	0.419	0.445	0.107	0.175	0.714

Specifications 1-3,5-7 are probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure as well as ER and monthly fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

Table 10: Estimates of Overqualification with Year and Prov. FE

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Current	0.084	0.089	-0.127	0.323*	0.074	0.082	-0.109**	0.194
Urate×100	(0.086)	(0.088)	(0.077)	(0.259)	(0.118)	(0.088)	(0.044)	(0.298)
Urate at	0.095**	0.198*	0.098**	-0.476**	-0.053	0.063	0.018	0.225
Hire×100	(0.041)	(0.117)	(0.046)	(0.204)	(0.056)	(0.135)	(0.035)	(0.214)
S_1					-0.174***	-0.105***	-0.059***	1.014***
(COG)					(0.005)	(0.005)	(0.001)	(0.031)
S_2					0.049***	0.137***	0.051***	-0.395***
(MAN)					(0.005)	(0.005)	(0.001)	(0.015)
S_3					0.073***	0.051***	0.029***	-0.438***
(MAN)					(0.002)	(0.002)	(0.002)	(0.006)
S_4					-0.002	-0.010**	0.004**	-0.126***
(MAN)					(0.001)	(0.004)	(0.002)	(0.005)
S_5					-0.027***	0.011***	-0.026***	0.184***
(COG)					(0.002)	(0.002)	(0.002)	(0.007)
HS	-0.734***		0.232***	3.001***	-0.982***		0.106***	4.615***
	(0.009)		(0.008)	(0.054)	(0.013)		(0.009)	(0.066)
PS	-0.362***	0.119***	0.177***	2.042***	-0.582***	0.005	0.072***	3.410***
	(0.007)	(0.006)	(0.009)	(0.042)	(0.005)	(0.006)	(0.008)	(0.033)
BA	-0.261***	0.022***	0.047***	1.212***	-0.292***	-0.006	0.028***	1.512***
	(0.010)	(0.005)	(0.003)	(0.034)	(0.008)	(0.005)	(0.003)	(0.018)
Exp	-0.002**	-0.003***	0.002**	0.006**	-0.000	-0.002***	0.001***	-0.006***
	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.001)
Exp^2	0.002*	0.007***	-0.003***	0.011**	-0.001	0.005***	0.003***	0.036***
x 100	(0.001)	(0.000)	(0.001)	(0.006)	(0.001)	(0.002)	(0.001)	(0.003)
Married	-0.019***	-0.007*	0.000	0.097***	-0.005***	-0.004	0.005*	0.017***
	(0.003)	(0.004)	(0.002)	(0.019)	(0.002)	(0.004)	(0.002)	(0.005)
Tenure	-0.000***	-0.0004***	-0.0001***	0.002***	0.000***	-0.0002**	-0.000	-0.0004***
	-(0.000)	(0.0000)	(0.0000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.0001)
N	1450984	605743	1450984	1744784	1450984	605743	1450984	1744784
R^2	0.252	0.0514	0.088	0.417	0.441	0.106	0.174	0.713

Specifications 1-3,5-7 are Probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses clustered at the 73 economic regions. Results weighted with LFS final weights. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. Workers with education below high school are excluded from overeducation regressions because by definition, LHS is the lowest possible education requirement. R_p^2 reported for probit specifications

Table 11: Estimates of Overqualification: Immigration Subsample

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Current Urate×100	-0.025	-0.317**	-0.202	1.036	0.164	-0.203**	-0.143*	-0.156
	(0.147)	(0.138)	(0.128)	(0.759)	(0.152)	(0.093)	(0.084)	(0.347)
Urate at Hire×100	0.138**	0.420*	0.171**	-0.610*	-0.057	0.333	0.111	0.111
	(0.066)	(0.239)	(0.074)	(0.342)	(0.077)	(0.250)	(0.068)	(0.219)
S_1					-0.205***	-0.082***	-0.048***	1.048***
(COG)					(0.005)	(0.005)	(0.002)	(0.033)
S_2					0.061***	0.096***	0.044***	-0.418***
(MAN)					(0.005)	(0.005)	(0.002)	(0.014)
S_3					0.092***	0.063***	0.019***	-0.476***
(MAN)					(0.003)	(0.002)	(0.003)	(0.006)
S_4					-0.001	0.003	0.003	-0.124***
(MAN)					(0.004)	(0.005)	(0.003)	(0.006)
S_5					-0.035***	0.038***	-0.031***	0.206***
(COG)					(0.003)	(0.006)	(0.002)	(0.009)
LHS				4.957***				7.000***
				(0.084)				(0.099)
HS	-0.859***		0.178***	3.133***	-1.162***		0.083***	4.720***
	(0.010)		(0.010)	(0.075)	(0.018)		(0.007)	(0.077)
PS	-0.409***	0.087***	0.129***	2.138***	-0.674***	-0.203	0.050***	3.483***
	(0.010)	(0.007)	(0.010)	(0.067)	(0.015)	(0.093)	(0.007)	(0.049)
BA	-0.290***	0.022**	0.033***	1.236***	-0.337***	0.000	0.018***	1.543***
	(0.015)	(0.009)	(0.004)	(0.043)	(0.011)	(0.009)	(0.004)	(0.031)
Exp	-0.001*	-0.002*	0.001**	0.006**	0.000	-0.001	0.001*	-0.005***
	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)
Exp^2 x100	0.001	0.003	-0.001	0.007	-0.003***	0.001	-0.001	0.002***
	(0.001)	(0.003)	(0.011)	(0.004)	(0.001)	(0.003)	(0.012)	(0.000)
Married	-0.027***	-0.003	0.001	0.103***	-0.011***	-0.001	0.004	0.023***
	(0.004)	(0.006)	(0.002)	(0.015)	(0.003)	(0.006)	(0.002)	(0.008)
Tenure	-0.0002***	-0.0002***	-0.0001***	0.0012***	-0.0001***	-0.0001***	0.0000**	-0.0022***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(-0.0083)
Immigrant	0.094***	0.046***	0.008	-0.289***	0.051***	0.018***	-0.001	-0.062***
	(0.007)	(0.009)	(0.005)	(0.062)	(0.009)	(0.004)	(0.003)	(0.020)
Firm Size	-0.010***	-0.018***	-0.006***	0.105***	0.014***	-0.007**	0.004***	-0.042***
	(0.002)	(0.003)	(0.001)	(0.011)	(0.002)	(0.003)	(0.001)	(0.003)
Job Switch	-0.005	-0.010***	-0.022***	0.265***	0.008*	-0.013***	-0.010**	0.089***
	(0.009)	(0.004)	(0.002)	(0.038)	(0.005)	(0.003)	(0.002)	(0.015)
Permanent Job	-0.056***	-0.016	0.003	0.240***	0.021***	0.025	0.028***	-0.171***
	(0.007)	(0.015)	(0.005)	(0.025)	(0.005)	(0.015)	(0.005)	(0.015)
N	504915	217814	504915	588566	504915	217814	504915	588566
R^2	0.268	0.013	0.058	0.408	0.457	0.059	0.124	0.717

Specifications 1-3,5-7 are Probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses clustered at the 73 economic regions. Results weighted with LFS final weights. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. R_p^2 reported for probit specifications

Table 12: Estimates of Overqualification: Conditional on Worker Fixed-Effects

	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Current Urate×100	0.412 (1.168)	0.039 (0.812)	0.467 (0.804)	0.015 (0.031)	0.799 (2.101)	0.347 (0.833)	0.162 (0.842)	-0.010 (0.019)
Urate at Hire×100	1.995** (0.858)	-0.470 (0.877)	0.695 (0.802)	-0.082* (0.050)	1.038 (1.635)	-1.043 (0.940)	0.052 (0.879)	0.052 (0.032)
S_1 (COG)					-3.591*** (0.057)	-0.592*** (0.019)	-0.767*** (0.019)	1.024*** (0.001)
S_2 (MAN)					1.152*** (0.034)	0.786*** (0.023)	0.633*** (0.021)	-0.431*** (0.001)
S_3 (MAN)					1.545*** (0.035)	0.365*** (0.018)	0.324*** (0.016)	-0.496*** (0.001)
S_4 (MAN)					-0.080*** (0.028)	-0.012 (0.017)	0.091*** (0.015)	-0.213*** (0.001)
S_5 (COG)					-0.565*** (0.029)	0.119*** (0.017)	-0.308*** (0.015)	0.183*** (0.027)
LHS	-42.310 (836.87)			7.202*** (0.043)	-64.895 (1672682)			7.362*** (0.027)
HS	-25.995 (513.58)		-0.321 (0.498)	5.225*** (0.041)	-33.388 (679.212)		-0.427 (0.513)	5.307*** (0.026)
PS	-21.50 (513.58)	1.209* (0.648)	0.115 (0.491)	4.282*** (0.040)	-27.673 (679.212)	1.193* (0.649)	-0.123 (0.502)	4.394*** (0.026)
BA	-17.117 (513.58)	1.288** (0.631)	-0.155 (0.504)	2.001*** (0.039)	-20.522 (679.212)	1.258** (0.630)	-0.051 (0.516)	1.986*** (0.025)
Exp	-0.326*** (0.063)	-0.544 (0.046)	0.124*** (0.044)	0.014*** (0.002)	-0.574*** (0.098)	-0.035 (0.048)	0.123*** (0.046)	0.014*** (0.001)
Exp^2 × 100	0.419*** (0.001)	0.129 (0.113)	-0.298*** (0.001)	0.005 (0.004)	0.809*** (0.199)	0.088 (0.034)	-0.267** (0.105)	0.003 (0.003)
Married	0.069 (0.175)	0.018 (0.113)	-0.002 (0.103)	-0.005 (0.005)	-0.229 (0.323)	0.034 (0.114)	-0.003 (0.105)	0.001 (0.003)
Tenure	-0.004*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)	0.001 (0.001)	-0.0004 (0.0003)	0.0003 (0.0003)	-0.0004*** (0.0000)
N	43432	97197	99102	1744784	43532	97197	99102	1744784
N person	10676	19715	20803	444526	10676	19715	20803	44526

Specifications 1-3,5-7 are conditional logit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and year fixed-effects. Regression coefficients reported, rather than marginal effects. Specifications 4 and 8 are fixed-effects regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements.

Table 13: Estimates Accounting for Sample Selection with Time and ER Fixed-Effects

Outcome	(1) Pr(OQ) O*NET	(2) Pr(OQ) GH-PS	(3) Pr(OQ) GH-HS	(4) $E_j - E_i$ O*NET	(5) Pr(OQ) O*NET	(6) Pr(OQ) GH-PS	(7) Pr(OQ) GH-HS	(8) $E_j - E_i$ O*NET
Current	0.081	–	-0.061*	0.609	-0.049	–	-0.059	-0.574***
Urate×100	(0.059)	–	(0.035)	(0.307)	(0.030)	–	(0.045)	(0.187)
Urate at	0.049	–	0.133***	-0.134*	-0.016	–	0.084	0.428**
Hire×100	(0.034)	–	(0.047)	(0.177)	(0.030)	–	(0.051)	(0.179)
S_1					-0.152***	–	-0.059***	1.004***
(COG)					(0.004)	–	(0.046)	(0.033)
S_2					0.046***	–	0.058***	-0.361***
(MAN)					(0.004)	–	(0.001)	(0.016)
S_3					0.063***	–	0.035***	-0.390***
(MAN)					(0.002)	–	(0.003)	(0.006)
S_4					-0.001	–	0.003	-0.082***
(MAN)					(0.003)	–	(0.002)	(0.005)
S_5					-0.024***	–	-0.026***	0.191***
(COG)					(0.002)	–	(0.002)	(0.008)
LHS	-1.795***			4.746***	-1.864***			6.681***
	(0.009)			(0.063)	(0.012)			(0.091)
HS	-0.624***		0.217***	2.916***	-0.844***		0.117***	4.453***
	(0.007)		(0.010)	(0.055)	(0.008)		(0.010)	(0.069)
PS	-0.302***	–	0.156***	1.967***	-0.495***	–	0.080***	3.292***
	(0.006)	–	(0.010)	(0.042)	(0.004)	–	(0.008)	(0.036)
BA	-0.225***	–	0.045***	1.167***	-0.252***	–	0.031***	1.493***
	(0.009)	–	(0.003)	(0.036)	(0.006)	–	(0.003)	(0.019)
Exp	-0.001**	–	0.001	0.005	-0.000	–	0.002***	-0.002
	(0.001)	–	(0.001)	(0.004)	(0.000)	–	(0.000)	(0.001)
Exp^2	0.001	–	-0.000	0.014**	-0.000	–	-0.004***	0.025***
×100	(0.001)	–	(0.000)	(0.006)	(0.000)	–	(0.001)	(0.003)
Married	-0.014***	–	-0.003	0.099***	-0.002	–	0.005*	0.096***
	(0.003)	–	(0.002)	(0.002)	(0.002)	–	(0.003)	(0.005)
Tenure	-0.0002***	–	-0.002***	0.0001***	0.0001***	–	-0.0000	0.0004***
	(0.0000)	–	(0.0000)	(0.0000)	(0.0000)	–	(0.0000)	(0.0001)
Selection	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)
Fraction of	1.252***	–	1.215***	1.251***	1.251***	–	1.257***	0.698***
Peers Stay	(0.055)	–	(0.054)	(0.055)	(0.055)	–	(0.059)	(0.028)
N	1372357	–	1444987	1372357	1338530	–	1149216	1372357
σ				1.512				1.215
χ^2	0.16	–	5.55***	60.27***	6.02**	–	1.77	13699.8***

Specifications 1-3,5-7 are Probit selection corrected estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are selection corrected OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses clustered at the 73 economic regions. Results weighted with LFS final weights. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. χ^2 is a Wald statistic is to test for correlation in the error terms, $H_0 : \rho = 0$. Peers Stay is the exclusion restriction in the first stage regression for selection into job staying, the observed sample in first stage mismatch regressions. Fraction of Peers Stay is the coefficient on the exclusion restriction from the selection equation.

Table 14: Estimates Accounting for Sample Selection with Year and Prov. FE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(OQ)	Pr(OQ)	Pr(OQ)	$E_j - E_i$	Pr(OQ)	Pr(OQ)	Pr(OQ)	$E_j - E_i$
Outcome	O*NET	GH-PS	GH-HS	O*NET	O*NET	GH-PS	GH-HS	O*NET
Current	0.086	0.177	-0.126*	0.366	0.072	-0.086	-0.127***	-0.817**
Urate×100	(0.078)	(0.087)	(0.069)	(0.309)	(0.201)	(0.106)	(0.045)	(0.349)
Urate at	0.080**	0.306***	0.106**	-0.399*	0.312	-0.027	0.034	0.421*
Hire×100	(0.036)	(0.115)	(0.069)	(0.216)	(0.387)	(0.049)	(0.041)	(0.236)
S_1					-0.152***	-0.103***	-0.058***	1.002***
(COG)					(0.005)	(0.006)	(0.001)	(0.005)
S_2					0.044***	0.135***	0.052***	-0.355***
(MAN)					(0.004)	(0.005)	(0.001)	(0.016)
S_3					0.063***	0.048***	0.029***	-0.389***
(MAN)					(0.002)	(0.002)	(0.002)	(0.006)
S_4					-0.002	-0.009**	0.004	-0.079***
(MAN)					(0.003)	(0.004)	(0.002)	(0.005)
S_5					-0.024***	0.011***	-0.027***	0.190***
(COG)					(0.002)	(0.002)	(0.002)	(0.008)
LHS	-1.826***			4.710***	-2.113***			6.706***
	(0.015)			(0.067)	(0.039)			(0.090)
HS	-0.627***		0.223***	2.890***	-0.852***		0.114***	4.468***
	(0.008)		(0.011)	(0.057)	(0.011)		(0.010)	(0.069)
PS	-0.305***	0.109***	0.161***	1.941***	-0.503***	0.005	0.076***	3.309***
	(0.006)	(0.004)	(0.011)	(0.044)	(0.004)	(0.006)	(0.009)	(0.033)
BA	-0.226***	0.013***	0.047***	1.165***	-0.254***	-0.005	0.031***	1.497***
	(0.009)	(0.005)	(0.004)	(0.036)	(0.007)	(0.005)	(0.003)	(0.019)
Exp	-0.001**	-0.002**	0.000	0.006	-0.000	-0.002***	0.001***	-0.003*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	0.001	(0.000)	(0.001)
Exp^2	0.001	0.006***	-0.000	0.014**	-0.001	0.004**	-0.003***	0.025***
×100	(0.001)	(0.000)	(0.000)	(0.006)	(0.000)	(0.002)	(0.001)	(0.003)
Married	-0.015***	0.001	-0.002	0.094***	-0.004**	0.000	0.005*	0.103***
	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)
Tenure	-0.0002***	-0.0003***	-0.0001***	0.002***	0.0000***	-0.0002***	-0.0000	0.0004***
	(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Selection	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)	Pr(Stay$_i$)
Fraction of	1.252***	1.346***	1.215***	1.251***	1.251***	1.404***	1.257***	0.707***
Peers Stay	(0.055)	(0.062)	(0.054)	(0.055)	(0.055)	(0.066)	(0.059)	(0.029)
N	1372357	718000	1444987	1372357	1372357	597403	1183043	1372357
σ				1.514				1.217
χ^2	0.00	2.38	6.65***	85.59***	12.25***	2.19	1.48	13821.54***

Specifications 1-3,5-7 are Probit selection corrected estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are selection corrected OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses clustered at the 73 economic regions. Results weighted with LFS final weights. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. χ^2 is a Wald statistic is to test for correlation in the error terms, $H_0 : \rho = 0$. Peers Stay is the exclusion restriction in the first stage regression for selection into job staying, the observed sample in first stage mismatch regressions. Fraction of Peers Stay is the coefficient on the exclusion restriction from the selection equation.

Table 15: Estimates accounting for Sample Selection (Immigrant subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(OQ)	Pr(OQ)	Pr(OQ)	$E_j - E_i$	Pr(OQ)	Pr(OQ)	Pr(OQ)	$E_j - E_i$
Outcome	O*NET	GH-PS	GH-HS	O*NET	O*NET	GH-PS	GH-HS	O*NET
Current Urate×100	0.218	-0.429	-1.133*	-0.217	1.119	-0.591*	-0.905*	-0.815**
	(0.245)	(0.400)	(0.623)	(0.259)	(0.741)	(0.357)	(0.511)	(0.349)
Urate at Hire×100	0.462*	1.249**	0.720*	-0.476**	-0.100	0.823	0.635	-0.019
	(0.245)	(0.552)	(0.429)	(0.204)	(0.371)	(0.688)	(0.450)	(0.217)
S_1					-0.971***	-0.212***	-0.250***	1.030***
(COG)					(0.048)	(0.014)	(0.015)	(0.035)
S_2					0.294***	0.235***	0.244***	-0.367***
(MAN)					(0.033)	(0.013)	(0.011)	(0.015)
S_3					0.434***	0.163***	0.097***	-0.422***
(MAN)					(0.012)	(0.007)	(0.015)	(0.006)
S_4					-0.008	-0.012	0.010	-0.076***
(MAN)					(0.019)	(0.015)	(0.017)	(0.006)
S_5					-0.169***	0.104***	-0.174***	0.215***
(COG)					(0.014)	(0.016)	(0.126)	(0.011)
LHS	-8.318***			4.763***	-11.687***			6.708***
	(0.777)			(0.080)	(0.223)			(0.099)
HS	-2.992***		0.890***	2.991***	5.469***		0.516***	4.518***
	(0.067)		(0.075)	(0.063)	(0.195)		(0.050)	(0.073)
PS	-1.398***	0.192***	0.621***	2.080***	-3.148***	-0.020	0.316***	3.330***
	(0.034)	(0.020)	(0.065)	(0.054)	(0.098)	(0.032)	(0.042)	(0.047)
BA	-1.032***	0.042***	0.168***	1.232***	-1.592***	0.008	0.126***	1.512***
	(0.063)	(0.021)	(0.026)	(0.037)	(0.091)	(0.025)	(0.023)	(0.029)
Exp	-0.002	-0.002	0.002	0.004*	-0.001	-0.002	0.006**	-0.005***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Exp^2	0.003	0.005	-0.001	0.007	-0.015**	0.002	-0.010	0.025***
×100	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.001)	(0.006)	(0.004)
Married	-0.096***	0.019	0.001	0.214***	-0.050***	-0.021	0.027	0.091***
	(0.015)	(0.028)	(0.016)	(0.013)	(0.015)	(0.027)	(0.017)	(0.009)
Tenure	-0.0007***	-0.0004***	-0.0006***	0.002***	0.0002**	-0.0001	-0.0002**	0.0005***
	-(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm Size	-0.027***	-0.032***	-0.030***	0.109***	0.073***	-0.007	0.024***	-0.024***
	(0.009)	(0.007)	(0.004)	(0.012)	(0.007)	(0.008)	(0.004)	(0.003)
Permanent Job	-0.199**	-0.006	0.039	0.580***	0.102***	0.121**	0.164***	0.072***
	(0.032)	(0.033)	(0.034)	(0.033)	(0.026)	(0.050)	(0.040)	(0.018)
Immigrant	0.345***	0.100***	0.051**	-0.405***	0.239***	0.039***	0.007	-0.141***
	(0.026)	(0.019)	(0.020)	(0.056)	(0.034)	(0.013)	(0.022)	(0.021)
Selection	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)	Pr(Stay_i)
Fraction of Peers Stay	0.998***	1.059***	0.977***	0.238***	0.998***	1.064***	1.257***	1.251***
	(0.026)	(0.034)	(0.025)	(0.015)	(0.026)	(0.041)	(0.059)	(0.055)
N	57263	322333	618147	57263	57263	268258	507011	57263
σ				1.807				1.239
χ^2	1.24	8.24***	0.00	1632.29***	0.37	4.41**	0.94	4799.79***

Specifications 1-3,5-7 are Probit estimates of the probability of overqualification, conditional on dummies for education (LHS HS PS BA PG), experience and its quadratic, marital status, job tenure and provincial and year fixed-effects. Average marginal effects reported instead of coefficients. Specifications 4 and 8 are OLS regressions on the linear distance measure. O*NET measures are based on expert ratings of required education, while GH measures are based on whether or not the market pays a return to College or High school education respectively, within a workers occupation Gottschalk and Hansen (2003). Standard errors in parentheses clustered at the 73 economic regions. Results weighted with LFS final weights. S are skill requirements generated from factor analysis of occupations. Skill requirements 1 and 5 represent cognitive, while 2-4 represent manual, job requirements. χ^2 is Wald statistic for

Table 16: First Stage Regressions - Sample Selection

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

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

Table 17: 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 4: 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 5: Skill Requirements

Instructions for Making Abilities Ratings

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

Each ability in this questionnaire is named and defined.

For example:

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

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

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

For example:

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

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

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

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

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

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

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

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

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

1 O*NET Abilities Questionnaire

Figure 6: A Binary Measure for Assessing Mismatch

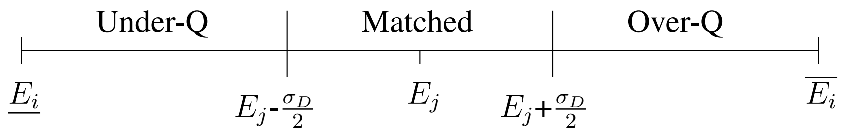

Figure 7: Scree Plot of Rotated Eigenvectors