

Education and Work in the 21st Century: Credential Inflation or Transformation?

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Executive Summary

In this paper, we reviewed recent employment trends and analyze scholarship around education and work. We then used the unique nature of the Program for the International Assessment of Adult Competencies (PIAAC) dataset and its precursors—the International Adult Literacy Survey (IALS) and the Adult Literacy and Lifeskills (ALL) survey—to conduct our own tests of the relationships between education, cognitive skills, the use of technology, and work. Based on these preliminary results, we find that education and skills often had independent, but significant effects related to labor market outcomes (employment, job tasks, and earnings).

Many sociologists have argued that education is a marker of status and that education does not actually improve workers' cognitive abilities. If educational credentials hold no inherent value then education may actually be less valued by employers if more people are educated. Although the data were cross-sectional and our models did not support causal inferences, we found little evidence to support the idea that education has become less valuable over time. Instead, we found that even as schooling increased across the population between 1994 and 2012, workers were more likely to complete complex job tasks and education was more strongly related to earnings. We encourage policymakers to continue to focus on improving access to higher education and formal lifelong learning programs in cooperation with community colleges and universities. Because both education and cognitive skills can have strong effects on how people fare in the labor market, we also encourage educators to consider how curricula can be re-designed to build greater cognitive skills.

Introduction

As the United States gears up for another presidential election, higher education and income inequality are shaping up to be defining campaign issues. Among many policymakers, educational policy and income inequality go hand in hand. For example, Thomas Piketty's popular book, *Capital in the Twenty-First Century* (2014) gained attention for its provocative argument that income inequality worsened in recent decades because college-going rates stopped increasing in the 1980s.¹

While some have argued that higher education is one of the best ways to improve equity and social mobility, others have argued that increasing access to higher education will cause rapid credential inflation in the labor market. In *The Global Auction: The Broken Promises of Education, Jobs, and Incomes*, Phillip Brown, Hugh Lauder, and David Ashton (2011) suggested that government funding and student loans that finance higher education were being squandered because "widening access to a college education lowers the value of credentials in the competition for jobs" (p. 7). Through a series of interviews with corporate executives around the globe, Brown and colleagues concluded that companies incorporate technology into jobs to lower wages (they called this process *digital Taylorism*). Whereas Piketty suggested that policymakers could reduce income inequality by increasing access to higher education, Brown, Lauder and Ashton concluded that increased access to higher education is at least partially to blame for stagnant middle-class wages.

The Global Auction struck a chord in the wake of the global economic recession. Many young adults had borrowed heavily to pay for higher education, but they graduated during hard economic times and some did not find full-time work or high-paying jobs (Lambert, 2014). Though credential inflation appeared to be a new phenomenon in the American labor market, sociologists have forecasted it for decades (see, e.g., Berg, 1971; Dore, 1976; Labaree, 2010). The general idea behind credential inflation was that employers rewarded graduates with higher pay because educational degrees held value. Inflationists argued that credentials lost their value as access to education increased and high school diplomas, followed by baccalaureate degrees, became more common. In the eyes of inflationists, this led to the collapse of the high school labor market. The contemporary fear is that "the college degree is the new high school diploma" (Rampell, 2013), but inflationists have even depicted "the master's as the new bachelor's" degree (Pappano, 2011). If the credential inflation argument is true, it would create an interesting paradox for policymakers: would policymakers advocate for increased access to higher education to help less-educated Americans be more successful in the labor force, or would they be more concerned with protecting the value of a college education and prevent the flooding of the labor market with bachelor's and master's degrees?

In this paper, we analyze recent employment trends and scholarship on the relationship between education and work. We then use the unique nature of the Program for the International Assessment of Adult Competencies dataset to conduct our own tests of the relationships between education, cognitive skills, technology, and work in the twenty-first century.

¹ Piketty's book and arguments were also widely covered in popular American news outlets. For examples, see Porter (2014) and Sherter (2014).

Literature Review

Workers with greater levels of education tend to do better in the labor market than workers with less education (Baker, 2009, 2011; 2014; Carnevale, Rose, & Cheah, 2011; Banerjee & Lee, 2015; Bowles, 1972; Bowles & Gintis, 1976, 2002; Boylan, 1993; Julian & Kominiski, 2011; Mayer, 2014; Sum & Khatiwada, 2010). However, the issue at the heart of this paper is not whether workers with more schooling earn more than workers with less schooling. Instead, we focus on whether workers with similar levels of schooling had similar types of employment and earnings in 2012 as they did in previous decades.

Education and Work: Recent Trends and Future Forecasts

The number of unemployed and underemployed (working less than full-time) college graduates has increased significantly in the twenty-first century. According to a recent article released by the Federal Reserve Bank of New York, the percentage of new college graduates who were underemployed increased by 10% between 2001 and 2012 (Abel, Deitz, & Su, 2014). Additionally, high school and community college graduates were less likely to be employed full-time and were more likely to be unemployed or underemployed (Mayer, 2014). As the United States' underemployment rate has increased, black and Hispanic workers, less-educated workers, and workers in low-skill and low-wage jobs have been the most likely to suffer (Sum & Khatiwada, 2010).

Although Americans often focus on unemployment rates, policymakers should also consider the negative consequences of underemployment. Workers are underemployed if they are willing and able to work full-time but they work as “involuntary part-time workers” because of the state of the economy (Mayer, 2014).² Underemployed Americans tend to have lower future earnings and rarely receive employer-sponsored health care or retirement benefits. Yet individual workers are not the only ones to be negatively affected by underemployment. In the fourth quarter of 2009, the total cost of underemployment (including foregone earnings, benefits, and tax revenues) on the U.S. economy was estimated at approximately \$78 billion (Sum & Khatiwada, 2010).

Even as high-school, community college, and university graduates were more likely to be unemployed or underemployed, projections predict that the fastest areas of job growth in the U.S. economy are those that will require higher education (Lacey & Wright, 2010). For example, Sommers & Morisi (2012) found that “the fastest projected employment growth, 21.7 percent over the decade, is among occupations with a master’s degree as the typical entry-level education needed” (p. 13). Thus, Americans with similar levels of education were more likely to be underemployed or unemployed in recent years, but projections predicted that the fastest growing employment sectors will require high levels of schooling from new workers. In

² Mayer (2014) explained that the Bureau of Labor Statistics (BLS) has several different measures of unemployment and underemployment. We adopted Mayer’s suggested definition of underemployment: “U-6 includes those who are working part time for economic reasons. These individuals worked fewer than 35 hours in the CPS [Current Population Survey] reference week, but they want, and are available, to work full time. People in this group are often described as ‘underemployed’ or as ‘involuntary part-time workers.’ U-6 is the sum of those working part time for economic reasons, those marginally attached to the labor force, and unemployed workers, divided by the sum of those marginally attached to the labor force and the civilian labor force.” (Mayer, 2014)

summary, we find that recent studies of the nation's labor force reflect the tensions inherent in the theory of credential inflation.

The Relationship between Education and Labor

While many researchers seem to agree that many employers prefer and are willing to pay more for highly educated workers, they disagree about *why* workers benefit from schooling.³ Several theories have attempted to explain the relationship between education and the labor market, but these theories can be sorted into two categories based on how they answer the following question: “Do people learn vocationally or occupationally useful things in school, or do schools simply sort people, and what is the basis for any sorting?” (Bills, 2003, p. 443). It is important to review different assumptions about how education relates to employability because these theories hold important implications for making educational policy.

Education and Status

Many sociologists have suggested that education primarily confers status, as opposed to skills, and that schools help to sort people into a fixed number of positions in the labor market (Berg, 1971; Bowles, 1972; Bowles & Gintis, 1976, 2002; Dore, 1976). Bowles and Gintis (2000) summarized their decades of work with the argument that “most of the contribution of schooling to economic success is unrelated to the learning of cognitive skills in school” (p. 22). Other scholars have argued that educational credentials tend to improve wages through “sheepskin effects” (Banarjee & Lee, 2015) that do not represent true differences in a worker's job market abilities or merit.

If scholars think of schools as producing status and not skills, then they subscribe to one version of the history and future of American society. For example, in *Someone Has to Fail: The Zero-Sum Game of Public Schooling*, David F. Labaree argued:

The rise in the education level of Americans in the last 150 years has been extraordinarily rapid, but this change has not succeeded in shuffling the social deck. People who had an educational edge on the competition were by and large able to maintain this edge by increasing their schooling at the same rate as those below them in the status order. The effect of this process over time was to increase the average education level of everyone in the labor queue, which artificially inflated educational requirements for jobs. . . . They were forced to run to stay in place. (2010, p. 241)

Labaree's argument about credential inflation was a potent one. If the supply of good jobs remains relatively fixed, and the number of educational credentials increases, then each person's credential must be worth relatively less in the labor market. This idea made its way into popular news stories that declared the bachelor's degree as the new high school diploma and the master's degree as the new bachelor's degree (see, e.g. Pappano, 2011; Rampell, 2013).

³ For example, Bills (2003) identified seven theories that were commonly used to study education and work: human capital; screening or filtering; signaling; control; cultural capital; institutional; credentialism.

In *The Global Auction*, Brown, Lauder, and Ashton (2011) discussed the effects of credential inflation in terms that are relatable to the average American family. If credential inflation is real, then Americans must stay enrolled (or re-enroll) in college for longer periods of their life to earn additional credentials that hold more value in the labor market. To do this, they must pay greater amounts of tuition (presumably borrowed through student loans) and forego the wages they would earn if they were not in school. Students from wealthier backgrounds may be better able to bear these costs, but “aspiring working-class families have been forced into the scramble for paper qualifications even though they are at a distinct disadvantage compared to those from more affluent backgrounds” (Brown, Lauder, & Ashton, 2011, p. 138). According to this school of thought, minorities and lower-class people are in a double-bind: they are more likely to be unemployed and underemployed (Sum & Khatiwada, 2010) and they are also less likely to be able to compete in an educational arms race fueled by credential inflation.

Education and Skills

While many sociologists have argued that education confers status, many economists have argued that schools increase human capital by improving students’ cognitive skills; in turn, employers recognize that these skills are useful in the workplace (Bills, 2003; see also Becker, 1964). However, studies that use a human capital framework often carry strong assumptions and challenging limitations. Rosenbaum (1986) noted that few human capital studies use measures of cognitive skills, and many human capital studies assumed that managers could assess job candidates’ cognitive skills despite evidence to the contrary.

Educational researchers have also found that education improves workers’ earnings, but because they did not have (or at least did not use) measures of cognitive skills they could only speculate about the relationship between schooling and skills. For example, Carnevale, Rose, and Cheah (2011) concluded that some college graduates earn more because they have “college-level skills” that they can use “to perform more productive activities and attain higher pay” (p. 16). Similarly, Monks (2000) demonstrated that indicators of college “quality” affect wages, however, he admitted that “it is still unknown whether the wage premiums earned by more selective, private, university students are due to greater human capital accumulation” (p. 288). When policymakers argue for increasing access to higher education, they often assume that by doing so they will help students develop skills that employers value, but the empirical basis for this claim is not as strongly developed as some might think.

The human capital perspective suggests that there is a strong skill-based relationship between education and jobs. However, as with the status-oriented theories, human capital theory is limited in that it proposes that educational systems are primarily reactive to labor markets—that is, schools teach the skills that employers want. Many higher education studies that use human capital theory do not consider whether the demand for cognitive skills will increase or decline as more people attend college.

Educational Transformation of Work

A third perspective suggests that schools teach skills, but it also proposes that the educational system is such a strong social institution that the labor market changes the structure of work in

response to the cognitive skills that students develop. According to the educational transformation argument, education, skills, and the nature of work have all evolved together as the United States has moved from an industrial- to a knowledge-based economy.

The educational transformation argument has suggested that education directly improves cognitive skills and ultimately changes the nature of work (Baker, 2009; Meyer, 1977). A multidisciplinary team composed of a sociologist, neurologist, psychologists, and education researchers performed experimental research to provide evidence that education improves cognitive skills such as numeracy (Baker, et al, 2015; see also, Baker, Salinas, & Eslinger, 2012). In addition to demonstrating that education improves workers' cognitive abilities, Baker argued that workplace tasks have become more complex so that employers and employees can take advantage of these increased skills (Baker, 2009, 2011, 2014; see also, Goldin & Katz, 1998; Spenner, 1983; Teichler, 1999).

Through his careful synthesis of economic and sociological literature, Baker developed the argument that there has been an educational transformation in society that has changed—for the better—the skills and job descriptions of workers across the global economy. However, Baker concluded that “up until now there has never been a thorough investigation of the relationship among education, job skill and technology. There are research literatures on the relationship between any two of these, but not all three together” (Baker, 2009, p. 180). Our analysis of three surveys that each measure education and literacy skills will allow us to determine whether the credential inflation argument or the educational transformation argument provides a more appropriate basis for understanding the relationship and challenges between income inequality and educational policy.

The Demographics of Education and Labor

Until now, we have analyzed studies and theories that explain how education and labor markets work at a societal level, yet we must also acknowledge that American workers have many different demographic and socioeconomic backgrounds that make them more immune or more easily affected by economic and educational structures. In the American labor market, workers tend to earn more if they have greater levels of work experience (Sommers & Morisi, 2012, p. 21-22). Younger college graduates may have more trouble finding high-paying jobs or full-time work (Abel et al., 2014; Mayer, 2014). Therefore, it is important to consider workers' age groups because age can be related to work experience, education, and changes in income over the life course (Julian & Kominiski, 2011).

Women, immigrants, and racial or ethnic minorities are often less likely to be employed and less likely to be paid as much as white males, often even when they hold similar levels of education (Aydemir & Sweetman, 2006; Bowles & Gintis, 2002; Carnevale, Rose, & Cheah, 2011; Golden & Gebreselassie, 2007; Julian & Kominiski, 2011; Mayer, 2014; Papademetriou, & Sumption, 2011; Thomas & Zhang, 2005). In some instances, scholars have found that because many minorities do not earn college degrees, minority graduates have the biggest income gains from additional schooling (see, e.g. Long, 2010). Aside from individual-level characteristics, there are also structural characteristics of the labor market that can affect employment, the nature of jobs, and earnings. For example, Sommers and Morisi (2012) noted that wages “are generally higher

in some types of occupations—notably those in management and in technical fields—than others with the same or higher education requirements, such as counseling or social work” (p. 20). Zhang (2008) suggested that gender and race may actually reflect other socio-economic realities that influence educational attainment such as family income, performance in school, the number of hours worked, and the quality of colleges and universities attended; however, this does not change the need to examine differences in income among different status groups.

Research Questions

Scholars, practitioners, and policymakers who are interested in education policy and reducing income inequality should consider the saliency of the credential inflation argument. If the idea of credential inflation is accepted as true, then it suggests that increasing access to higher education will not help American’s get better jobs. But the educational transformation argument suggests that education improves cognitive skills and when mass segments of the population are educated the labor market transforms to accommodate new workers with more complex tasks and better pay. This leads us to ask the following research questions:

1. Is there any relationship between years of education and employment status and type of employment (supervisory duties and job tasks) over time?
2. Are respondents with similar levels of education likely to work similar numbers of hours per week (testing for underemployment) over time?
3. Do respondents with similar levels of education tend to have similar earnings over time (after adjusting for inflation)?
4. Was years of education or literacy skills a better predictors of labor market outcomes in 2012 than 2003 or 1994?

Study Design and Methodology

We analyzed data from the Program for the International Assessment of Adult Competencies (PIAAC: 2012) and compared our findings with estimates from the Adult Literacy and Lifeskills (ALL: 2003) survey and the International Adult Literacy Survey (IALS: 1994). The three surveys were designed to have some continuity in sampling designs, assessment domains, and background questionnaires. When we analyzed these three surveys as cross-sectional data, we can compare results to determine whether relationships between education, skills, and employment changed between 1994 and 2012. The similarities in the surveys allowed us to achieve a rudimentary understanding of whether relationships between education, skills, and occupations may have changed over time.

Availability and Compatibility of the Data

Restricted-use data files for American workers who were included in the PIAAC (2012) and ALL (2003) studies were obtained from the National Center for Education Statistics (NCES), and public-use IALS (1994) data on American workers were received from Statistics Canada.⁴ Even though PIAAC, ALL, and IALS sought to assess adult cognitive skills in similar ways, the

⁴ Restricted-use IALS data were not available from NCES.

assessments for literacy skills changed over the decades. Fortunately, plausible values from the ALL and IALS assessments were re-scaled to match the most recent assessments used in PIAAC. ALL and IALS were successfully updated to include the plausible values that were re-scaled by Statistics Canada. The re-scaling included combining two separate literacy scales (prose and document literacy) into one scale and re-scaling numeracy based on information from all countries to improve item parameters.⁵ Without this re-scaling, literacy and numeracy scores in ALL and IALS would not be comparable to PIAAC.

Sample

For this study we used all respondents between the ages of 25 and 54 from the three surveys identified above. We chose to remove respondents with ages below 25 and above 54 because they are significantly more likely to be out of the workforce due to school or retirement, creating a homogenous set of respondents for the study.

Respondents missing current employment status (denoting whether they were employed, a student, unemployed, etc.) were deleted from the sample ($N = 227$) because it was not appropriate to impute that information. Respondents who were missing employment status were also missing all economic outcome variables (such as number of hours worked, earnings, and job tasks). Therefore, we could only impute economic outcomes using background characteristics, education, and skills; however, these variables are our only independent variables so imputed values would not have provided new information. Before imputation, the final sample included 7,116 observations with 3,036 from PIAAC (2012), 2,175 from ALL (2003), and 1,905 from IALS (1994). All research questions dealing solely with employment status use the full sample, while research questions analyzing work-related outcomes such as earnings and job skills used a sub-sample of the data, including only respondents that were employed at the time of the survey.

Variables

Variables used for this study were designated as “trend” variables in PIAAC (2012). A full list of variables and their equivalent survey variable name can be found in Appendix B. This means that the questions remained the same across all three surveys. However, the categories of responses to some questions changed between IALS and ALL; this forced us to combine some responses into larger categories in order to make valid comparisons. For example, the variable that recorded whether workers participate in “reading directions or instructions” as a job task had five response categories in IALS (1994) (daily, a few times a week, once a week, less than once a week, or rarely/never) while ALL (2003) has only four responses (at least once per week, less than once per week, rarely, or never). This means these the responses had to be reconstructed as a three level variable (at least once per week, less than once per week, or rarely/never).

We have a number of dependent variables across the four research questions. *Current work situation* was rescaled as a binary variable, denoting whether a respondent was working at the time of the survey or not. *Status on the job* describes whether a worker is a supervisor or self-employed and is a categorical variable with four levels (not supervisor, supervise less than 5

⁵ Statistics Canada provided documentation on the ways that IALS and ALL literacy scores were re-scaled so that they would be comparable with PIAAC plausible values. These documents are on file with the authors.

people, supervise more than 5 people, self-employed or unpaid family worker). *Hours per week on the job* and monthly income are both continuous variables. We re-coded hours per week into a dichotomous variable to represent whether respondents worked full-time (35 hours per week, see e.g., Mayer, 2014). Monthly income was not available for IALS (1994), so we only ran models for ALL (2003) and PIAAC (2012).

Income was not be modeled for IALS (1994) because NCES was unable to provide access to restricted IALS data, and public-use IALS data only provided income quintiles. PIAAC (2012) and ALL (2004) reported monthly earnings data. We used ordinary least squares estimation to regress logged earnings on worker's cognitive skills, years of education, and background characteristics (discussed further below). ALL income was adjusted for inflation and set to 2012 constant dollars (to be consistent with PIAAC) using the Bureau of Labor Statistics CPI inflation calculator.⁶

A set of six work related tasks are measured as categorical variables with three levels (at least once a week, less than once a week, rarely/never). The tasks include (1) *read or use directions or instructions*, (2) *read or use letters, memos, e-mails*, (3) *read or use reports, articles, magazines, or journals*, (4) *read or use manuals, reference books, or catalogues*, (5) *read or use bills, invoices, spreadsheets, or budget tables*, and (6) *read or use diagrams or schematics*. Finally, two personal task related variables were present in ALL (2003) and PIAAC (2012) including whether or not a person has used a computer, and on a three level scale similar to job tasks, how often do you read letters, notes, or e-mails.

Background characteristics include *gender* (coded as 1 for female and 0 for male), *age* in ten year bands (25-34, 35-44, and 45-54), and whether a respondent was *born in the United States* (1 = born in U.S., 0 = not born in U.S.). We coded respondents' *parental education* as the highest level of education achieved by either parent (i.e., if a respondent's mother was more highly educated than her father, then we used the mother's parental education in our models). Across the three surveys, parental education was coded using three levels: less than high school, high school degree, or greater than high school. These variables (gender, age, born in the US, and parental education) were used as controls in all of our models.

Our three independent variables of interest were years of education, literacy skills, and information technology (ICT) skills at work. Personal education was defined as the number of years of formal schooling completed by the respondent⁷. All three surveys measured respondents' literacy, while only PIAAC (2012) measured ICT skills at work. ICT skills at work is a derived variable that measures technology use, such as computer use, internet use, and computer skills, in the work place. Both literacy, numeracy and ICT skills are coded as continuous variables, with ten plausible values for literacy and numeracy, and a single ICT score. As previously mentioned, the OECD rescaled IALS (1994) and ALL (2003) literacy scores to match PIAAC (2012) scores allowing for comparison across the surveys.

⁶ CPI inflation calculator available at http://www.bls.gov/data/inflation_calculator.htm

⁷ We ran a parallel set of models that used categories of educational attainment (less than high school; high school diploma; some college or associate's degree; and bachelor's degree and above), and these models led to similar results. We reported our findings using the *Years of Education* variable because we preferred to discuss estimated changes in employment outcomes in terms of an additional year of schooling.

In addition to assessing skills, PIAAC (2012) also surveyed respondents about their work conditions. PIAAC grouped workers according to job types using the International Standard Classification of Occupations (ISCO). We used the ISCO categories as control variables in our final model because we expected that workers' use of information communication technology would vary across occupational categories.

Imputation process

Despite removing a small number of observations for missing data, approximately 10% of observations were missing at least one dependent or independent variable. Missing data is problematic when the observations with missing information are not at random, meaning there is a systematic pattern that can explain missing values. In our analysis, those who were employed, but missing job skill and earnings data were more likely to be respondents with lower literacy scores or lower education. Multiple imputation is a common strategy used to fill in information that is not missing completely at random with plausible values (Allison, 2002). The strategy is called multiple imputation because it creates several versions of the missing data, adding random variation to each imputation. Running regression models on a single imputation is unlikely to capture the true representation of an individual observation, but combining multiple imputations (typically five or more) using Rubin's rules for imputation provides an accurate representation of both the coefficient and standard error (Allison, 2002).

The imputation process requires two steps as many of our research questions examine economic outcomes and skills, which should only be imputed for respondents who were employed at the time of the survey. For example, we did not impute earnings or job task information for individuals that did not have a job. For all imputations, we used a chained imputation process, which meant the variable missing the least amount of data was filled using several variables with full information, which we will call the right side of the imputation equation. Once the first variable was filled in, it joins the right side of the equation and is used to fill in the variable missing the second least information, and so on. For models with employment status as a dependent variable, we created a set of imputations for all observations. Immigrant status, personal education, mother's education, father's education, and years of personal education were imputed using gender, age, and employment status, which were present for all respondents. Next, a second set of imputations was created using the subset of respondents that were working at the time of the survey. Immigrant status, personal education, years of personal education, mother's education, father's education, six job task variables, number of hours worked, status on the job, and income were imputed using gender, age, and employment status. A random seed was set and used for both imputation processes to ensure replicability. After implementation, descriptive statistics and simple regressions across imputations were examined to ensure imputed values were stable across each imputation, meaning the means and coefficients were similar but not the same, which meant that the means for variables across imputations were similar, but not identical.

Analytic Plan

We used the Stata 13 statistical package to estimate cross-sectional models for each survey (PIAAC, ALL, IALS). Because, education, cognitive skills, and wages are often highly correlated, we will begin by checking correlations between the variables that will be used in our statistical models (Cawley, Heckman, & Vytlačil, 2001). None of the correlations exceeded the 0.7 threshold that would suggest we remove the variable from the model (Tabachnick & Fidell, 1996). This precautionary step will help to prevent multicollinearity issues. Throughout our analyses, appropriate sampling weights and jackknife replicate weights will be included in estimated models. Rather than using listwise deletion, we used multiple imputations to account for missing data. By imputing missing data, we were able to estimate unbiased coefficients and standard errors (Allison, 2002). Regression models were specified following the general forms:

$$\text{OLS Model: } Y = \alpha + D\beta + E\gamma + F\delta + S\theta + \varepsilon$$

$$\text{Logistic Model: } \log\left(\frac{\pi}{1-\pi}\right) = \alpha + D\beta + E\gamma + F\delta + S\theta$$

$$\text{Multinomial Model: } \log\left(\frac{\pi_{ij}}{\pi_{ij*}}\right) = \alpha + D\beta + E\gamma + F\delta + S\theta$$

where Y represents the relevant dependent variable; $\log(\pi / 1 - \pi)$ is the likelihood a given event will occur, such as the likelihood a participant is employed; $\log(\pi_{ij} / \pi_{ij*})$ is the likelihood of being in group j compared to group j*, the reference group; D represents workers' socioeconomic characteristics including age, gender, and immigrant status; E represents respondents' educational backgrounds; F represents occupational fields as classified by ISCO; S represents cognitive skills as measured by literacy and ICT assessments; ε represents the error term.

To test our research questions, we specified a series of OLS, logistic, and multinomial logistic regression models. To examine our first research question, relating to whether respondents with similar education levels have similar employment outcomes, we used OLS and logistic regressions depending on the dependent variable. Table 1 provides a breakdown of our models.

We estimated a series of models to answer our first research question (Do respondents with similar levels of education tend to have similar work situations and similar job duties over time?). We first estimated logistic regression models, with the dependent, dichotomous variables *Employed* and *Supervisor*. The model using *Employed* as a dependent variable used a sample including all participants in the specified age range. All other models use a subset of participants that were employed at the time of the survey. We then estimated several multinomial logistic regression models to see how strongly respondents' educational backgrounds predict the types of job tasks they are asked to complete (e.g., read or use budget spreadsheets). We chose to use multinomial logistic regression because we preferred the interpretation of this model, which examines two levels of job tasks in comparison to the third, rather than the interpretation of an ordered logistic regression, which would be the likelihood a given variable will put you in the next highest group. With only three groups, the multinomial models provide simpler interpretation.

In addition to specifying a model that predicts unemployment (described above), we were also interested in whether workers were increasingly underemployed across the three survey waves. To answer our second research question, we estimated a logistic regression model for full-time employment with those who worked fewer than 35 classified as underemployed (we recoded PIAAC variable D_Q10_T into a dichotomous variable where 1 = full-time employment and 0 = underemployed). Full-time employment models only included individuals that were working at the time of the survey. Each of these models included demographic and socioeconomic control variables, but *Years of Education* (PIAAC variable YRSQUAL) was the independent variable of interest. To test for relationships between education and *Income*, we estimated an ordinary least squares model that predicts employees' wages in ALL (2003) and PIAAC (2012).

Finally, to answer our fourth research question, we re-specified and re-estimated all the models discussed in this section with the addition of measures of cognitive skills (*Literacy*) and personal education. Adding estimates of literacy skills did not create issues of multicollinearity, so we were able to compare the relationships among education and cognitive skills on employment, underemployment, job tasks, supervisory responsibilities, and income.

To compare whether odds ratios were statistically different between the 1994, 2003, and 2012 survey waves, we calculated z-scores for each pair of estimated coefficients (β_{12} and β_{11}) across surveys using the following formula:

$$Z = \frac{\hat{\beta}_{12} - \hat{\beta}_{11}}{\sqrt{SE(\hat{\beta}_{12})^2 + SE(\hat{\beta}_{11})^2}}$$

Where the numerator is the difference of the log odds ratios and denominator is the standard error of the difference between the log odds ratios. A corresponding p-value was calculated for each z-score, with significant differences having a p-value less than 0.05.

Table 1

Summary of Analytic Plan

Model	Research Question	Dependent Variables	Independent Variables	Type of Regression
1,2	1	Employed, Supervisor	Years of Education	Binary Logistic Regression
3,4,5,6,7,8	1	Work tasks	Years of Education	Multinomial Logistic Regression
9	2	Hours Worked	Years of Education	OLS Regression
10	2	Underemployment	Years of Education	Binary Logistic Regression
11	3	Earnings	Years of Education	OLS Regression
12,13	4	Employed, Supervisor	Literacy, Years of Education	Binary Logistic Regression

14,15,16, 17,18,19	4	Work tasks	Literacy, Years of Education	Multinomial Logistic Regression
20	4	Hours Worked	Literacy, Years of Education	OLS Regression
21	4	Underemployment	Literacy, Years of Education	Binary Logistic Regression
22	4	Earnings	Literacy, Years of Education	OLS Regression
23	3	Earnings	Literacy, Years of Education, ICT at Work	OLS Regression

Note: All models included controls for gender, age, born in the US, and parental education.

Findings

Prior to answering our research questions, we first examined the descriptive statistics for years of education and skills across the three surveys. After accounting for the complex design of the survey, there were small increases in mean years of education across the three surveys. Using education by category showed that consistent with the credential inflation argument, the percentage of respondents with high school degrees dropped significantly while the percentage with a four year degree or higher rose steadily. For literacy, there is a decrease across the 25th percentile, mean, and 75th percentile, although it appears that movement in the extremes (25th percentile and 75th percentile) were responsible for more movement than those in the middle.

Table 2

Descriptive Statistics of Key Independent Variables

<u>Variable</u>		<u>IALS (1994)</u>	<u>ALL (2003)</u>	<u>PIAAC (2012)</u>
Years of Education	Mean	13.80	13.88	13.98
Education (Categories)	Less than High School	9.1%	8.2%	7.9%
	High School	46.0%	47.3%	37.6%
	2-Year or Some College	17.4%	13.2%	20.0%
	4-Year Degree	27.5%	31.3%	34.5%
Literacy	25 Percentile	252.6	248.5	243.9
	Mean	282.9	275.2	276.1
	75 Percentile	321.5	308.5	311.3

The first research question focused whether there were relationships between years of education and work status between 1994 and 2012 (whether respondents were likely to be employed, whether they were likely to be supervisors, and whether they were likely to have similar job tasks). For logistic regressions, the years of education odds-ratio should be interpreted as an increase in the likelihood of being employed. This means odds ratios below 1 indicate negative

effects. In IALS (1994), each additional year of education increased the odds of being employed by 1.19 times, holding all other variables constant. All other variables are dummy variables, coded as 1 for that group and 0 for those not in the group. This means that females in IALS (1994) had 0.27 times the odds of being employed compared to males, meaning they were 3.7 times less likely to be employed. In other words, an odds ratio of 1.19 means that workers were 19% more likely to be employed for each additional year of education they completed.

We found that years of education had a smaller effect on whether respondents were employed in the ALL (2003) dataset, but that the coefficient was similar in IALS (1994) and PIAAC (2012). This was confirmed by a z-test, showing a significant decrease between IALS to ALL, and a significant increase between ALL and PIAAC. According to the credential inflation argument, we should see a significant decline from 1994 to 2012. The similar relationship between years of education and employment status in the earliest and latest surveys suggest that education is not becoming less valuable in the labor market. See Table 3.

Table 3

Logistic Regression Estimates Predicting Employment, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds-Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.19	1.20	0.04	0.00
Female	-1.30	0.27	0.14	0.00
Born in U.S.	-0.12	0.88	0.19	0.51
Age (35 to 44)	0.21	1.24	0.16	0.18
Age (45 to 54)	-0.02	0.98	0.19	0.93
Parental Education (Less than High School)	0.06	1.06	0.20	0.77
Parental Education (High School Diploma)	0.33	1.39	0.22	0.12
Constant	-0.25	0.78	0.56	0.65
Adult Literacy and Lifeskills Survey (2003)				
Years of Education	0.08	1.08	0.02	0.00
Female	-0.70	0.50	0.13	0.00
Born in U.S.	-0.05	0.95	0.21	0.80
Age (35 to 44)	0.31	1.36	0.13	0.02
Age (45 to 54)	0.39	1.48	0.17	0.02
Parental Education (Less than High School)	-0.43	0.65	0.22	0.05
Parental Education (High School Diploma)	-0.08	0.92	0.18	0.66
Constant	0.55	1.74	0.36	0.12
Program for the International Assessment of Adult Competencies (2012)				
Years of Education	0.16	1.17	0.02	0.00
Female	-0.69	0.50	0.09	0.00
Born in U.S.	-0.29	0.75	0.14	0.04
Age (35 to 44)	0.13	1.14	0.10	0.22
Age (45 to 54)	0.16	1.17	0.11	0.14
Parental Education (Less than High School)	-0.03	0.97	0.16	0.87
Parental Education (High School Diploma)	0.14	1.15	0.10	0.19

Constant	-0.59	0.55	0.27	0.03
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Note: Bold parameter estimates indicate statistical significance at $p < 0.05$.

We were also interested in whether the nature of jobs has changed for more educated workers, so we estimated a logistic regression model to predict whether workers with more education were likely to supervise other employees. Comparing coefficients across the three cross-sections suggests that years of education was more predictive of supervisor status in the 1990s than in the 2000s and 2010s. This was confirmed by a z-test comparing the coefficients across all three models. In these models, women were not more likely to be supervisors in later survey years. In IALS (1994), age was not related to supervisor status, but in ALL (2003) and PIAAC (2012), older workers were more likely to be supervisors than younger workers (less than 35 years of age). Additional results are in Table 4.

Table 4

Logistic Regression Estimates Predicting Supervisor Status, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds-Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.18	1.20	0.03	0.00
Female	-0.50	0.60	0.11	0.00
Born in U.S.	0.17	1.19	0.26	0.50
Age (35 to 44)	-0.08	0.93	0.17	0.65
Age (45 to 54)	-0.14	0.87	0.15	0.33
Parental Education (Less than High School)	0.17	1.19	0.22	0.44
Parental Education (High School Diploma)	0.43	1.54	0.14	0.00
Constant	-2.94	0.05	0.52	0.00
Adult Literacy and Lifeskills Survey (2003)				
Years of Education	0.05	1.05	0.02	0.01
Female	-0.45	0.64	0.10	0.00
Born in U.S.	0.20	1.22	0.19	0.30
Age (35 to 44)	0.37	1.45	0.16	0.02
Age (45 to 54)	0.48	1.62	0.15	0.00
Parental Education (Less than High School)	-0.33	0.72	0.20	0.10
Parental Education (High School Diploma)	-0.14	0.87	0.13	0.28
Constant	-1.59	0.20	0.41	0.00
Program for the International Assessment of Adult Competencies (2012)				
Years of Education	0.11	1.11	0.02	0.00
Female	-0.51	0.60	0.08	0.00
Born in U.S.	-0.14	0.87	0.13	0.25
Age (35 to 44)	0.14	1.15	0.11	0.20
Age (45 to 54)	0.31	1.36	0.10	0.00
Parental Education (Less than High School)	-0.23	0.79	0.20	0.23

Parental Education (High School Diploma)	-0.03	0.97	0.12	0.82
Constant	-1.78	0.17	0.34	0.00

Note: Bold parameter estimates indicate statistical significance at $p < 0.05$.

Figure 1

Percentage of workers performing task “less than once per week” by year and education level⁸



⁸ Education level was created using ISCED categories. Less than high school consists of those with ISCED levels of primary or less, or lower secondary. High school education refers to those whose highest level of education is upper secondary. Two-year refers to those with between high school and four-year, such as post-secondary, non-tertiary and tertiary professional. Four-year describes all tertiary bachelor's, master's, and research degrees.

In addition to supervisory status, we were interested in whether the nature of work changed across the three surveys, as measured by a series of job tasks. We used cross tabulations to calculate the percentages of workers who reported completing certain job tasks once per week, by level of education⁹ (less than high school diploma, high school diploma, two-year degree, or four-year degree). We organized the results from our cross tabulations into bar graphs to show that the as Americans became more highly educated between IALS (1994), ALL (2003), and PIAAC (2012), employers increasingly asked workers to complete job tasks identified in the surveys. See Figure 1 above.

When we ran a series of multinomial logistic regression models, we did not find compelling evidence that there have been widespread shifts in job tasks across the labor market. However, we found that workers with higher years of education were more likely to complete certain types of tasks across all three datasets (e.g., read or use manuals, reference books, and catalogues; read or use letters, memos, and e-mails; read or use reports, articles, magazines, and journals). Multinomial estimation results were reported in Table 5.

Table 5

Multinomial Logistic Regression Estimates Predicting Job Tasks, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds-</u> <u>Ratio</u>	<u>Std.</u> <u>Err.</u>	<u>P>t</u>		<u>Coef.</u>	<u>Odds-</u> <u>Ratio</u>	<u>Std.</u> <u>Err.</u>	<u>P>t</u>
Read Directions or Instructions					Read or Use Manuals, Reference Books, Catalogues				
<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>				
IALS	0.08	1.08	0.02	0.00	IALS	0.29	1.34	0.03	0.00
ALL	0.14	1.15	0.03	0.00	ALL	0.25	1.28	0.03	0.00
PIAAC	0.10	1.10	0.03	0.00	PIAAC	0.12	1.13	0.02	0.00
<i>Less than Once Per week</i>					<i>Less than Once Per week</i>				
IALS	0.14	1.15	0.04	0.00	IALS	0.18	1.19	0.04	0.00
ALL	0.15	1.16	0.03	0.00	ALL	0.20	1.22	0.03	0.00
PIAAC	0.11	1.12	0.05	0.02	PIAAC	0.14	1.16	0.03	0.00
Read or Use Letters, Memos, E-mails					Read or Use Bills, Invoices, Spreadsheets, Budget Tables				
<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>				
IALS	0.38	1.46	0.04	0.00	IALS	0.13	1.14	0.02	0.00
ALL	0.28	1.33	0.03	0.00	ALL	0.09	1.10	0.02	0.00
PIAAC	0.40	1.49	0.03	0.00	PIAAC	0.08	1.08	0.02	0.00
<i>Less than Once Per week</i>					<i>Less than Once Per week</i>				
IALS	0.06	1.07	0.07	0.35	IALS	0.19	1.21	0.04	0.00
ALL	0.11	1.11	0.05	0.02	ALL	0.15	1.17	0.04	0.00
PIAAC	0.13	1.13	0.05	0.01	PIAAC	0.16	1.17	0.03	0.00

⁹ Level of education was created by collapsing ISCED values. See previous footnote for details.

Read or Use Reports, Articles, Magazines, Journals					Read or Use Diagrams or Schematics				
<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>				
IALS	0.35	1.42	0.04	0.00	IALS	0.20	1.22	0.03	0.00
ALL	0.27	1.30	0.03	0.00	ALL	0.15	1.17	0.03	0.00
PIAAC	0.34	1.41	0.03	0.00	PIAAC	0.10	1.10	0.03	0.00
<i>Less than Once Per week</i>					<i>Less than Once Per week</i>				
IALS	0.24	1.28	0.05	0.00	IALS	0.21	1.24	0.04	0.00
ALL	0.20	1.22	0.05	0.00	ALL	0.20	1.22	0.03	0.00
PIAAC	0.19	1.21	0.04	0.00	PIAAC	0.19	1.21	0.03	0.00

Note: We selected workers who responded that they rarely or never completed job task as base categories. We controlled for gender, nationality, age, and parental education (estimated coefficients excluded from table). Bold parameter estimates indicate statistical significance at $p < 0.05$.

The second research question sought to test whether workers with more education were less likely to be employed full-time in later surveys when compared to IALS (1994). We estimated logistic regression models (using appropriate survey and jackknife replicate weights) to determine whether workers were employed for at least 35 hours per week (see e.g., Mayer, 2014). The years of education variable was not statistically significant in the IALS model. In the ALL (2003) and PIAAC (2012) samples, workers were between 5% and 10% more likely to work at least 35 hours a week for each additional year of education they acquired. Across the three samples, women were significantly less likely to be employed full-time. Detailed results for these models appear in Table 6.

Table 6

Logistic Regression Estimates Predicting Full-Time Employment, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds- Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.06	1.06	0.04	0.16
Female	-1.85	0.16	0.26	0.00
Born in U.S.	-0.1	0.90	0.34	0.77
Age (35 to 44)	0.14	1.15	0.20	0.49
Age (45 to 54)	0.16	1.17	0.33	0.62
Parental Education (Less than High School)	0.21	1.23	0.33	0.52
Parental Education (High School Diploma)	0.31	1.36	0.25	0.23
Constant	2.04	7.69	0.49	0.00
Adult Literacy and Lifeskills Survey (2003)				
Years of Education	0.05	1.05	0.03	0.07
Female	-1.33	0.26	0.18	0.00
Born in U.S.	-0.02	0.98	0.19	0.94
Age (35 to 44)	-0.22	0.80	0.19	0.26
Age (45 to 54)	0.05	1.05	0.21	0.83
Parental Education (Less than High School)	0.26	1.30	0.24	0.27

Parental Education (High School Diploma)	0.26	1.30	0.23	0.25
Constant	1.86	6.42	0.50	0.00

Program for the International Assessment of Adult Competencies (2012)

Years of Education	0.09	1.09	0.03	0.00
Female	-1.1	0.33	0.14	0.00
Born in U.S.	-0.12	0.89	0.19	0.52
Age (35 to 44)	0.03	1.03	0.17	0.85
Age (45 to 54)	-0.04	0.96	0.14	0.79
Parental Education (Less than High School)	0.26	1.30	0.25	0.30
Parental Education (High School Diploma)	0.09	1.09	0.14	0.53
Constant	1.09	2.97	0.46	0.02

Note: Full-time employment defined as 35 hours or more per week. Bold parameter estimates indicate statistical significance at $p < 0.05$.

Our third research question tested the relationship between education and earnings. In this model, we again controlled for gender, nationality, age, and parental education. Years of education had a larger effect on predicting earnings among PIAAC (2012) workers when compared to ALL (2003) workers. This was confirmed by a z-test comparing the coefficients across each survey. Although these estimates are cross-sectional and not causal, our findings suggest that contrary to the argument that education has become less valuable in the labor market, education may actually be more important for earning higher wages. See Table 7.

Table 7

OLS Estimation of Logged Income on Education, 2003 and 2012

	ALL (2003)			PIAAC (2012)		
	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t
Years of Education	0.07	0.01	0.00	0.12	0.01	0.00
Female	-0.50	0.07	0.00	-0.43	0.04	0.00
Born in U.S.	0.03	0.09	0.72	0.03	0.05	0.61
Age (35 to 44)	0.20	0.07	0.00	0.23	0.04	0.00
Age (45 to 54)	0.33	0.08	0.00	0.26	0.04	0.00
Parental Education (Less than High School)	-0.11	0.11	0.32	-0.14	0.06	0.02
Parental Education (High School Diploma)	-0.09	0.07	0.22	-0.05	0.03	0.10

Note: Bold parameter estimates indicate statistical significance at $p < 0.05$.

Finally, our last research question was meant to help us determine whether cognitive skills have statistically significant effects on labor market outcomes, independent of the effects of formal schooling. It was only possible to answer our fourth research question (was years of education or literacy skills a better predictors of labor market outcomes in 2012 than 2003 or 1994?) because the IALS (1994), ALL (2003), and PIAAC (2012) datasets included comparable measures of education and cognitive (literacy) skills. Therefore, we re-estimated our models including measures of literacy skills. Results from the more-fully specified models are presented in the order that they addressed the original research questions. Table 8 reports results from the new model that used literacy scores to test whether respondents were employed. Likewise, Table

9 includes estimates of the effects of literacy skills on whether a worker has supervisory status. We also tested the relationship between literacy skills and six job tasks that were recorded across IALS (1994), ALL (2003), and PIAAC (2012). See Table 10 and Table 11 for our results regarding job tasks.

Please note that in the tables that follow, we multiplied the parameter estimates for *Literacy skills* by 50. Therefore, in the tables that follow, we can interpret parameter estimates (coefficients or odds-ratios) as representing the effect of a 50-point change in literacy scores. It would be difficult to interpret the estimated effects of a one point difference in literacy. However, we found a 50-point difference in literacy to be meaningful because many of the differences in literacy proficiency levels are separated by 50 points.¹⁰ In other words, a 50-point difference in literacy scores separated a PIAAC respondent with Level 1 proficiency from a worker with more advanced (Level 2) proficiency. This can be the difference between the ability to read simple documents for a single piece of information and reading and synthesizing across multiple documents.

The credential inflation argument suggested that there would be a weaker relationship between years of education and employment status for PIAAC (2012) workers when compared to previous cohorts. Instead, we see in Table 8 that workers with more schooling were about as likely to be employed in PIAAC as in IALS (1994), controlling for age, gender, immigrant status, literacy skills, and parental education. Interestingly, after controlling for literacy skills, years of education was not significant for workers who were sampled in ALL (2003). However, literacy skills had a larger effect on employment among ALL (2003) workers when compared to IALS (1994) and PIAAC (2012) workers, which was confirmed by a z-test comparing the coefficients. Results for the three cross-sectional models presented in Table 8 suggest that workers were more likely to be employed if they had higher literacy scores (in 50 point increments). The coefficients suggest that the relationship between literacy and employment was larger than the relationship between employment and one additional year of schooling.

Table 8

<i>Logistic Regression Estimates Predicting Employment, 1994, 2003, and 2012</i>				
	<u>Coef.</u>	<u>Odds-Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.14	1.15	0.04	0.00
Female	-1.36	0.26	0.13	0.00
Born in U.S.	-0.35	0.71	0.18	0.05
Age (35 to 44)	0.21	1.24	0.16	0.19
Age (45 to 54)	-0.02	0.98	0.19	0.91
Parental Education (Less than High School)	0.17	1.19	0.19	0.37
Parental Education (High School Diploma)	0.34	1.40	0.22	0.13
Literacy Skills	0.24	1.27	0.09	0.01
Constant	-0.81	0.44	0.59	0.17
Adult Literacy and Lifeskills Survey (2003)				

¹⁰ For a breakdown of literacy proficiency scores, see <https://nces.ed.gov/surveys/piaac/litproficiencylevel.asp>

Years of Education	0.03	1.03	0.03	0.23
Female	-0.70	0.49	0.13	0.00
Born in U.S.	-0.30	0.74	0.22	0.18
Age (35 to 44)	0.32	1.38	0.13	0.01
Age (45 to 54)	0.43	1.54	0.17	0.01
Parental Education (Less than High School)	-0.20	0.82	0.23	0.39
Parental Education (High School Diploma)	-0.01	0.99	0.18	0.97
Literacy Skills	0.38	1.46	0.08	0.00
Constant	-0.70	0.49	0.46	0.13

Program for the International Assessment of Adult Competencies (2012)

Years of Education	0.13	1.14	0.02	0.00
Female	-0.68	0.50	0.09	0.00
Born in U.S.	-0.37	0.69	0.14	0.01
Age (35 to 44)	0.13	1.14	0.10	0.21
Age (45 to 54)	0.17	1.19	0.11	0.11
Parental Education (Less than High School)	0.05	1.05	0.16	0.75
Parental Education (High School Diploma)	0.16	1.18	0.10	0.11
Literacy Skills	0.16	1.17	0.06	0.02
Constant	-1.08	0.34	0.35	0.00

Note: We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

We were also interested in whether the nature of jobs changed across the three samples. The results in Table 4 suggested that years of education was significantly related to whether workers were supervisors in all three surveys. Additionally, years of education was a stronger predictor of being a supervisor in the early 1990s than in the later surveys, although only significantly stronger than in ALL (2003). Across the three surveys, literacy skills was not a statistically significant predictor of supervisory status at the $p < 0.05$ level. Again, it is worth noting that when we compared results across the three surveys, women became more likely to hold supervisory roles between IALS (1994) and ALL (2003), but the results between IALS (1994) and PIAAC (2012) were comparable. See Table 9.

Table 9

Logistic Regression Estimates Predicting Supervisor Status, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds-Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.16	1.18	0.04	0.00
Female	-0.53	0.59	0.11	0.00
Born in U.S.	0.08	1.08	0.30	0.78
Age (35 to 44)	-0.08	0.92	0.17	0.63
Age (45 to 54)	-0.15	0.86	0.15	0.32
Parental Education (Less than High School)	0.24	1.26	0.23	0.31
Parental Education (High School Diploma)	0.43	1.54	0.14	0.00
Literacy Skills	0.12	1.12	0.10	0.26
Constant	-3.26	0.04	0.56	0.00

Adult Literacy and Lifeskills Survey (2003)

Years of Education	0.04	1.04	0.02	0.07
Female	-0.45	0.64	0.10	0.00
Born in U.S.	0.14	1.15	0.20	0.49
Age (35 to 44)	0.38	1.46	0.16	0.02
Age (45 to 54)	0.49	1.63	0.15	0.00
Parental Education (Less than High School)	-0.28	0.75	0.20	0.16
Parental Education (High School Diploma)	-0.13	0.88	0.13	0.31
Literacy Skills	0.10	1.10	0.08	0.23
Constant	-1.91	0.15	0.43	0.00

Program for the International Assessment of Adult Competencies (2012)

Years of Education	0.09	1.10	0.02	0.00
Female	-0.51	0.60	0.08	0.00
Born in U.S.	-0.19	0.83	0.13	0.13
Age (35 to 44)	0.14	1.15	0.11	0.22
Age (45 to 54)	0.31	1.36	0.11	0.00
Parental Education (Less than High School)	-0.19	0.83	0.20	0.33
Parental Education (High School Diploma)	-0.01	0.99	0.12	0.94
Literacy Skills	0.09	1.09	0.08	0.27
Constant	-2.05	0.13	0.43	0.00

Note: We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

Table 10

Multinomial Logistic Regression Estimates Using Education and Literacy to Predict Job Tasks, 1994, 2003, and 2012

Read Directions or Instructions					Read or use Letters, Memos, and E-mails					Read or Use Reports, Articles, Magazines, Journals				
	Coef.	Odds-Ratio	Std. Err.	P>t		Coef.	Odds-Ratio	Std. Err.	P>t		Coef.	Odds-Ratio	Std. Err.	P>t
<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>				
IALS					IALS					IALS				
Education	0.05	1.05	0.02	0.02	Education	0.28	1.32	0.03	0.00	Education	0.25	1.29	0.04	0.00
Literacy	0.20	1.22	0.09	0.03	Literacy	0.64	1.90	0.09	0.00	Literacy	0.59	1.80	0.09	0.00
ALL					ALL					ALL				
Education	0.13	1.14	0.03	0.00	Education	0.22	1.25	0.03	0.00	Education	0.22	1.25	0.03	0.00
Literacy	0.14	1.15	0.13	0.30	Literacy	0.54	1.72	0.12	0.00	Literacy	0.34	1.41	0.10	0.00
PIAAC					PIAAC					PIAAC				
Education	0.09	1.09	0.04	0.02	Education	0.31	1.37	0.04	0.00	Education	0.30	1.36	0.03	0.00
Literacy	0.06	1.07	0.10	0.53	Literacy	0.61	1.84	0.10	0.00	Literacy	0.26	1.30	0.08	0.00
<i>Less than Once Per Week</i>					<i>Less than Once Per Week</i>					<i>Less than Once Per Week</i>				
IALS					IALS					IALS				
Education	0.08	1.08	0.04	0.08	Education	-0.03	0.97	0.07	0.72	Education	0.17	1.18	0.05	0.00
Literacy	0.39	1.48	0.20	0.05	Literacy	0.59	1.81	0.20	0.00	Literacy	0.47	1.60	0.15	0.00
ALL					ALL					ALL				
Education	0.11	1.12	0.03	0.00	Education	0.08	1.08	0.06	0.17	Education	0.16	1.18	0.05	0.00
Literacy	0.34	1.40	0.17	0.04	Literacy	0.31	1.37	0.28	0.26	Literacy	0.29	1.33	0.16	0.07
PIAAC					PIAAC					PIAAC				
Education	0.05	1.05	0.05	0.32	Education	0.04	1.04	0.05	0.44	Education	0.13	1.14	0.04	0.01
Literacy	0.39	1.47	0.14	0.01	Literacy	0.67	1.94	0.16	0.00	Literacy	0.40	1.49	0.11	0.00

Note: We selected workers who responded that they rarely or never completed job task as base categories. We controlled for gender, nationality, age, and parental education (parameter estimates excluded from table). We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

Table 11

Multinomial Logistic Regression Estimates Using Education and Literacy to Predict Job Tasks, 1994, 2003, and 2012

Read or Use Manuals, Reference Books, Catalogues					Read or Use Bills, Invoices, Spreadsheets, Budget Tables					Read or Use Diagrams or Schematics				
	Coef.	Odds- Ratio	Std. Err.	P>t		Coef.	Odds- Ratio	Std. Err.	P>t		Coef.	Std. Err.		P>t
<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>					<i>At Least Once Per Week</i>				
IALS					IALS					IALS				
Education	0.17	1.19	0.03	0.00	Education	0.07	1.08	0.03	0.01	Education	0.15	1.16	0.04	0.00
Literacy	0.77	2.16	0.10	0.00	Literacy	0.37	1.45	0.09	0.00	Literacy	0.30	1.36	0.10	0.00
ALL					ALL					ALL				
Education	0.22	1.24	0.03	0.00	Education	0.08	1.08	0.03	0.01	Education	0.13	1.14	0.03	0.00
Literacy	0.26	1.29	0.09	0.01	Literacy	0.12	1.13	0.10	0.22	Literacy	0.19	1.21	0.10	0.04
PIAAC					PIAAC					PIAAC				
Education	0.11	1.12	0.03	0.00	Education	0.04	1.04	0.02	0.09	Education	0.07	1.07	0.03	0.02
Literacy	0.04	1.04	0.09	0.62	Literacy	0.25	1.28	0.08	0.00	Literacy	0.21	1.23	0.07	0.01
<i>Less than Once Per Week</i>					<i>Less than Once Per Week</i>					<i>Less than Once Per Week</i>				
IALS					IALS					IALS				
Education	0.06	1.06	0.05	0.27	Education	0.11	1.12	0.05	0.02	Education	0.19	1.21	0.05	0.00
Literacy	0.76	2.14	0.24	0.00	Literacy	0.53	1.71	0.16	0.00	Literacy	0.15	1.16	0.11	0.20
ALL					ALL					ALL				
Education	0.14	1.15	0.03	0.00	Education	0.10	1.11	0.05	0.03	Education	0.16	1.18	0.03	0.00
Literacy	0.44	1.56	0.14	0.00	Literacy	0.42	1.53	0.14	0.00	Literacy	0.27	1.31	0.10	0.01
PIAAC					PIAAC					PIAAC				
Education	0.11	1.12	0.03	0.00	Education	0.11	1.12	0.04	0.01	Education	0.12	1.13	0.04	0.00
Literacy	0.20	1.23	0.11	0.06	Literacy	0.35	1.41	0.13	0.01	Literacy	0.49	1.63	0.13	0.00

Note: We selected workers who responded that they rarely or never completed job task as base categories. We controlled for gender, nationality, age, and parental education (parameter estimates excluded from table). We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

We also tested for effects of education and cognitive skills on job tasks (see Tables 10 and 11 above). Clearly both education and cognitive skills were related to the types of tasks people were asked to complete on the job, across all three surveys. In many categories, literacy skills were larger predictors of the nature of peoples' work.

We then re-visited the second research question (testing underemployment, or conversely full-time employment), and added measures of respondents' literacy skills to our previously specified models. As with supervisory status, literacy did not help predict full-time employment. Interestingly, years of education was not statistically significant in IALS (1994) or ALL (2003), but education was statistically significant in PIAAC (2012); however the changes across time were not significant when using a z-test. Results from the new model were included in Table 10.

Table 12

Logistic Regression Estimates Predicting Full-Time Employment, 1994, 2003, and 2012

	<u>Coef.</u>	<u>Odds-Ratio</u>	<u>Std. Err.</u>	<u>P>t</u>
International Adult Literacy Survey (1994)				
Years of Education	0.07	1.07	0.05	0.16
Female	-1.85	0.16	0.26	0.00
Born in U.S.	-0.07	0.93	0.36	0.84
Age (35 to 44)	0.14	1.15	0.20	0.49
Age (45 to 54)	0.16	1.17	0.33	0.63
Parental Education (Less than High School)	0.19	1.21	0.34	0.57
Parental Education (High School Diploma)	0.31	1.36	0.25	0.23
Literacy Skills	-0.04	0.96	0.12	0.76
Constant	2.14	0.12	0.58	0.00
Adult Literacy and Lifeskills Survey (2003)				
Years of Education	0.04	1.04	0.03	0.20
Female	-1.33	0.26	0.18	0.00
Born in U.S.	-0.06	0.94	0.21	0.78
Age (35 to 44)	-0.21	0.81	0.19	0.27
Age (45 to 54)	0.05	1.05	0.22	0.82
Parental Education (Less than High School)	0.3	1.35	0.23	0.19
Parental Education (High School Diploma)	0.27	1.31	0.22	0.22
Literacy Skills	0.06	1.06	0.13	0.61
Constant	1.63	0.20	0.62	0.01
Program for the International Assessment of Adult Competencies (2012)				
Years of Education	0.08	1.08	0.08	0.01
Female	-1.09	0.34	-1.09	0.00
Born in U.S.	-0.15	0.86	-0.15	0.45
Age (35 to 44)	0.03	1.03	0.03	0.86
Age (45 to 54)	-0.04	0.96	-0.04	0.80
Parental Education (Less than High School)	0.29	1.34	0.25	0.25
Parental Education (High School Diploma)	0.1	1.11	0.13	0.47
Literacy Skills	0.06	1.05	0.10	0.56

Constant	0.92	2.51	0.52	0.08
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Note: Full-time employment defined as 35 hours or more per week. We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

Finally, we used literacy and ICT skills to estimate workers' earnings. Among ALL (2003) and PIAAC (2012) workers, literacy skills were better predictors of earnings than were years of education (though both were significant and had independent effects). Older workers tended to earn more, which is consistent with previous studies that we cited in the literature review. We also estimated a new model using PIAAC's measure of ICT skills to perform a rudimentary test of the "digital Taylorism" argument that employers try to lower wages by increasingly ask workers to use technology (Brown, Lauder, & Ashton, 2011). The results in Table 14 suggest that instead of using technology to pay workers less, employees with higher ICT skill levels are more likely to work in jobs with higher earnings. Results from the final models were organized in Table 13 and Table 14.

Table 13

OLS Estimation of Logged Income on Education and Literacy, 2003 and 2012

	ALL (2003)			PIAAC (2012)		
	<u>Coef.</u>	<u>Std. Err.</u>	<u>P>t</u>	<u>Coef.</u>	<u>Std. Err.</u>	<u>P>t</u>
Years of Education	0.06	0.01	0.00	0.10	0.01	0.00
Female	-0.50	0.07	0.00	-0.42	0.04	0.00
Born in U.S.	-0.06	0.09	0.55	-0.05	0.06	0.44
Age (35 to 44)	0.20	0.06	0.00	0.22	0.04	0.00
Age (45 to 54)	0.34	0.08	0.00	0.26	0.04	0.00
Parental Education (Less than High School)	-0.03	0.10	0.73	-0.07	0.06	0.28
Parental Education (High School Diploma)	-0.07	0.07	0.32	-0.03	0.03	0.43
Literacy Skills	0.13	0.03	0.00	0.13	0.03	0.00

Note: We multiplied the parameter estimates for Literacy Skills by 50 for interpretation. Bold parameter estimates indicate statistical significance at $p < 0.05$.

Table 14

OLS Estimation of Logged Income on Education, Literacy, and ICT Skills, 2012 (PIAAC)

	<u>Coef.</u>	<u>Std.</u>	<u>P>t</u>
		<u>Err.</u>	
Years of Education	0.05	0.01	0.00
Female	-0.33	0.04	0.00
Born in U.S.	0.02	0.08	0.78
Age (35 to 44)	0.24	0.05	0.00
Age (45 to 54)	0.25	0.04	0.00
Parental Education (Less than High School)	-0.05	0.10	0.64
Parental Education (High School Diploma)	-0.01	0.04	0.73
Literacy Skills	-0.02	0.06	0.79
Professionals	-0.21	0.07	0.00

Technicians And Associate Professionals	-0.38	0.08	0.00
Clerks	-0.52	0.08	0.00
Service Workers & Shop & Market Sales Workers	-0.09	0.19	0.64
Skilled Agricultural & Fishery Workers	-0.26	0.10	0.01
Craft Etc Trades Workers	0.01	0.09	0.90
Plant & Machine Operators & Assemblers	-0.61	0.12	0.00
Elementary Occupations	0.00	0.00	0.08
Information Communication Technology (ICT) Skills	0.14	0.02	0.00

Note: Bold parameter estimates indicate statistical significance at $p < 0.05$. We also tested an interaction term between Years of Education and Information Communication Technology (ICT) Skills, but the interaction was not significant. Results on file with authors.

Discussion

We began by laying out two competing theories. One theoretical camp (what we called the credential inflation argument) suggested that as more people went to college, the value of education declined. If this were true, we would have expected to find that between 1994 and 2012 education was less likely to be positively related to employment and earnings. The second theoretical tradition (what we call educational transformation) suggested that the education system and labor market were synergetic (Baker, 2012). According to the latter argument, when the average level of education increased, the relationship between education, employment and earnings should have not have declined—and perhaps would have gotten stronger. Additionally, as workers became more highly educated, we should see evidence that employers changed the frequency or complexity of job tasks.

Summarizing Results for Research Questions

Our first research question asked whether there was any relationship between years of education and employment status and type of employment (supervisory duties and job tasks) over time. We found that for each additional year of education, workers were 20% more likely to be employed in 1994 and 17% more likely to be employed in 2012. After we added literacy skills to the model, we found that IALS (1994) and PIAAC (2012) workers with one more year of education were 15% and 14% more likely to be employed, respectively. When we tested whether workers were likely to hold supervisor roles, we found that for each additional year of education, the likelihood of being a supervisor was higher in 1994 than in 2012. Literacy skills were not significantly related to whether workers supervised fellow employees.

We then focused on testing relationships between education, literacy skills, and job tasks. Our results demonstrated that (a) workers with higher levels of education were more likely to complete complex job tasks; (b) workers with similar levels of education were more likely to complete these job tasks “less than once per week” in 2012, compared to 2003 and 1994 (see Figure 1). When we used multinomial logistic estimation with education and cognitive skills, we found that in many cases literacy had a stronger relation to job tasks than years of education. In most cases, both education and literacy work have direct, independent effects as predictors of worker’s job duties. For some job tasks (such as Read Directions or Instructions; Read or use Letters, Memos, and E-mails; Read or Use Reports, Articles, Magazines, Journals), education seemed to have a stronger relationship in 2012 when compared to 1994. This suggests that as

Americans have become more educated, employers have changed job tasks to incorporate education and skills in the workplace. These findings fit with the “schooled society” or “educational transformation” argument we introduced earlier in this report (see also, Baker, 2014).

Next, we examined whether the likelihood of working full-time, or at least 35 hours, among respondents in our sample. Years of education was only significant in PIAAC (2012), indicating that each year of education increased the likelihood of being fully employed by 9%, which was a slightly larger effect compared to IALS (1994) and ALL (2003). This effect was consistent even after controlling for literacy. While PIAAC had the only significant coefficient for years of education, z-tests for changes across time were not significant. Literacy was not a significant predictor of full-time employment in any of the models.

Finally, we used ordinary least squares estimation to determine the extent to which education and skills were related to earnings in 2003 and 2012. Before we considered literacy, our OLS models indicated that education had larger effects on predicted earnings among PIAAC (2012) workers when compared to ALL (2003) workers. A z-test confirmed that the differences in regression estimates among the surveys were statistically significant. We added literacy scores to our earnings models and found that the effects of cognitive skills on earnings were similar in 2003 and 2012. Yet, the one additional year of schooling was related to a 40% larger increase in earnings in 2012 when compared to 2003. Additionally, we tested the “digital Taylorism” argument to see whether employers are hiring more educated workers and requiring them to use technology in the workplace to lower wages. We found that both years of education and ICT skills were positively related to earnings.

The Effects of Social Backgrounds

Across the three surveys, women were less likely to be employed than men, but in ALL (2003) and PIAAC (2012) women were more likely to be employed than in IALS (1994). In other words, while women with similar education and skills were still less likely to be employed than men in all three surveys, similarly skilled women were more likely to be employed in recent years. Looking back to IALS data from 1994, we found that women were even less likely to be employed when we added measures of literacy skills than when we tested only for education effects. Additionally, in our logistic estimation models, women were less likely to be supervisors than men in all three surveys. Lastly, policymakers should be concerned that in our OLS models, women tended to earn less in 2003 and 2012 than their male counterparts (although the estimated coefficients were less negatively related to earnings in 2012 than in 2003).

In many of our models, the estimated effects of parental education and immigrant status (being born in the U.S.) were not statistically significant. Consistent with the literature, older workers tended to have higher earnings. In some instances older workers were also more likely to be supervisors. Again, this was expected based on our review of the literature and the reality that older workers were more likely to have higher levels of work experience or seniority in their jobs or careers.

Limitations

We acknowledge several limitations to our work. First, we did not use analytic methods that supported causal inferences. Thus, we remind readers that our findings represent snapshots over the past three decades. However, we used appropriate sampling weights and plausible values to ensure that each cross-sectional model yielded unbiased estimates. We also took the additional step of calculating z-tests to determine when differences in parameter estimates across survey waves were statistically significant.

Second, we recognize that our measure of full-time employment was limited because we did not consider workers' intentions or desire to attain a full-time job. Therefore, we used several other measures of successful employment (holding any job, holding a supervisor job, and earnings) to test the effects of education and cognitive skills on workers' success in the labor market. Many of our subsequent analysis only looked at fully-employed workers. However, even though our measure of full-time work may be limited, our general findings about the relationship between education and work remained consistent across models.

Third, readers may question whether our PIAAC (2012) analysis was valid because the survey data were collected in the wake of the Great Recession. However, according to the National Bureau of Economic Research, the recession ended in June 2009.¹¹ We also compiled several economic indicators for each survey year (on file with authors), and we did not conclude that the economic climate was substantially worse in 2012 than in 2003 or 1994. We also limited our sample to exclude the youngest workers who would have been most likely to have difficulty finding work after graduating from high school or college.

Conclusion

We found little evidence to support the argument that education would have smaller effects on earnings as access to higher education increased in recent years. We also did not find evidence of “digital Taylorism” (Brown, Lauder, & Ashton, 2011). On the contrary, after controlling for occupational classifications, both education and use of information communication technologies at work were positively related to higher earnings. Many of our models support the conclusions that education has strong effects on labor market outcomes. Rather than fretting that college graduates may have more difficulty finding good jobs, policymakers (and journalists) should focus on the positive effects of additional schooling and work to increase access to higher education.

Furthermore, our findings suggest that future research on the effects of education on labor market outcomes must include measures of education *and* measures of cognitive skills in order to achieve unbiased results. Adding literacy skills moderated the estimated coefficients for years of education across several models and across various years of data. In this study, we chose to use years of education, but scholars and policymakers may also be interested in the relationships between earning degrees or credentials and labor market outcomes (we calculated but did not report these results in this paper). This study underscores the need for PIAAC-type datasets that include multiple measures of education, cognitive skills, and job characteristics.

¹¹ See the following link for more information: <http://cnmmon.ie/1XBcE8Q>

We encourage policymakers to continue to expand access to higher education. Although we discussed years of education and cognitive skills separately, we did not mean to suggest that they are not related. On the contrary, evidence shows that even modest amounts of schooling lead to the development of greater cognitive skills (see e.g., Baker et al, 2015). We encourage policymakers and practitioners to seek ways to incorporate cognitive skill development in formal and informal education. We call special attention to community colleges and open-access higher education institutions as places where students might develop cognitive skills and gain an additional year of education without needing to enroll in a multi-year and costly degree-granting program.

References

- Abel, J. R., Deitz, R., & Yaqin, Su. (2014). Are recent college graduates finding good jobs? *Federal Reserve Bank of New York Current Issues in Economics and Finance*, 20(1), 1-8. Retrieved from https://www.newyorkfed.org/medialibrary/media/research/current_issues/ci20-1.pdf
- Allison, P. D. (2002). *Missing data: Quantitative applications in the social sciences* #136. Thousand Oaks, CA: Sage.
- Aydemir, A., & Sweetman, A. (2006). *First and second generation immigrant educational attainment and labor market outcomes: A comparison of the United States and Canada* (Discussion Papers, No. 2298). Retrieved from Institute for the Study of Labor (IZA) website: <http://www.econstor.eu/handle/10419/34204>
- Baker, D. P. (2009). The educational transformation of work: towards a new synthesis. *Journal of Education and Work*, 22(3), 163-191.
- Baker, D. P. (2011). Forward and backward, horizontal and vertical: Transformation of occupational credentialing in the schooled society. *Research in Social Stratification and Mobility*, 29(1), 5-29.
- Baker, D. P. (2014). *The Schooled Society: The Educational Transformation of Global Culture*. Stanford, CA: Stanford University Press.
- Baker, D. P., Eslinger, P. J., Benavides, M., Peters, E., Dieckmann, N. F., & Leon, J. (2015). The cognitive impact of the education revolution: A possible cause of the Flynn Effect on population IQ. *Intelligence*, 49, 144-158.
- Banerjee, R., & Lee, B. Y. (2015). Decreasing the Recent Immigrant Earnings Gap: The Impact of Canadian Credential Attainment. *International Migration*, 53(2), 205-218.
- Baum, C. F. (2001). Residual diagnostics for cross-section time series regression models. *The Stata Journal*, 1(1), 101-104.
- Beck, N., Katz, J. N., & Tucker, R. (1998). Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. *American Journal of Political Science*, 1260-1288.
- Becker, G. S. (1964). *Human capital: A theoretical analysis with special reference to education*. New York, NY: Columbia University Press.
- Berg, I. E. (1970). *Education and Jobs: The Great Training Robbery*. Boston: Beacon Press.
- Bowles, S. (1972). Schooling and inequality from generation to generation. *The Journal of Political Economy*, 80(3, part 2), S219-S251.
- Bowles, S., & Gintis, H. (1976). *Schooling in capitalist America: Educational reform and the contradictions of economic life*. New York: Basic Books.
- Bowles, S., & Gintis, H. (2000). *The inheritance of economic status: Education, class, and genetics* (Santa Fe Institute Working Paper 2001-01-005). Retrieved from <http://www.santafe.edu/media/workingpapers/01-01-005.pdf>
- Bowles, S., & Gintis, H. (2002). Schooling in capitalist America revisited. *Sociology of Education*, 75(1), 1-18.
- Boylan, R. D. (1993). The effect of the number of diplomas on their value. *Sociology of Education*, 66(3), 206-221.
- Brown, P., Lauder, H., & Ashton, D. (2011). *The global auction: The broken promises of education, jobs, and income*. New York: Oxford University Press.
- Carnevale, A. P., Rose, S. J., & Cheah, B. (2011 August). *The college payoff: Education,*

- occupations, lifetime earnings*. Washington, DC: Georgetown University Center on Education and the Workforce.
- Cawley, J., Heckman, J., & Vytalil, E. (2001). Three observations on wages and measured cognitive ability. *Labour Economics*, 8(4), 419-442.
- Dore, R. (1976). *The diploma disease: Education, qualification, and development*. Berkeley, CA: University of California Press.
- Gintis, H. (1971). Education, technology, and the characteristics of worker productivity. *The American Economic Review*, 61(2) 266-279.
- Goldin, C., & Katz, L. (1998). The origins of technology-skill complementarity. *Quarterly Journal of Economics*, 113(3), 693-732.
- Julian, T., & Kominski, R. (2011, September). *Education and synthetic work-life earnings estimates* (American Community Survey Reports, ACS-14). Washington, DC: U.S. Census Bureau.
- Labaree, D. F. (2010). *Someone has to fail: The zero-sum game of public schooling*. Cambridge, MA: Harvard University Press.
- Lacey, T. A., & Wright, B. (2009). Employment outlook: 2008-18 occupational employment projections to 2018. *Monthly Labor Review*, 132(11), 82-123.
- Lambert, L. (2014, October 17). Underemployment hits recent graduates the hardest. *The Chronicle of Higher Education*. Retrieved from <http://chronicle.com/blogs/data/2014/10/17/underemployment/>
- Long, M. C. (2010). Changes in the returns to education and college quality. *Economics of Education Review*, 29(3), 338-347.
- Mayer, G. (2014 November). The increased supply of underutilized labor from 2006 to 2014. *Monthly Labor Review*. Retrieved from: <http://www.bls.gov/opub/mlr/2014/article/the-increased-supply-of-underutilized-labor-from-2006-to-2014.htm>
- Meyer, J. W. (1977). The effects of education as an institution. *American Journal of Sociology*, 83(1), 55-77.
- Papademetriou, D. G., & Sumption, M. (2011). *Rethinking Points Systems and Employer-Selected Immigration*. Washington, DC: Migration Policy Institute.
- Pappano, L. (2011, July 22). The master's as the new bachelor's. *The New York Times*, p. ED16. Retrieved from http://www.nytimes.com/2011/07/24/education/edlife/edl-24masters-t.html?_r=0
- Piketty, T. (2014). *Capital in the twenty-first century*. Harvard University Press.
- Porter, E. (2014, March 11). Q&A: Thomas Piketty on the Wealth Divide. *New York Times*. Retrieved from http://economix.blogs.nytimes.com/2014/03/11/qa-thomas-piketty-on-the-wealth-divide/?_php=true&_type=blogs&_r=0
- Rampell, C. (2013, February 19). It takes a B.A. to find a job as a file clerk. *The New York Times*, p. A1. Retrieved from <http://www.nytimes.com/2013/02/20/business/college-degree-required-by-increasing-number-of-companies.html?smid=pl-share>
- Sherter, A. (2014, June 5). Economist says U.S. inequality reaching "spectacular" heights. *CBS Moneywatch*. Retrieved from <http://www.cbsnews.com/news/economist-says-u-s-inequality-reaching-spectacular-heights/>
- Sommers, D., & Morisi, T. L. (2012). Employment projections through the lens of education and training. *Monthly Labor Review*, 135(4), 13-28.
- Spencer, K. (1983). Deciphering Prometheus: Temporal change in the skill level of work. *American Sociological Review*, 48(6), 824-837.

- Sum, A., & Khatiwada, I. (2010). The nation's underemployed in the "Great Recession" of 2007-2009. *Monthly Labor Review*, 133(11) 3-15.
- Tabachnick, B. G., & Fidell, L. S. (1996). *Using multivariate statistics* (3rd Edition). New York: Harper Collins.
- Teichler, U. (1999). Research on the relationships between higher education and the world of work: Past achievements, problems and new challenges. *Higher Education*, 38(2), 169-190.
- Thomas, S. L., & Zhang, L. (2005). Post-baccalaureate wage growth within four years of graduation: The effects of college quality and college major. *Research in Higher Education*, 46(4), 437-459.
- Zhang, L. (2008). Gender and racial gaps in earnings among recent college graduates. *The Review of Higher Education*, 32(1), 51-72.

Appendix A

Three Sources of Data Used in the Study

<u>Survey</u>	<u>Source</u>	<u>Year</u>	<u>N</u>
Program for the International Assessment of Adult Competencies (PIAAC)	NCES	2012	5,010
International Adult Literacy survey (ALL)	NCES	2003	3,420
International Adult Literacy Survey (IALS)	Statistics Canada	1994	3,045

Note: Although IALS did not measure participants' numeracy skills, all three surveys included comparable measures of literacy skills. We used literacy skills as a measure of cognitive abilities.

Appendix B*List of Variables Used in the Study*

Variable	IALS (1994)	ALL (2003)	PIAAC (2012)
Years of Education	a7	a3_dv	yrsqual_t
Female	gender	gender	a_n01_t
Born in US	a1	a1	j_q04a_t
Age	age	age_resp_dv	ageg10lfs_t
Parental Education	c5 and c11	c2 and c6	j_q06b_t and j_q07b_t
Literacy Skills	pvlit*	pvlit*	pvlit*
Occupation	iscor	iscor_2	isco08_c
ICT Skills at Work	N/A	N/A	ictwork
Employment Status	d1	d1	c_q07_t
Income	N/A	earnjob2	earnmthallus
Supervisor Status	d11	d29	d_q04_t
Number of Hours Worked	d13	d37	d_q10_t
Read or Use Directions or Instructions	e1g	e1g	g_q01a_t
Read or Use Letters, Memos, and E-mails	e1a	e1a	g_q01b_t
Read or Use Reports, Articles, Magazines, Journals	e1b	e1b	g_q01c_t
Read or Use Manuals, References Books, Catalogues	e1c	e1c	g_q01f_t
Read or Use Bills, Invoices, Spreadsheets, Budget Tables	e1e	e1e	g_q01g_t
Read or Use Diagrams or Schematics	e1d	e1d	g_q01h_t