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Trends in Educational and Skill Mismatch in the United States

Dong-Hoon Shin [1,*] and David Bills [2]

[1] National Youth Policy Institute, Sejong-si 30147, Korea
[2] Department of Educational Policy and Leadership Studies, University of Iowa, Iowa City, IA 52242, USA
* Correspondence: dhshin@nypi.re.kr

Abstract: We examined trends in the incidence and correlates of educational and skill mismatch in the United States. We focused on trends over time in the associations between various types of mismatch and a range of factors including contextual conditions. We explored whether contextual conditions at the transitional period from school to jobs increase or decrease the probability of mismatch and whether such relationships persist throughout the working career. Our central questions were how the incidence of and relationship between educational and skill mismatch in the U.S. changed between 1994, 2003, and 2012 and how this differed by age, gender, immigration status, educational attainment, and occupation. We used three cross-sectional surveys that had not previously been implemented for such an effort. These were the International Adult Literacy Survey (IALS) in 1994, the Adult Literacy and Life-skills (ALL) survey in 2003, and the Program for the International Assessment of Adult Competencies (PIAAC) in 2012. Repeated cross-sectional data provided us with substantial analytic leverage. Our findings point toward the key role of occupational or positional factors rather than individual worker characteristics as being most implicated in trends in mismatch. We describe the importance of our results for labor market theories.

Keywords: skill mismatch; educational mismatch; trends; labor markets; school-to-work

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Citation: Shin, Dong-Hoon, and David Bills. 2021. Trends in Educational and Skill Mismatch in the United States. *Social Sciences* 10: 395. https://doi.org/10.3390/socsci10100395

Academic Editor: Queralt Capsada-Munsech

Received: 28 June 2021
Accepted: 10 October 2021
Published: 15 October 2021

1. Introduction

The transition from school to work is an inflection point that sets the career into motion. Higher levels of education is expected to have a direct or indirect impact on rewards for having good jobs. There are various views on how education is linked to jobs. Some scholars pay attention to the impact of education on people's cognitive and affective growth that subsequently helps them to find higher paying jobs (i.e., human capital theory), while other scholars argue that the symbolic aspect of education has an important impact on the acquisition of jobs (e.g., signaling theory, screening theory, and credentialism). In an ideal labor market, regardless of the underlying theories, jobs acquired during the transitional period would be tightly connected to previous schooling. More realistically, a career may not begin with a job that matches a person's interests, capabilities, or academic backgrounds.

It is often observed that the level of education and/or skill of workers is too high or too low for them to do their job. Although research about mismatch differs across disciplines, most scholars agree on the undesirable circumstances of this mismatch. The gap between the required and actual capability of workers is closely linked to social and economic costs at both the micro and macro levels (Brunello and Wruuck 2021). Typically, individuals with skill surplus suffer from their inability to convert skills into occupational advantages. They earn less and experience persistent career losses compared to well-matched workers with similar levels of skills (Quintini 2011a; Liu et al. 2016). Labor productivity and economic growth are also negatively affected when there are many workers with skill shortage at macro levels such as firms and the labor market (McGowan and Andrews 2015; McGuinness et al. 2017). Furthermore, the tension between roles in the family and occupation, as an influencing factor of mismatch, is linked to inequality by individual backgrounds (e.g., Kler 2006; Luksyte and Spitzmueller 2011).

There are various reasons for this mismatch. Searching for a job does not always permit job seekers to reveal their ability. An individual may have imperfect information about the heterogeneity in jobs (Sattinger 2012). Geographically, some may have a limited range of choices (Kalleberg 2007). The preconceived notions of an employer about job seekers' backgrounds may affect the chances of employment (Støren and Wiers-Jenssen 2010). Occupational characteristics may play a significant role in job assignment. Workers employed in some occupations may need to compile experience with entry level tasks until obtaining positions fully utilizing their skills (Robst 1995; Sicherman 1991). Other companies may solely rely on observable credentials with less consideration of heterogeneity in candidates due to their lack of resources (Sattinger 2012).

Several contextual factors further differentiate the probability that job seekers find the "right" position. Economic conditions can create an imbalance between supply and demand in the labor market (European Centre for the Development of Vocational Training (CEDEFOP) 2010; Rumberger 1981). When people with certain skill or educational levels are abundant, this may decrease the likelihood of finding a job for which they have the appropriate skill or educational levels (Freeman 1976; Vaisey 2006).

These contextual conditions may interact with characteristics of both job seekers and employers during job search. The association between the supply and demand for education and skills may change depending on the age of workers, supply of skills in the labor market (typically through educational expansion), and demands of technology, work, and employers (typically increasing). Thus, the incidence of mismatched workers will likely change over time; likewise, understanding what drives changes will provide information about how the relationships between schooling, skills, and jobs change over time.

The results that are derived from various types of mismatch, typically educational and skill mismatch, may inform different aspects of how workers are assigned to their jobs. The literature has often treated education and skills as if they were interchangeable, but they are not the same. Furthermore, the relationship between educational mismatch and skill mismatch is not necessarily strong (Allen and van der Velden 2001; Green and McIntosh 2007). Job seekers may not find occupations that match their credentials if assignment in the labor market is based on factors other than educational attainments. Credentials by themselves do not ensure one's employment because employers also consider non-cognitive skills such as personality and experience (Bills 1988b; Bowles et al. 2001). In this case, skill mismatch may not correspond to educational mismatch. By examining the relation between educational and skill mismatches, Quintini (2011b) observed "only a weak link between qualification and skill mismatch suggesting that qualification mismatch may be due primarily to skill heterogeneity within qualification groups" (p. 5).

At the same time, the relationship between educational and skill mismatch is coupled with how the labor market functions. Although the relationship between two concepts is often ambiguous, it may provide an abstract idea of how the labor market functions. A close relationship, for example, might indicate that educational attainments provide clear signaling about the skill levels preferred by employers, while a minimal relationship could imply that the skills of workers with the same educational credentials are heterogeneous in that some workers with educational mismatch in fact have well-matched skills for their occupations (Green and McIntosh 2007). Ultimately, trends in the relationship between educational and skill mismatch could help us understand how credentials are perceived by the labor market over time.

In the literature of educational and skill mismatch, many studies have been conducted to understand the incidence, determinants, and impacts of mismatch in the labor market (e.g., Allen et al. 2013; Brunello and Wruuck 2021; Desjardins and Rubenson 2011; Luksyte and Spitzmueller 2011; Mavromaras et al. 2009; Quintini 2011a; Støren and Wiers-Jenssen 2010). However, only a little attention has been paid to better understanding how the number of workers with skill and educational mismatch has changed and how educational expansion and transformations in the labor market have contributed to such change (e.g., Groot and van den Brink 2000; Vaisey 2006). While the literature about the trends in educational and skill mismatch has provided a valuable insight, studies have mostly focused on results of overqualification and their concept of mismatch has been close to educational mismatch alone. The lack of data that include information about workers' jobs and skills may contribute to such gaps in the literature (Handel 2005; Verhaest and Omey 2006). Thus, in order to examine trends in educational and skill mismatch in the United States, the authors of this study used three datasets that have not previously been implemented for such an effort. Repeated cross-sectional data provided substantial information to examine the links between education, skills, and jobs by allowing for comparisons between time points.

This paper is structured as follows. We first review the pertinent literature with the intention of deriving some hypotheses about trends in educational and skill mismatch over an 18 year period. We then describe our data and analytic strategy. Finally, we present our results and close with conclusions about trends in mismatch.

2. Literature Review

The alignment between the education and skills held by job seekers and workers with those demanded by the workplace has long been of interest to labor market analysts. By varying accounts, workers can have too much, too little, or just the right amount of schooling or skill to perform their jobs. However, the literature has not offered a consistent or compelling theoretical account of the mechanisms that produce educational or skill mismatch, let alone those that lead to changes in mismatch (Sala 2011). Mismatch has the potential to occur in multiple contexts and dimensions, and it can be burdensome to precisely classify mechanisms into several categories. Nonetheless, distinguishing the mechanisms provides a background for understanding the concept of mismatch and predicting the incidence of mismatch in society. We offer three categories of potential causal mechanisms that could produce mismatch at two time points. These roughly correspond to individual, occupational, and contextual effects during hiring and post-hiring processes (see Figure 1 for this framework).

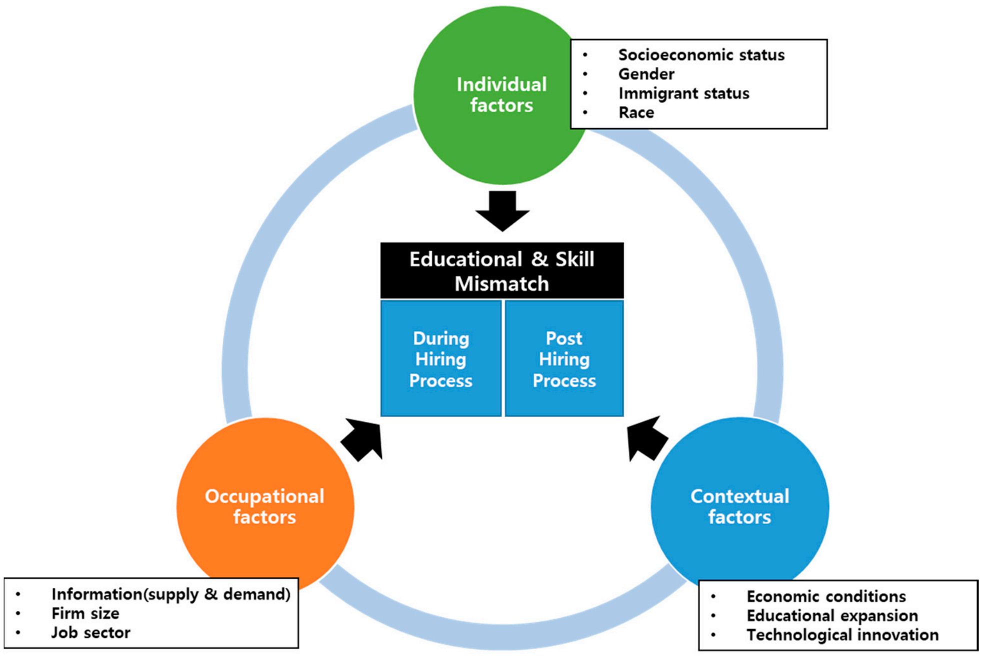

Figure 1. The mechanisms of producing educational and skill mismatch.

Studies regarding mismatch seem to implicitly favor one category over another for individual, occupation, or contextual effects. Handel (2003) observed that some studies may misinterpret an age effect as a cohort effect as a driver of mismatch. Furthermore, those effects often interact each other, making it difficult to empirically demonstrate the main effect. We were less interested here in how these effects can be modeled and estimated; rather, we were interested in the conceptual insights that might be gained by the individual–occupational–contextual perspective at two time points.

2.1. During Hiring Process

Individual factors: Mismatch arises at the time of the transition between schools to work—at the time of the search and hiring process (Brunello and Wruuck 2021; Sattinger 2012). Family responsibilities may reduce the likelihood of finding a job that fully utilizes a job seeker's skills in a limited geographic area. People may voluntarily avoid jobs that prevent them from balancing work and life. Some people might not be able to afford the costs incurred in the job search due to a lack of resources. Meanwhile, the types and forms of jobs are so diverse that it is likely that applicants will have difficulty finding suitable positions for themselves. Structurally, this may then generate a certain amount of mismatch even if equal opportunities are given for job seekers.

Demographic characteristics may also serve as discriminatory factors. Immigrants' academic backgrounds have lower transferability in host countries, leading them to be overeducated (Chiswick and Miller 2009). There are unequal opportunities in the employment process by gender and race (e.g., Levanon and Grusky 2016; Pager and Shepherd 2008). For example, finding a well-matched job can be challenging for women, as they are often expected to manage a family. Employers frequently exhibit different perceptions for the capabilities of men and women, which ultimately impact job assignments. In the investigation of employers' hiring criteria, Bills (1988a) discovered that the capabilities demanded for male and female job seekers were different. Employers tended to consider personality to be more important for women than schooling, in contrast to men (Bills 1988a). In such conditions, women are more likely to be mismatched to their jobs.

Occupational factors: Educational and skill mismatch are also generated by occupational factors. As with job seekers, employers must make employment decisions with limited observable information. Educational attainment is the most visible sign of applicants' ability, and various forms of mismatch can occur depending on how employers utilize this information in hiring decisions. Suppose, for example, that a job applicant's educational attainment does not match their skill level. If an employer decides to hire solely based on credentials, workers will be well-matched under the criteria of educational mismatch but the level of skill will not match. Similarly, when selection focuses on skill level, workers' skill might be appropriate for their jobs but educational mismatch may appear.

Well-matched selection may be related to occupational characteristics. The firm size or job sector is linked to hiring the job seekers that the company needs. By analyzing cross-national data, Quintini (2011b) revealed that workers in smaller companies were more similarly matched than those in larger companies. Potentially, smaller companies can specify workers' skills they need and concentrate on them during the hiring process. Likewise, Quintini (2011b) indicated that the job sector was closely related to mismatch. Private sector positions, specifically, tended to have larger variation in terms of workers' skill than the public sector.

Other research has reported that employers occasionally consider the unobservable characteristics of job seekers in the hiring process. Cooperation with other members, communication skills, and leadership are difficult to observe through documents or credentials, but those skills are likely to add competitiveness to job seekers in employment (Handel 2005). Because these abilities are primarily observed from evaluations during the recruitment and hiring process, they may lead to skill levels that are higher or lower than those normally associated with the job.

Contextual factors: Along with individual and occupational factors, contextual factors as possible determinants in balancing labor supply and demand, as the context at the time of entry to the labor market could influence the probability of finding a matched job. Shafranov-Kutsev (2016) referred to an insight of Rassadina (2014):

> ... *the choice of career depends directly on socioeconomic conditions; it aggregates the institutional contradictions in education and labor; it gives rise to numerous social problems in young people's lives. This engenders strong concern about making an error and getting a bad start in one's career.* (p. 265)

Some researchers have examined the extent of mismatch that is attributable to structural changes in the demand side of the labor market, such as job polarization and technological changes. When job polarization is extreme, workers at the middle level are less likely to match their skill level to what is demanded (Sparreboom and Tarvid 2016). Additionally, conditions in the workplace have been influenced by technological change (Autor et al. 2003; Kalleberg 2007; Livingstone 2009, p. 16). The skills demanded in 2020 differed from those in the 1980s. Moreover, the preferred fields of study and major by people are also likely to change. These results collectively confirm the impact of structural change in the demand side of the labor market on generating mismatched workers.

The degree of mismatch may fluctuate as business conditions change. Economic aspects have been suggested as important factors that affect mismatch by reshaping the features of demand: requirements and number of opening jobs (International Labour Office (ILO) 2014; Quintini 2011a; Vaisey 2006). There is some evidence that levels of mismatch rise and fall across the business cycle. Quintini (2011b) summarized an unpublished manuscript by Olitsky (2008) as:

> *The proportion of unskilled workers in skilled jobs and the overall proportion of mismatches are negatively correlated with the unemployment rate in the United States. Although this result is at odds with the prediction of models with one type of worker and one type of firm, the author finds that it is consistent with a model where unskilled workers are allowed to accept complex jobs.* (p. 23)

Structural changes in the supply side may also play an important role in generating mismatched workers. The expansion of education may lead to an increase in workers' skill proficiencies. Researchers have discussed that educational expansion is likely to be related to mismatches because it increases the quality of supply in the labor market (e.g., Livingstone 2009; Vaisey 2006). However, at the same time, educational expansion can lead to more skill heterogeneity across individuals within levels of education or may be less influential on skill upgrade (Handel 2003).

2.2. Post Hiring Process

Mismatch may emerge after the job search and employment process. The potential causal mechanisms here can be divided into the same three dimensions: individual, occupational, and contextual.

Individual factors: At the individual level, workers from certain demographics may be restricted from working in a place that permits education or skill match. The incidence of mismatch might change as people get older and their careers take on different trajectories (Kalleberg 2007). Young workers entering the labor market are more likely to be mismatched than more senior workers (Allen et al. 2013; International Labour Office 2013). They often begin with entry-level positions that require them to carry less challenging tasks (Rosenbaum and Binder 1997). As workers accrue labor market experience, their productive capacities become known to employers, they change jobs, and they tend to settle in to a more appropriate alignment of the skills they can supply and the skill demands of their employers. Evidence on mismatch as a transitory phase is mixed. Wirz and Atukeren (2005) reported that overeducation declines with labor market experience. Green and McIntosh (2007), however, showed that workers who are overeducated in one period are more likely to be overeducated at a later date than workers who are originally matched.

Occupational characteristics: The characteristics of a job sometimes require that incumbents use more or fewer skills. People in supervisory positions may be asked to use more skills in specific domains such as communication or problem-solving, or they may be expected to handle more things than their education may have prepared them for. They may struggle from overutilization. Alternatively, some workers develop their competencies during their career through training or experience (Livingstone 2009). In this case, they could meet the required skill or have exceeding skills than demanded for their jobs.

Contextual factors: The impact of contextual factors (e.g., business cycles) can be persistent at this stage. If there are many colleagues hired in a similar period, employers may be unable to find positions that fully utilize workers' competencies. If there are fewer colleagues, employers might expect workers to do more than they can.

Structural changes in supply can also have a lasting impact. The expansion of educational opportunities is a continuous, not temporary, change. If the education and skill levels of the newly introduced labor market population increase and the existing workers' education and skill levels become widespread, skill mismatch can occur. Mendes de Mendes de Oliveira et al. (2000) demonstrated that technological progress differentiates job requirements, creating a gap between workers employed prior to and after advancements. As a result, these new workers are overqualified and, as firms adapt to new technologies, existing workers become underqualified.

2.3. Which Narratives Is It?

The individual, occupational, and contextual dimensions presented so far have independent influences and further interact with other factors. Most likely, individual, occupational, and contextual factors are all present to some extent and work in both reinforcing and countervailing ways. For example, with educational expansion, employers could be more selective, and growing supply may further limit opportunities for the employment of immigrants and women. These factors illustrate the challenges of predicting the trends of mismatch and what drives the trends.

Individual factors generally work in a way that limits job seekers; choice of career options. Mismatch resulting from this mechanism will thus mostly take the form of overeducation or overskilling. Assuming that the value of people's pursuit changes over time (typically prioritizing the balance between life and work), discrimination against women and races becomes less severe, and employers' understanding of other cultures and educational systems increases, the incidence of mismatch is likely to decline over time.

Unlike individual factors, mismatch caused by occupational factors is not unidirectional. If employment or promotion criteria change or if the available information about job seekers varies over time, the incidence of mismatch may also change over time; however, predicting the directionality is challenging to do. Otherwise, if the required degree of skill by occupational levels or particulars roles in occupations have not meaningfully changed, the relationship between occupational factors and mismatch may be persistent over time.

Contextual factors are more complex. One narrative might be that schooling expanded more rapidly than the demand for skills, resulting in overeducation or skill underutilization. Often in this narrative, there is a proliferation of low skilled jobs and a deskilling in others. Alternatively, a second narrative might assert that employers' demands for skills have outpaced the ability of schools to provide them, leading to undereducation or skill shortage. In this narrative, employers are desperate for workers with the skills that are required in a rapidly changing workplace.

Economic conditions may temporarily shift the balance in the labor market. An additional room for employers or for job seekers may be given depending on economic conditions, especially when they enter the labor market. In a tight labor market (i.e., one in which there are relatively more jobs than workers, thus favoring job seekers), employers must be less selective when hiring. This increases the likelihood of undereducation or overutilization, as job seekers without strong credentials can still find jobs. In a loose labor market (i.e., one in which there are relatively more job seekers than jobs), employers can be more selective when hiring. This increases the likelihood of overeducation or underutilization, as employers can choose highly educated candidates to fill lesser positions.

We address two major research questions by focusing on two types of mismatch (educational and skill mismatch) in the United States. First, we examined trends over time in educational and skill mismatch incidence and correlates, as well as assessing the changing relationships between them. Second, we investigated trends over time in the associations between various types of mismatch and several factors including contextual conditions. We examined whether contextual conditions at the transitional period from school to jobs increase or decrease the probability of mismatch and whether such relationships persist during the career. The research questions are as follows:

1. How did the incidence of educational and skill mismatch in the U.S. change between 1994, 2003, and 2012?
2. How did this differ by age, educational attainment, and occupation?
3. How did the relationship between educational and skill mismatch in the U.S. change between 1994, 2003, and 2012?
4. How did this differ by age, educational attainment, and occupation?
5. How did the association between mismatch and individual, occupational, and contextual factors in the U.S. change between 1994, 2003, and 2012?
6. How did the relationship between mismatch and contextual factors interact with individual factors that have been known to be determinants of mismatch?
7. Did the impact of contextual factors on mismatch last during the career?

3. Methodology

3.1. Data

The data were drawn from three cross-sectional surveys: the International Adult Literacy Survey (IALS) in 1994, the Adult Literacy and Life-skills (ALL) survey in 2003, and the Program for the International Assessment of Adult Competencies (PIAAC) in 2012. In 1994, Statistics Canada and ETS designed the IALS to provide comparative data about the literacy skill and use of adult populations (16–65 years of age), which was defined by prose, document, and quantitative skills. The skills were specifically assessed by item response theory (IRT), which provides reliable data. At the same time, the level of skill use was measured by individual workers' strategies of using their skill in the workplace and during their daily lives. The IALS collected data from a nationally representative sample. For the U.S. survey, 4901 persons from various race/ethnicity and educational backgrounds were selected, with a probability proportional to primary sampling units.

The ALL survey was developed by the OECD, Statistics Canada, and several institutions at the U.S. Department of Education as a successive survey of the IALS to provide a broader range of information about adult literacy and life skills (OECD and Canada Statistics 2005). Hence, many items used in the ALL survey and methodologies for data collection were consistent with the IALS. Participants aged 16–65 took surveys and evaluations measuring literacy and numeracy skill proficiencies, as well as the use of skills in the workplace and their daily lives. The same sampling strategy of the IALS was used to ensure a nationally representative sample. In the U.S., a nationally representative sample of 3420 took this survey in the first half of 2003.

In 2012, the OECD, one of the developers of previous comparative surveys (i.e., IALS and ALL) for adult skills, conducted the PIAAC. The PIAAC accounted for adult skills and also improved the quality of data by adjusting and adding skills and use that were matched to technology-rich environments. The enhanced design and method of the PIAAC specifically allowed for the measurement of dynamics among individual backgrounds, job attainments, and experiences in the workplace. The PIAAC also selected a nationally representative sample by utilizing the strategies used in previous versions of surveys. For U.S. data collection, over 5000 nationally representative adults (aged between 16 and 65) participated in this survey from August 2011 to April 2012.

The IALS, ALL, and PIAAC surveys contain a considerable number of parallel items (Paccagnella 2016). All three surveys aimed to gather information about the adult population's skill level and use in the workplace and daily lives, although specific items in each survey measuring for skill use were not perfectly consistent. Of particular importance for this survey was that literacy and numeracy skill proficiencies and utilization in working environment were measured consistently with the two previous surveys. Items' measuring skill uses were modified according to the required skill in the workplace condition at each period the survey was conducted. For example, in 1994, reading and writing e-mails were not considered, but in 2003 and 2012, reading and writing e-mails were measured as a part of literacy skill use (see Box A1 in Appendix A). It is expected that different skill-use questionnaires account for the skill mismatch derived from the skill requirement change. As such, the authors of the present study could observe the reason for change in the trends of skill mismatch as there being far less concern about the influence of changing environments in jobs on demanded skills between 1994, 2003, and 2012.

3.2. Analytic Sample

The IALS did not include participants working at elementary level occupations, which led to fewer participants in the analytic sample. Skilled workers in some occupations—agricultural, forestry, and fishery (major group 6) and armed forces (major group 10)—were not included in the analysis due to small sample sizes. Lastly, the authors of this study focused on employed participants, and self-employed workers were excluded.

Some samples contained missing data. Missing information was mainly observed in items including parent's educational background, supervisory roles in occupation, firm size, and work hours. However, the size of sample with missing information was less than 3% for each item. Thus, we conducted the list-wise deletion of samples with missing data based on the remaining samples from the analytical sample selection procedure.

The final sample size was about 6550: 1600 (IALS), 1800 (ALL), and 3150 (PIAAC). All plausible values were utilized. As recommended by the survey developer, final weight was used to ensure the representative of sampled respondents, and replication weights were used when estimating standard error (Gonzalez 2014); this procedure helped each survey to similarly contribute to the results driven from a pooled sample.

3.3. The Key Variables and Measurements

Cohort: A cohort was defined by age group (10 years), with seven cohorts from cohort 1 (born in 1928–1937) to cohort 7 (born in 1988–1996).

Educational mismatch: We compared individuals' educational attainment and the average workers' educational level in the same occupations. Individual workers' occupations were classified by the International Standard Classification of Occupations (ISCO). Although the ISCO divides job classification into either one or two digits, the authors of this study used a one-digit classification because a two-digit classification was not provided by the IALS. With the one-digit classification, heterogeneity in occupations may have been less controlled.

Individuals' educational attainment was defined by the International Standard Classification of Education (ISCED). Because the index of the ISCED was updated three times (1976, 1997, and 2011), information about participants' educational attainment did not perfectly align between surveys. However, the year of schooling supplement in the ISCED allowed for a degree of educational attainment matching across datasets. Participants had one of eight credentials: (1) primary or less; (2) lower secondary; (3) upper secondary; (4) post-secondary, non-tertiary; (5) tertiary—professional degree; (6) tertiary—bachelor degree; (7) tertiary—master degree; and (8) tertiary—research degree.

Workers were defined as educationally mismatched when their educational attainment abnormally deviated from the average educational level of people working at the same occupation. Workers with educational attainment one level above or below relative to the average level of education were classified as "well-matched"; those with abnormally (more than one level) high educational attainment relative to the mean were classified as "overeducated"; and those with abnormally (more than one level) low educational attainment were classified as "undereducated". For example, workers who attained a high school diploma are considered to be undereducated when their occupation requires at least a bachelor's degree. Alternatively, they are defined as overeducated when they are employed at jobs demanding a primary level of education. We allowed one level above and below to account for variations within the same occupations. In addition, the average workers' educational attainment reflects time-sensitive requirements (International Labour Office 2014), so we were able to control for variations in the time point of interest when supply and demand forces changed by structural factors such as technological development.

This statistical approach was only practically applicable for this study. For example, self-reported items were not consistently measured across the IALS, ALL, and PIAAC. Nevertheless, there is a limitation of this approach that is applicable to most measurements of educational mismatch. Inherently, workers with the highest (or lowest) level of schooling are impossible to be classified as undereducated (or overeducated) because their comparison groups always have lower educational attainments (or higher). At the same time, in certain occupations requiring too high (or low) educational attainment, overeducated (or undereducated) workers may be not observable. Therefore, results should be interpreted with caution, especially in relation to educational attainment and occupation skill level variables.

Skill mismatch[1]: As skills are complex constructs, it is challenging to accurately measure individual skill levels. This might be the reason why a variety of measurements for skill mismatch have been suggested (see Flisi et al. (2017) for a summary of these measurements). Among these measurements, the statistical approach was identically applicable for the IALS, ALL, and PIAAC when considering the items included across datasets. We specifically employed the skill mismatch measurement that Allen et al. (2013) suggested. When a worker's standardized skill level was significantly (1.5) higher or lower than their standardized skill use, this worker was defined as overskilled or underskilled, respectively. However, we compared workers' skill level and use within the same occupations instead of entire participants. Allen et al. (2013) expressed concerns about the measurement suggested by the OECD (e.g., Pellizzari and Fichen 2017) in which skill mismatch is defined based on a comparison between hypothetically defined (based on self-reported items about their jobs) well-matched workers' and individual's skill levels within the same occupations. Their main concern is about collapsing two different occupations (ISCO 1 and 2) into a category despite the heterogeneity in the skill requirements of those occupations. The researchers worried about the possibility that heterogeneity in skill requirements would lead to more subpopulations categorized as mismatched workers. Although we agree, we do not see the concern when applied to their measure for skill mismatch. The measurement of Allen et al. (2013) does not need to define hypothetically well-matched workers, which reduces samples due to missing data in the self-reported items and consequently requires combining some occupational categories with insufficient samples. Alternatively, their measurement utilizes items about skill use in the workplace, which keeps sufficient samples within each occupation. Therefore, we measured skill mismatch by each occupation following the procedure for categorizing skill mismatch shown in Box A2 of Appendix A.

Among various measured skills such as literacy, numeracy, and problem-solving, we focused on literacy and numeracy. The measurements for literacy skill were more consistent than other skill measurements. Numeracy skill was also consistently assessed in a broad sense, although the IALS was intended to measure quantitative literacy in a specific lens. Findings from numeracy skill should be carefully interpreted with consideration of this difference. In contrast, the problem-solving skill was not measured by the IALS. Therefore, we concentrated on literacy and numeracy skills but did not consider problem-solving skills in this study.

Economic condition: To measure economic condition, we used the GDP growth rate. For each cohort, we coded the mean of GDP growth rate between the time when the youngest and most aged workers within the cohort were 25 years old. Because the traditional age seeking of occupations is about 25, it approximately reflects the economic condition at the period of entrance into the labor market for each cohort.

Educational expansion: To estimate the relationship between educational expansion and mismatches, we incorporated U.S. Census data about years of school completed by people between 25–34 years old. Each cohort was given a mean value over the 10 year period that the cohort spanned. Within cohort, based on their educational attainment, they were given the percentages of each level of education graduates (here, we utilized 4 levels to match U.S. Census data: (1) lower than high school; (2) high school; (3) some college; and (4) college and above college). For example, the percentage of high school diploma holders between 1973 and 1982 was about 40%. As such, workers who were born between 1948 and 1957 and attained high school diplomas were given 40 for this item. Because some participants in the latest cohort were born between 1988 and 1996 but had not yet reached 25 years of age, the statistics between 2013 and 2015 were utilized. The 25 year gap was purposively set in order to match the typical age for entering the labor market. By including this variable, we could delineate if more or less mismatch arises when there are many peers with similar levels of schooling when entering into the labor market.

3.4. Analytic Plan

We adopted three broad approaches to address our research questions: descriptive statistics, correlation analysis, and multinomial logistic regression. For the first set of research questions, we provided the proportion of mismatched workers among all workers by cohorts and then estimated the same indicator for each subpopulation. To address the second set of research questions, we conducted correlation analyses, examining the relationship between educational and skill mismatch, and the same analyses were conducted by subpopulations. The results drawn from these approaches were analyzed intuitively rather than systematically. This was because the generated results often had ambiguous patterns due to a lack of time points.

For the last set of research questions, all analyses were independently conducted by each type of mismatch. Specifically, a series of multinomial logistic regression analyses estimated the coefficients of individual, occupational, and contextual variables. We independently analyzed each survey with the same models that successively included individual and occupational variables. In both models, an individual's work hours, skill proficiencies, parental education, and number of livings in home were controlled.

To have a better representation of the relationship over time between individual, occupational, and contextual factors and mismatch, it is essential to simultaneously consider multiple factors in various dimensions. Very few studies have accounted for such multidimensional factors in generating mismatched workers.

Thus, with a pooled sample, we subsequently ran two cohort models. In the first cohort model, contextual variables, economic condition, and educational expansion were added to the variables in the previous models. In the second model, we substituted contextual variables to the dummy-coded cohort variable. This model was expected to provide an idea about which cohorts were more likely to belong to mismatched workers and elucidate patterns.

Based on the first cohort model, a pooled sample was then analyzed by age. This analysis examined the last research question: whether the impact of contextual factors persists during career. The main interest of all models with a pooled sample was the impact of contextual variables. Therefore, in reporting the results, we focused on the coefficients of such variables.

4. Results

4.1. The Incidence and Chance of Skill and Educational Mismatch

Figures 2–4 present how the incidence of skill and educational mismatch changed over the last two decades. The first column (Intracohort-Change) in these figures indicates how the incidence of mismatch for each cohort differs between time points. The second column (Within-Age-Change) in these figures shows the difference in incidence of mismatch within the same age group between time points. For both the first and second columns, a wider gap between time points means larger changes in the incidence of mismatch. The last column (Period) provides a collective idea about the extent of mismatched workers over time.

Literacy skill mismatch: The results of literacy skill mismatch are shown in Figure 2 (see Table A1 in Appendix A as well). In general, well-matched workers decreased during last 20 years. Although well-matched workers in 1994 comprised 80.06% of entire employed workers, the proportion dropped in 2003 and further in 2012 to 75.7% and 73.12%, respectively.

Most of this change came from overutilization (comparable to underskilled or undereducated). The proportion of overutilization increased over time: 4.07% from 1994 (8.36%) to 2003 (12.43%) and 2.68% from 2003 (12.43%) to 2012 (15.11%). Accordingly, the proportion of overutilization gradually increased for each cohort. However, the size of difference varied by cohorts. Specifically, the increase in the proportion of overutilized workers was mainly attributable to the change between 1994 and 2003 for most cohorts. Two cohorts (1948–1957 and 1958–1967) also experienced many changes between 2003 and 2012. Due to these cohorts, the results of within-age-change were also noticeable compared to those of other cohorts; every age groups' overutilization tended to increase, but the increase was much higher for two age groups (45–54 and 55–65).

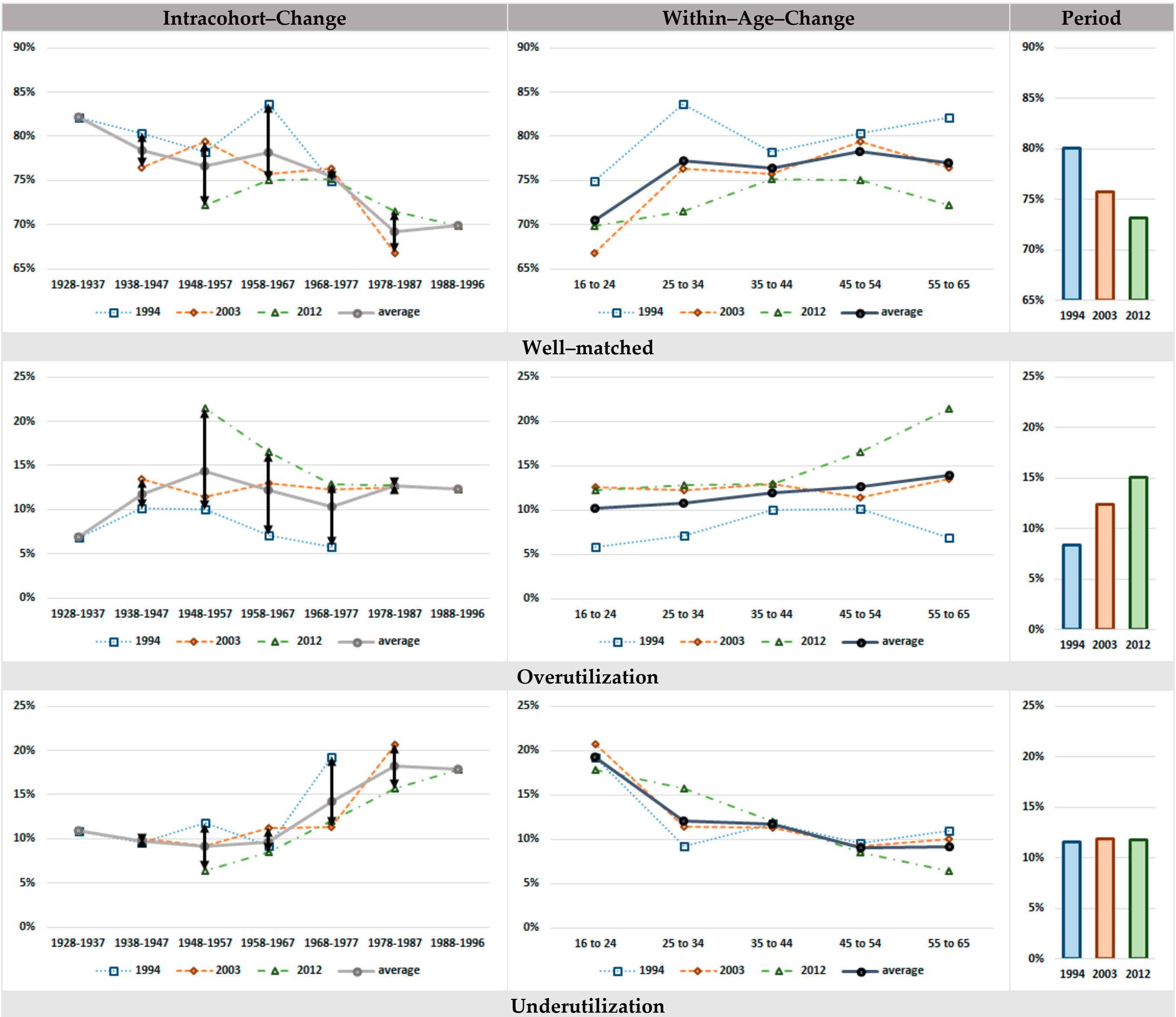

Figure 2. The incidence and change of literacy skill mismatch.

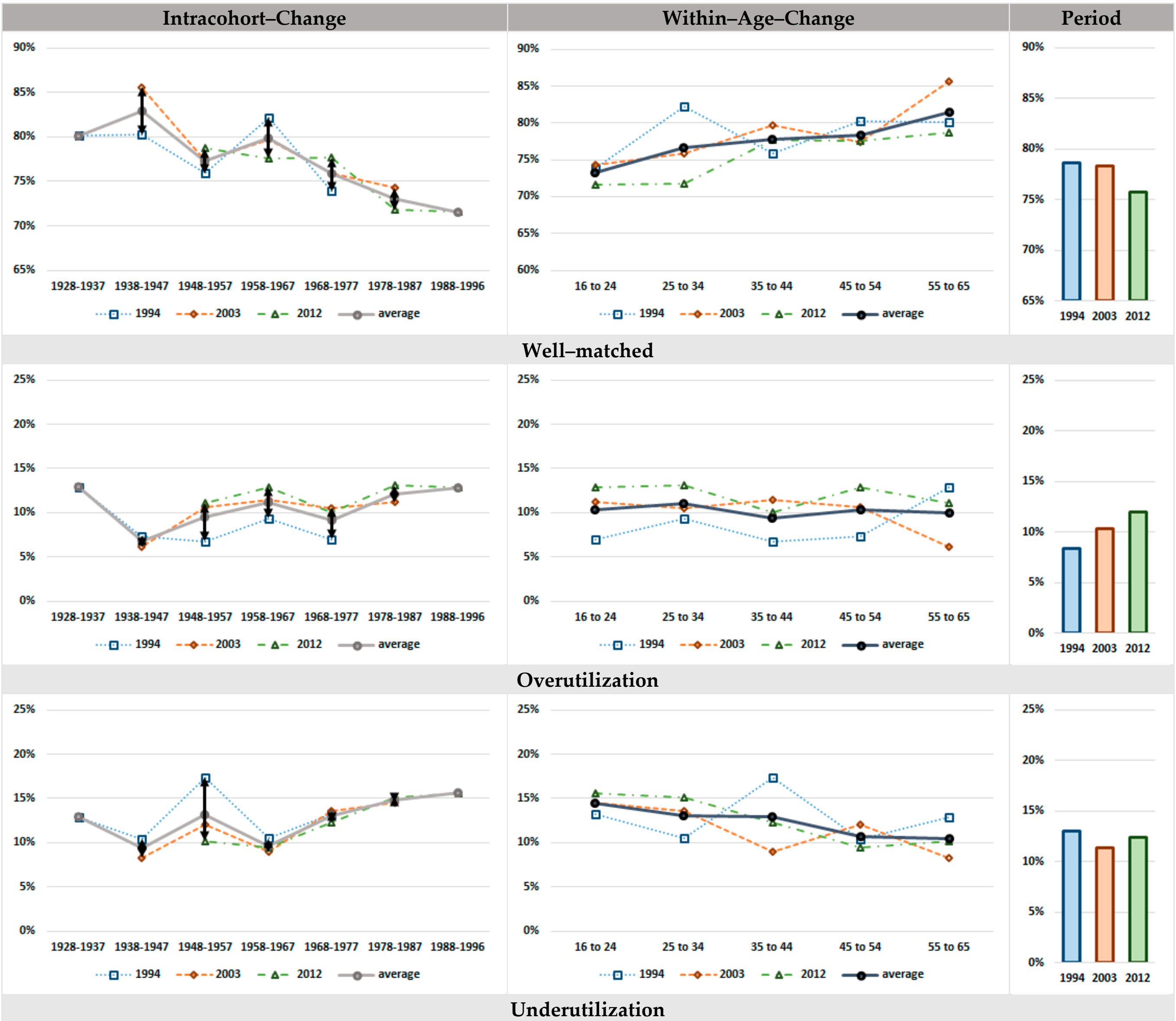

Figure 3. The incidence and change of numeracy skill mismatch.

With respect to underutilization (comparable to overskilled or overeducated), some cohorts' changes were substantial (especially 1968–1977) but overall intracohort-change was negligible between time points. This seemingly divergent result was explained by within-age-change. Although the proportions between time points of some age groups (25–34 and 55–65) were different, other age groups did not show a clear difference. This means that some intracohort changes in underutilization were derived from the career trajectory (i.e., younger workers' skill mismatch adjusted during their career), as some cohorts less enjoyed the impact of career trajectory.

Numeracy skill mismatch: Figure 3 presents the incidence of numeracy skill mismatch and change over time (see Table A2 in Appendix A as well). Compared to the results of literacy skill mismatch, there was relatively small change. The overall change in well-matched workers was less than 3%, and it came from the proportional change in overutilization. Similar to literacy skill, the proportion of overutilization was found to have regularly increased for most cohorts, but it was not explained by career trajectory. Uniquely, many workers of the second oldest cohort (1938–1947) did not experience this increasing tendency, as their overutilization in 2003 (6.12%) remained similar to that in 1994 (7.36%), whereas other cohorts generated more overutilized workers. Such an unusual pattern was also reflected by within–age–change. Within-age-change for the 55–65 age group notably dropped between 1994 and 2003. Except for this case, cohorts that participated in all surveys were similarly affected by the increasing tendency for overutilization.

In terms of underutilization, the proportions were mostly constant between 1994, 2003, and 2012. There were two unique cohorts: the second (1938–1947) and third (1948–1957) oldest cohorts. As stated, the second oldest cohort's proportion of overutilization did not significantly change between 1994 and 2003, whereas other cohorts experienced relatively larger change. This cohort also experienced smaller change in underutilization (from 10.42% to 8.31%) relative to other cohorts, which resulted in the largest proportion of well-matched workers (85.57%) in 2003. Alternatively, the third oldest cohort in 1994 started with lower percentages of overutilized workers (6.75%) and higher percentages of underutilized workers (17.38%). In the subsequent time point, each proportion of this cohort became more similar to those of other cohorts.

Overall, the patterns in underutilization were favorable to the career trajectory hypothesis. In 1994, the proportion of underutilized workers was arbitrarily distributed by age, but in 2003 and 2012, it was sequentially arranged by age (from 15.61% to 10.21%) except for one age group (45 to 54).

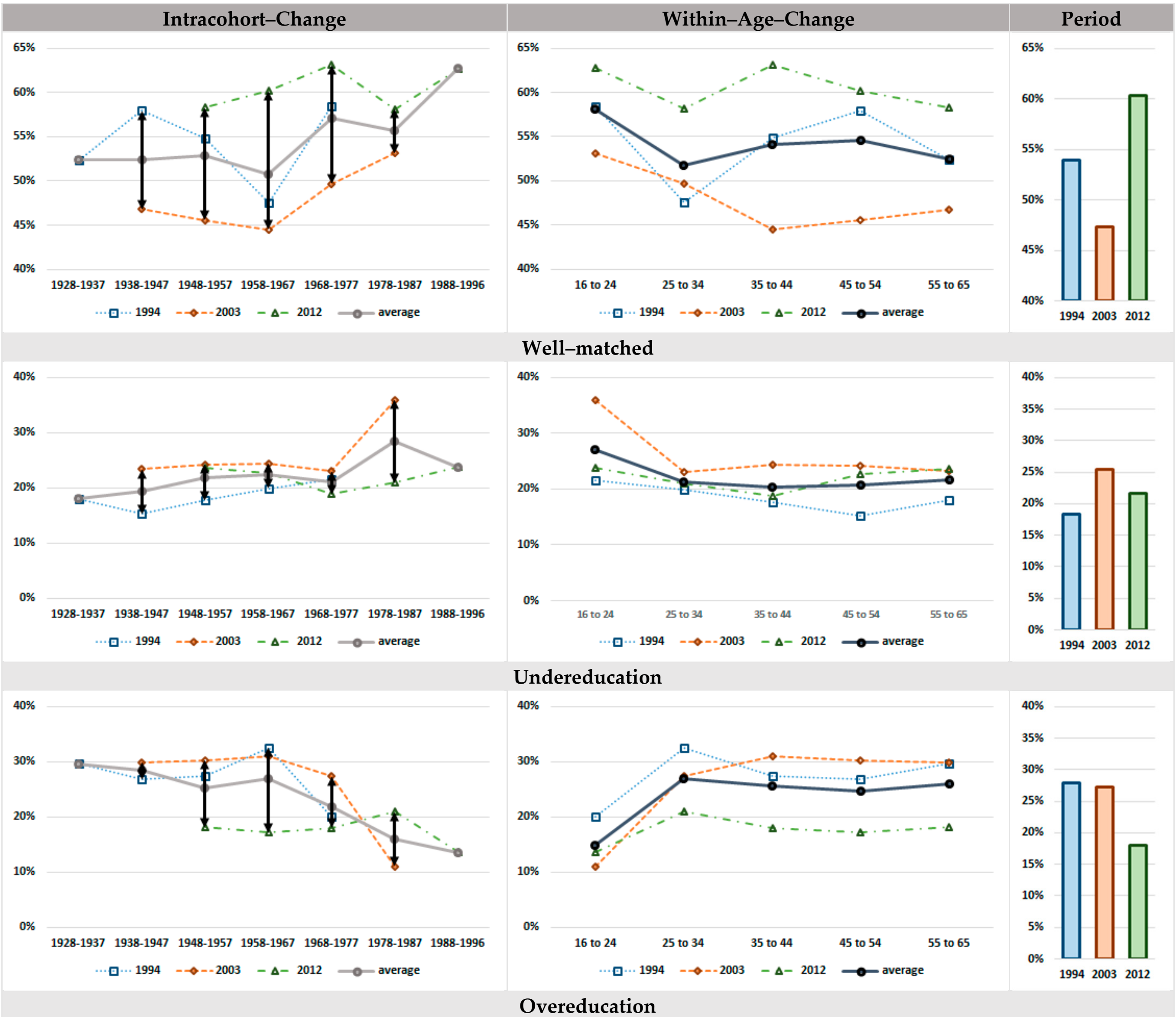

Figure 4. The incidence and change of educational mismatch.

Educational mismatch: Figure 4 presents the incidence of educational mismatch and change over time (see Table A3 in Appendix A as well). The trends in educational mismatch were much less evident. Between each time point, the incidence of educational mismatch was substantially different: there was more educational mismatch between 1994 and 2003 and less educational mismatch between 2003 and 2012. One noticeable tendency was the simultaneous change; where there was an increase between time points within age groups in undereducation, there was a decrease between time points within age groups in overeducation. This pattern may indicate that the incidence of undereducation is contingent on that of overeducation. This was not evident in the results of skill mismatch.

4.2. The Trends in Skill and Educational Mismatch by Subpopulations

Figures 5 and 6 illustrate how the trends in skill and educational mismatch differed by subpopulations. Because these results are descriptive, immediately visible differences by subpopulations are reported in this study; however, there may be less discernable, meaningful differences that require additional analyses.

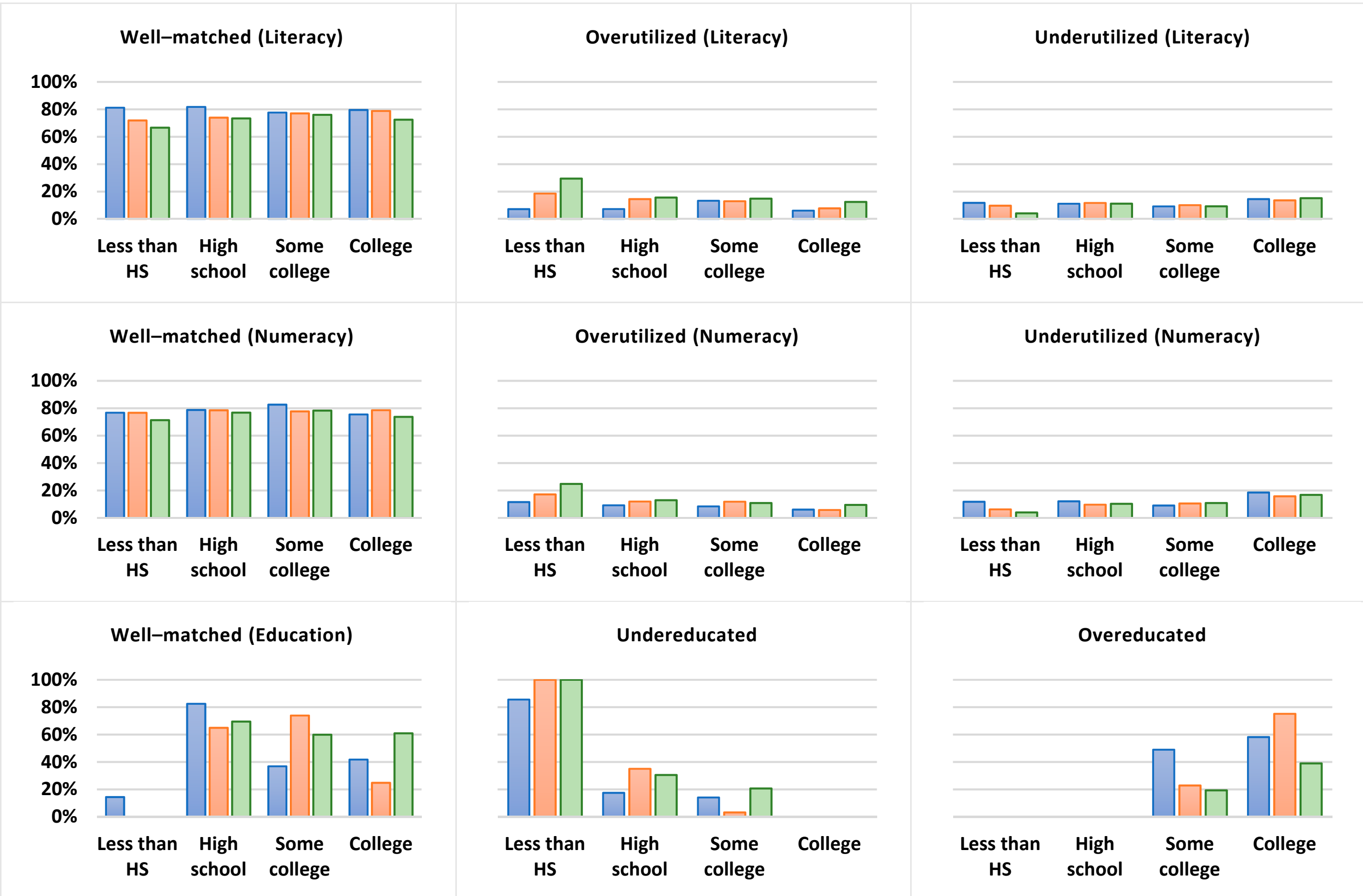

Figure 5. Skill and educational mismatch by educational attainment. Note: blue—IALS (1994); orange—ALL (2003); green—PIAAC (2012).

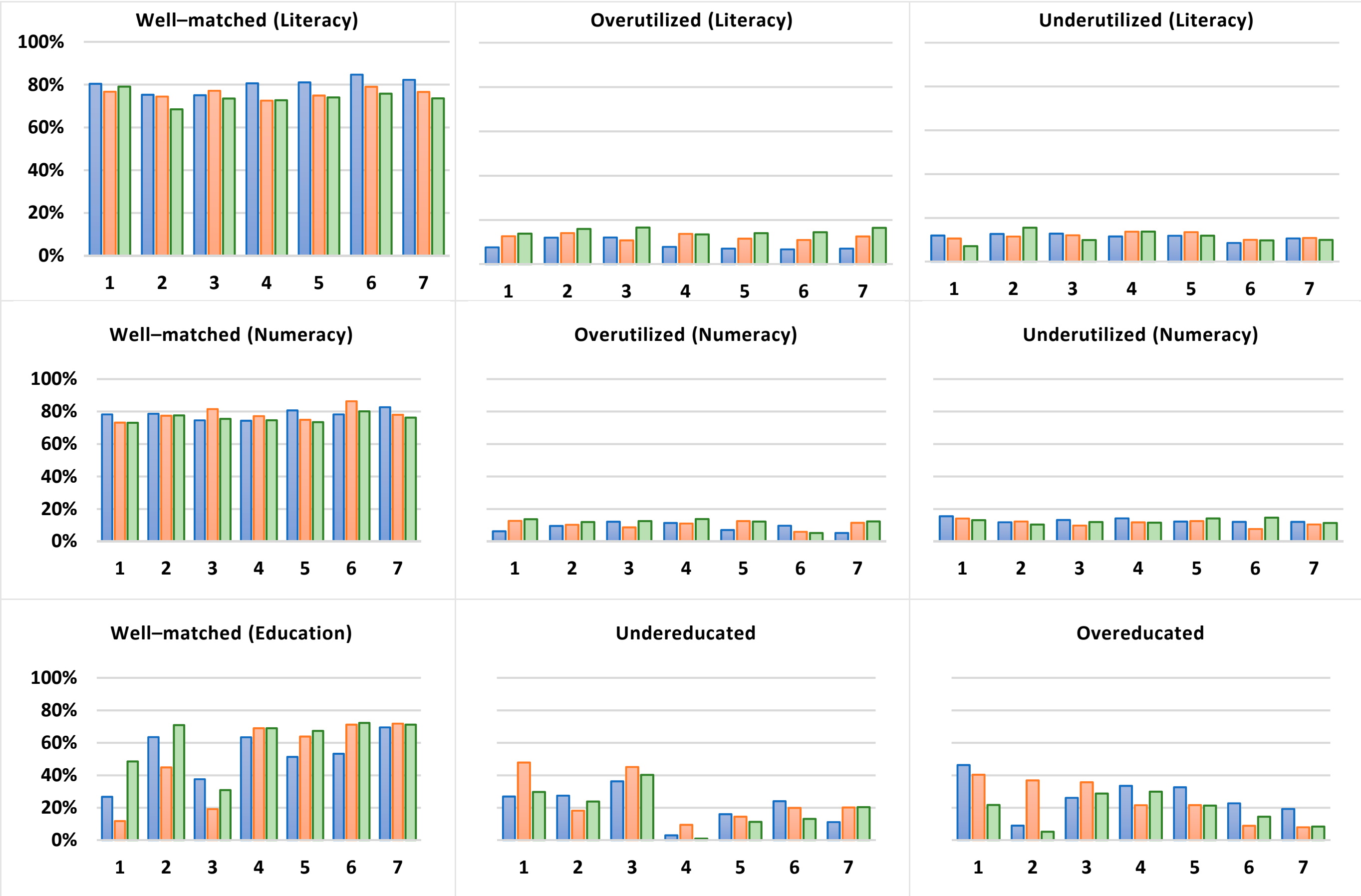

Figure 6. Skill and educational mismatch by occupational level. Note: blue—IALS (1994); orange—ALL (2003); green—PIAAC (2012); 1—ISCO 1; 2—ISCO 2; 3—ISCO 3; 4—ISCO4; 5—ISCO5; 6—ISCO 7; 7—ISCO 8.

The difference in skill and educational mismatch by workers' educational attainment is described in Figure 5. Even though workers with any levels of schooling underwent some changes, it was more common for workers whose schooling was less than high school. The proportion of overutilization gradually increased from 8% to 30% (literacy skill) and from 12% to 25% (numeracy skill). In contrast, underutilized workers decreased from more than 10% to less than 5% in both literacy and numeracy skill. Presumably, this result may reflect the impact of educational expansion. The skill upgrade of overall population may increase the average workers' skill level in that workers with the least educational attainment tend to be more affected by such change. At the same time, the upward tendency in overutilization among college graduates may reflect the increased skill heterogeneity within college graduates that has come as more people have gone to college.

Expanded educational opportunities may also have resulted in the decreased proportion of overeducation among workers with some college experience. It is believed that as their credentials or higher degrees became more common in 2012 (57%) than 1994 (46%) and 2003 (52%) (U.S. Census Bureau 2017), the possibility of being classified as overeducated was significantly reduced.

Figure 6 presents the trends in educational and skill mismatch by occupations. The less skilled occupations (ISCO 4–7) contributed to the decrease in well-matched workers in literacy skill by maintaining underutilization but increasing overutilization over the last 20 years. ISCO 1 showed a mixed pattern in skill mismatch; overutilized workers steadily increased, while underutilized workers gradually decreased. In terms of educational mismatch, workers in this occupation in 2012 had a substantially lower probability of being overeducated compared to those in 1994.

4.3. Correlation between Educational and Skill Mismatch

Table 1 shows the relationship between educational and skill mismatch in the U.S. between 1994, 2003, and 2012—focusing on differences in age groups. To begin with, as shown in the "Pooled" column, the correlation between educational mismatch and each literacy and numeracy skill mismatch tended to increase overtime from 0.06 to 0.12 and from 0.11 to 0.19, respectively. Despite increasing tendency, the strengths of associations were small under Cohen's (1992) conventions: small (0.1), medium (0.3), and large (0.5). This conventional rule will be referenced for the effect size of correlation for the rest of this study. There were no age groups with strong correlations. One notable trend was that in both the literacy and numeracy skills, the increase in correlations was faster for younger workers than older workers. Because of this faster growth, the strength of correlations for younger workers became more similar or exceeded that of older workers in 2012, which was divergent in 1994.

Table 2 delineates correlations between educational and skill mismatch by educational attainment. Because workers with schooling less than high school were only in the category of undereducated, except for the first survey, correlations were not estimated for them. In this table, the trends in correlations were overall less systematic.

Table 1. Correlation between educational and skill mismatch by age group.

		Literacy Skill Mismatch						Numeracy Skill Mismatch					
		Pooled	24 or Less	25–34	35–44	45–54	55 Plus	Pooled	24 or Less	25–34	35–44	45–54	55 Plus
Educational mismatch	1994	0.06	0.00	0.02	0.11	0.08	0.10	0.11	0.01	0.08	0.12	0.13	0.19
	2003	0.12	0.14	0.10	0.17	0.18	0.04	0.14	0.11	0.14	0.22	0.15	−0.02
	2012	0.12	0.15	0.10	0.09	0.15	0.13	0.19	0.22	0.23	0.19	0.20	0.10

Table 2. Correlation between educational and skill mismatch by educational attainment.

		Literacy Skill Mismatch					Numeracy Skill Mismatch				
		Pooled	Less than HS	HS	Some College	College	Pooled	Less than HS	HS	Some College	College
Educational mismatch	1994	0.06	0.07	0.08	0.10	0.05	0.11	0.02	0.07	0.03	0.18
	2003	0.12	-	0.10	−0.06	0.15	0.14	-	0.06	−0.02	0.07
	2012	0.12	-	0.06	0.07	0.06	0.19	-	0.10	0.16	0.17

Note: HS—high school.

The results of Table 3 show how educational and skill mismatch are associated by occupational level and how the association changes over time. Overall, the correlations tended to decrease for the occupation skill level of ISCO 1–3, when compared to the results of 1994–2012, and tended increased in less skilled occupations (ISCO 4–8). The exceptional case was ISCO 7, in which correlations between literacy skill mismatch and educational mismatch were seemingly arbitrary whereas correlations between numeracy skill mismatch and educational mismatch had an upward tendency.

Table 3. Correlation between educational and skill mismatch by occupational level.

		Literacy Skill Mismatch								Numeracy Skill Mismatch							
ISCO		Pooled	1	2	3	4	5	7	8	Pooled	1	2	3	4	5	7	8
Educational mismatch	1994	0.06	0.10	0.21	0.25	−0.02	−0.10	0.08	0.04	0.11	0.17	0.22	0.30	0.06	0.00	0.02	0.08
	2003	0.12	0.25	0.09	0.15	0.12	0.05	0.13	0.07	0.14	0.29	0.08	0.17	0.13	0.03	0.09	0.15
	2012	0.12	0.07	0.08	0.11	0.14	0.19	−0.01	0.36	0.19	0.20	0.13	0.21	0.22	0.25	0.11	0.26

Correlations between educational and skill mismatch are ultimately less informative because the relatively small strength of the relationship and unclear trends. The results regarding occupational level may indicate that schooling is more satisfactory for less skilled occupations than 20 years ago, although it has more recently been less successful in meeting the needs of skilled jobs.

4.4. Interim Conclusion from Descriptive Statistics

The trends in skill and educational mismatch largely convey two messages. First, the incidences of skill mismatch increased over the past two decades. Particularly, the growing number of overutilization substantially contributed to the trends. In contrast, educational mismatch became less prevalent in 2012. The incidence of overeducation mainly declined after 2003, leading to more well-matched workers.

A paucity of studies have examined the trends in skill mismatch; therefore, the findings of this study are difficult to compare with those of prior studies. Partially, the decreasing tendency in overeducation was directly comparable with some prior studies (e.g., Groot and van den Brink 2000; Vaisey 2006), which mostly investigated the trends of educational mismatch over the 1970–1990s period. However, these studies provided divergent findings. Groot and van den Brink (2000) conducted a meta-analysis covering studies between 1980 and 2000 in order to understand overeducation in the labor market. The authors suggested that although the results depended on how educational mismatch was measured, the incidence of overeducation generally declined or was maintained over the past 20 years. Additionally, they noted that the decline of overeducation in the U.S. was a leading cause for such trends. Vaisey (2006) found contradictory results from the 1972–2002 General Social Survey (GSS) data. In this study, overqualified workers were found to have increased from 30% to 55% during the time period. With a stricter standard to measure overeducation, far fewer numbers were observed (evenly dropped about 20% for most years), but they still showed increasing tendency.

This study may support and extend the results found by Groot and van den Brink (2000), as overeducation in the descriptive statistics of this study tended to decline from 1994 to 2012. However, the results derived by Vaisey (2006) may be also partially supported by this study. Specifically, in Vaisey's study, the increasing tendency in the study with GSS data hit a stagnation between 1992 and 2002, as the proportion of overqualified workers more than 3 years remained at 20%. This stagnation was observed in the results of this study between 1994 and 2003; overeducated workers of 1994 and 2003 comprised 27.82% and 27.27%, respectively. Consequently, this may indicate that overeducation in the U.S. increased between the 1970s and 1980s, persisted in the 1990s, and then declined 2000s. However, additional data (i.e., time) points would be required to verify this tendency during the 2000s.

The correlation between educational and skill mismatch generally increased during the period that data covered. This inclination might be attributable to the different trends in the incidence of each educational and skill mismatch; regardless of dynamics in skill mismatch, an increased proportion of well-matched workers in educational mismatch possibly affected the change in correlation. Alternatively, assuming that the other factors causing the mismatch are the same, an upward tendency may indicate that employers attain a better signal about preferred skills from educational attainment. One predictable reason for the stronger signal may be that the school system reflects the skills required by the labor market more than before. Under these conditions, the correlation between educational and skill mismatch is likely to increase (regardless of whether employers rely on educational credentials or skill proficiencies as a main source of their hiring decision).

Despite this increase, the strengths of the correlations were still found to be small at 0.12 (educational mismatch and literacy skill mismatch) and 0.19 (educational mismatch and numeracy skill mismatch). This result corresponded to previous findings that reported a 0.2 correlation between overqualified and overskilled workers in Britain (Green and McIntosh 2007). Collectively, more empirical evidence based on specific context is required for portraying the meaning of correlation between educational and skill mismatch.

The second message from descriptive results is that there are groups that are more affected by the increasing or decreasing tendency. Some cohorts often did not enjoy the impact of career trajectory, which reduced the incidence of mismatch by workers' aging. In addition, some cohorts began with high or low numbers of mismatched workers relative to other cohorts. Depending on workers' educational attainment, they were found to be more or less likely to be affected by the structural change in the supply side, such as the more highly educated newcomers into the labor market; further evidence is necessary to ascertain whether workers with lower educational attainments are influenced by the spillover of more educated workers.

Less skilled occupations experienced the most change. More mismatched workers were generated over time in those occupations. This may mean that the skill or level of education required by the job has changed in the last two decades while, at the same time, the skill or level of education of workers entering that job has changed most dramatically. By reviewing literature about the trends in skill requirements for jobs, Handel (2005) concluded that job skill requirements are generally rising but the rate of increases has slowed; also, jobs that mostly consist of K–12 graduates tend to require higher cognitive skills. In collaboration with the expansion of educational opportunities, this conclusion is in line with the trends in educational and skill mismatch in less skilled occupations.

Overall, these descriptive statistics generated meaningful findings that corresponded to previous studies and theories. However, as these analyses did not consider contextual factors, the results provide less explicit plausible narratives.

4.5. What Characterize Underskilled and Undereducated Workers Over the Last 20 Years?

Multinomial logistic regression models estimate the probability of overutilization/ undereducation (or underutilization/overeducation) relative to being well-matched. The reported values in results tables are coefficients, but when necessary, we suggested the relative risk ratio (RRR), which can be calculated by exponentiating the coefficients of multinomial logistic regression. The RRR is similar to the odds ratio of the logistic regression analysis, indicating the probability of belonging to the comparison group relative to reference group by changes with the independent variable.

What is the relationship between personal background and occupational characteristics with mismatch over the past 20 years? In order to address this research question, we conducted a series of multinomial logistic regression models that predicted the odds of being mismatched while controlling for skill proficiencies, parental education, number of livings, and work hours. Based on these control variables, we included personal demographics such as gender, age, immigrant status, and educational attainment in the first model to understand the relationship between individual characteristics and the probability of belonging to mismatched workers. This was applied to Models 1 and 3 in Tables 4–6. We subsequently added occupational characteristics variables in addition to the first model. This was applied to Models 2 and 4 in Tables 4–6. This subsequent model showed the relationship between occupational characteristics and mismatched workers, controlling for a range of workers' individual characteristics.

Individual characteristics: Models 1 and 3 in Table 4 present the probability of overutilization relative to being well-matched depending on an individual's profile. Among personal background variables, education was consistently related to the odds of overutilization across all types of skill and survey points. With similar levels of skill proficiencies, workers with higher educational attainments were more likely to be overutilized. In particular, the survey showed that the effect of educational attainment on numeracy skill overutilization became stronger overtime. For example, workers with a bachelor's degree had a 1.43 times higher probability of overutilization in numeracy skill relative to workers with some college experience in 1994—those were 1.47 and 1.64 in 2003 and 2012, respectively. This pattern was not evident in literacy skill overutilization. There was some evidence that gender and age variables were associated with overutilization, but only limited cases occurred. Specifically, female workers in 1994 were less likely to experience literacy skill shortage, and female workers in 2012 also tended to be less involved in numeracy skill deficit. The impact of age on overutilization was only found in 2012, as older workers were less likely to be overutilized compared to younger workers. One increase in generation decreased the probability of being overutilized by 12%.

Table 4. Literacy and numeracy skill mismatch: overutilized vs. well–matched.

Overutilized	Literacy						Numeracy					
	Model 1			Model 2			Model 3			Model 4		
	1994	2003	2012	1994	2003	2012	1994	2003	2012	1994	2003	2012
Female	−0.423 *	−0.053	0.096	−0.325	−0.211	0.187	−0.314	−0.118	−0.383 **	−0.511	−0.396	−0.363 **
	(0.223)	(0.208)	(0.153)	(0.214)	(0.250)	(0.182)	(0.254)	(0.217)	(0.164)	(0.323)	(0.267)	(0.180)
Age	0.064	0.006	0.046	0.056	−0.038	0.029	−0.057	−0.070	−0.124 **	−0.022	−0.114	−0.189 ***
	(0.082)	(0.103)	(0.057)	(0.104)	(0.118)	(0.058)	(0.131)	(0.098)	(0.060)	(0.135)	(0.108)	(0.065)
Immigrants	−0.418	−0.364	−0.196	−0.323	−0.513	−0.226	−0.642	−0.082	−0.127	−0.700	−0.087	−0.166
	(0.385)	(0.277)	(0.199)	(0.410)	(0.318)	(0.217)	(0.437)	(0.385)	(0.220)	(0.460)	(0.395)	(0.236)
Education	0.681 ***	0.503 ***	0.681 ***	0.264 *	0.235 *	0.438 ***	0.356 **	0.382 ***	0.496 ***	0.022	0.161	0.282 **
	(0.142)	(0.142)	(0.103)	(0.153)	(0.142)	(0.128)	(0.164)	(0.139)	(0.110)	(0.165)	(0.156)	(0.116)
Part-time				0.075	−0.262	−0.455				0.381	0.585	−0.074
				(0.795)	(0.539)	(0.285)				(0.616)	(0.461)	(0.314)
Firm size				0.107	0.116	−0.006				0.081	0.030	−0.135
				(0.087)	(0.100)	(0.064)				(0.084)	(0.097)	(0.083)
Occupational level				0.761 ***	0.913 ***	0.463 **				0.874 ***	0.919 ***	0.661 ***
				(0.248)	(0.174)	(0.183)				(0.230)	(0.249)	(0.177)
Some supervisory				0.616 *	0.121	0.658 ***				0.409	0.331	0.399 *
				(0.370)	(0.306)	(0.214)				(0.307)	(0.330)	(0.229)
Great supervisory				0.748 *	0.350	0.328				−0.233	0.487	0.607 **
				(0.405)	(0.306)	(0.243)				(0.544)	(0.380)	(0.260)
Training experience				0.698 **	0.863 ***	0.614 ***				0.215	0.885 **	0.229
				(0.304)	(0.279)	(0.208)				(0.355)	(0.372)	(0.211)
Constant	1.717 **	5.900 ***	5.816 ***	0.249	5.466 ***	5.173 ***	1.634 **	4.969 ***	4.233 ***	−0.350	3.872 ***	3.490 ***
	(0.691)	(0.841)	(0.630)	(1.012)	(1.046)	(0.777)	(0.811)	(0.897)	(0.509)	(0.938)	(1.046)	(0.838)
Observations	1658	1883	3246	1593	1809	3150	1658	1883	3246	1593	1809	3150

Note: Standard errors in parentheses. For brevity, the coefficients of control variables are not reported in the table. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

Table 5. Educational mismatch by survey.

	Undereducated						**Overeducated**					
	Model 1			**Model 2**			**Model 3**			**Model 4**		
	1994	**2003**	**2012**	**1994**	**2003**	**2012**	**1994**	**2003**	**2012**	**1994**	**2003**	**2012**
Female	0.105	0.601 ***	0.142	−1.082 ***	−0.984 *	−0.638 ***	−0.180	−0.324 *	−0.241 *	0.501 **	0.083	0.042
	(0.150)	(0.179)	(0.103)	(0.390)	(0.588)	(0.189)	(0.151)	(0.186)	(0.123)	(0.208)	(0.212)	(0.159)
Age	−0.024	0.202 ***	0.151 ***	0.084	0.350 ***	0.086	−0.162 *	0.076	−0.085	−0.094	0.096	−0.022
	(0.047)	(0.069)	(0.045)	(0.117)	(0.129)	(0.086)	(0.084)	(0.114)	(0.053)	(0.083)	(0.135)	(0.059)
Immigrant	0.789 ***	0.606 **	0.255 *	0.619 *	0.048	0.448 *	0.158	0.022	0.247 *	0.546 *	0.379	0.471 ***
	(0.229)	(0.290)	(0.152)	(0.356)	(0.388)	(0.241)	(0.289)	(0.272)	(0.137)	(0.328)	(0.278)	(0.157)
Education	−1.657 ***	−4.328 ***	−1.909 ***	−20.306 ***	−27.134 ***	−20.981 ***	1.873 ***	2.800 ***	1.611 ***	4.328 ***	4.336 ***	3.686 ***
	(0.139)	(0.355)	(0.102)	(1.246)	(3.338)	(4.658)	(0.154)	(0.193)	(0.091)	(0.642)	(0.216)	(0.177)
Part-time				−0.408	0.625	−0.057				0.582 ***	0.535	−0.008
				(0.383)	(0.857)	(0.348)				(0.212)	(0.516)	(0.246)
Firm size				0.001	0.167	0.134 *				0.026	−0.095	−0.099 **
				(0.069)	(0.298)	(0.079)				(0.068)	(0.067)	(0.044)
Occupational level				20.461 ***	22.487 ***	20.890 ***				−3.473 ***	−2.010 ***	−2.617 ***
				(1.227)	(3.378)	(4.639)				(0.690)	(0.256)	(0.165)
Some supervisory				0.352	0.570	0.399				0.102	0.373 *	−0.036
				(0.371)	(0.403)	(0.272)				(0.251)	(0.212)	(0.166)
Great supervisory				−0.507	2.004 ***	0.395				0.806 ***	0.946 ***	0.534 ***
				(0.672)	(0.654)	(0.276)				(0.286)	(0.215)	(0.177)
Training experience				0.576 *	0.074	0.091				0.064	0.032	−0.061
				(0.313)	(0.276)	(0.185)				(0.323)	(0.181)	(0.158)
Constant	1.483 ***	4.982 ***	0.919 **	1.048	8.936 ***	−2.519 ***	−3.644 ***	−9.740 ***	−5.644 ***	−7.220 ***	−11.881 ***	−7.396 ***
	(0.494)	(0.850)	(0.425)	(0.994)	(2.636)	(0.840)	(0.443)	(1.035)	(0.485)	(1.013)	(1.170)	(0.592)
Observations	1662	1883	3273	1593	1809	3150	1662	1883	3273	1593	1809	3150

Note: Standard errors in parentheses. For brevity, the coefficients of control variables are not reported in the table. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

Table 6. Literacy and numeracy skill mismatch: underutilized vs. well–matched.

Underutilized	Literacy						Numeracy					
	Model 1			Model 2			Model 3			Model 4		
	1994	2003	2012	1994	2003	2012	1994	2003	2012	1994	2003	2012
Female	0.233	0.430 **	0.182	−0.115	0.331	0.016	0.157	0.648 ***	0.116	0.095	0.563 **	0.049
	(0.300)	(0.208)	(0.154)	(0.361)	(0.238)	(0.174)	(0.188)	(0.229)	(0.181)	(0.266)	(0.263)	(0.205)
Age	−0.183 *	−0.293 ***	−0.261 ***	−0.131	−0.220 *	−0.207 **	0.078	−0.054	−0.117	0.115	0.023	−0.021
	(0.095)	(0.095)	(0.074)	(0.108)	(0.115)	(0.082)	(0.130)	(0.111)	(0.073)	(0.138)	(0.117)	(0.078)
Immigrants	0.249	−0.050	−0.080	0.275	−0.161	−0.012	0.011	0.585	−0.107	0.014	0.501	0.020
	(0.444)	(0.350)	(0.251)	(0.478)	(0.394)	(0.269)	(0.301)	(0.366)	(0.202)	(0.353)	(0.372)	(0.198)
Education	−0.614 ***	−0.433 ***	−0.542 ***	−0.342 **	−0.243 *	−0.252 **	−0.468 ***	−0.325 ***	−0.295 ***	−0.281	−0.205	−0.007
	(0.148)	(0.112)	(0.085)	(0.169)	(0.137)	(0.102)	(0.165)	(0.124)	(0.099)	(0.226)	(0.138)	(0.117)
Part-time				0.082	0.470	−0.104				0.164	0.082	0.314
				(0.503)	(0.407)	(0.322)				(0.477)	(0.376)	(0.313)
Firm size				0.068	−0.089	−0.065				0.159	0.102	0.055
				(0.084)	(0.098)	(0.087)				(0.097)	(0.081)	(0.061)
Occupational level				−0.374 *	−0.287 *	−0.522 ***				−0.488 **	−0.235	−0.658 ***
				(0.199)	(0.168)	(0.166)				(0.212)	(0.188)	(0.140)
Some supervisory				−0.747 **	−0.732 **	−0.369				−0.389	−0.651 **	−0.494 **
				(0.341)	(0.319)	(0.270)				(0.355)	(0.315)	(0.229)
Great supervisory				−0.703	−0.517	−0.427				−0.393	−0.816 **	−0.390 *
				(0.523)	(0.322)	(0.299)				(0.379)	(0.390)	(0.204)
Training experience				−0.513 **	−0.820 ***	−0.630 ***				−0.127	−0.595 **	0.010
				(0.250)	(0.292)	(0.206)				(0.282)	(0.287)	(0.220)
Constant	−11.291 ***	−10.885 ***	−13.574 ***	−10.907 ***	−11.067 ***	−12.848 ***	−9.825 ***	−10.597 ***	−9.644 ***	−10.258 ***	−10.400 ***	−9.734 ***
	(1.167)	(1.211)	(0.874)	(1.450)	(1.493)	(1.107)	(1.389)	(1.056)	(0.631)	(1.654)	(1.254)	(0.734)
Observations	1658	1883	3246	1593	1809	3150	1658	1883	3246	1593	1809	3150

Note: Standard errors in parentheses. For brevity, the coefficients of control variables are not reported in the table. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

Models 2 and 4 showed how the relationships between individual characteristics and overutilization changed with the inclusion of occupational characteristics in Models 1 and 3. In Model 2, the different odds of overutilization by gender in 1994 were no longer significant, while the effect of schooling remained constant even after controlling for occupational characteristics. The effect was especially stronger in 2012 (55% increase) relative to others (30% in 1994 and 26% in 2003). Regarding the trends in numeracy overutilization, the gradually stronger effect size by time points in Model 3 was confirmed in Model 4, as the impact of educational attainment was only constant in 2012 when considering occupational characteristics. Alternatively, gender and age differences in the probability of numeracy overutilization in 2012 were still discernable.

Model 1 in Table 5 estimates the odds of undereducation by personal characteristics. As noted, regarding educational mismatch measurement, the coefficients of educational attainment and occupational level are not sufficiently informative. Thus, we paid less attention to the results from both variables in relation to educational mismatch. The results of Model 1 in Table 5 substantially diverged from those of Model 1 and 3 in Table 4, where gender and age were occasionally associated with overutilization. Among personal profile variables, immigrant status was consistently related to the likelihood of undereducation during last 20 years. Relative to native residents, immigrants tended to hold jobs requiring higher level of credentials than they had, even though the effect sizes decreased overtime. In terms of age and gender, those often significantly increased the probability of underutilization depending on time points. For example, in 2003, female workers were found to have a 1.82 times higher probability of undereducation.

Such relationships shown in Model 1 in Table 5 were similarly found in Model 2, which included occupational characteristics. Immigrants still suffered from mismatch and age also related to undereducation in 2003, even though some cases turned out to be non-significant (immigrants in 2003 and age in 2012). One notable finding between Models 1 and 2 centered on gender differences. In Model 2, female workers were shown to generally be less likely to work at jobs demanding higher schooling than their educational attainment after accounting for occupational characteristics. This may indicate that there is noise in gender difference when analyzing without occupational characteristics.

Occupational characteristics: Models 2 and 4, shown in Table 4, estimated the relationship between occupational characteristics and the odds of belonging to workers who suffer from skill shortage, given the other variables in the model were held constant. Among variables, skill-relevant considerations such as occupational level and supervisory roles were found to be associated with both literacy and numeracy skill overutilization. Workers at skillful positions were specifically expected to have a higher probability than those in less skillful positions. In terms of the effect size, these relationships did not show an evident or systematic pattern over time. One exception might be the impact of great supervisory role; literacy skill overutilization decreased, while such an impact on numeracy skill overutilization increased over time.

Model 2, shown in Table 5, showed that occupational characteristics were relatively less associated with the probability of undereducation. Having a great supervisory role (in 2003) and working at larger size of companies (in 2012) were only estimated to increase the odds of undereducation. This result indicates that other than occupational level, the probability of undereducation may not significantly differ by occupational characteristics.

4.6. What Characterize Overskilled and Overeducated Workers Over the Last 20 Years?

Individual characteristics: Models 1 and 2, shown in Table 6, showed the expected probability of underutilization relative to being well-matched by the change in individuals' backgrounds. Among individual background variables, a close relationship between educational attainment and underutilization was estimated, which was comparable to those of Models 1 and 2 in Table 4. Having higher educational attainment decreased the probability of underutilization. This relationship was identically applied to both literacy and numeracy skills. In both skills, the impact of educational attainment on underutilization tended to decrease from 1994 to 2012. For example, in terms of numeracy skill mismatch in 1994, for bachelor's degree holders relative to workers with some college experience, the relative risk for being underutilized in comparison to being well-matched was expected to decrease by a factor of 0.626, and it was 0.745 in 2012. Unlike the results of overutilization relative to being well-matched in Table 4, the effect of age existed in Model 1 shown in Table 6. Older workers were less likely to experience literacy skill surplus. However, the probabilities of numeracy skill underutilization were not significantly different between age groups. With respect to gender differences, the odds of both literacy and numeracy skill underutilization in 2003 were predicted to be different by gender—female workers were less likely to hold jobs fully utilizing their skills.

Models 2 and 4, shown in Table 6, revealed whether the aforementioned relationships remained after including variables of occupational characteristics. Although age and educational attainment still showed relevance in predicting literacy underutilization, except for the age effect in 1994, gender differences became less critical. In contrast, the link between educational attainment and numeracy skill underutilization was no longer statistically significant in Model 4. Only gender differences were observed in the analysis with occupational characteristics. In 2003, female workers were 1.756 times more likely to experience numeracy skill surplus in their jobs.

In terms of the relationship with overeducation, Model 3 of Table 5 illustrated that individual backgrounds were occasionally—rather than consistently—associated with overeducation. These patterns of relationships became clearer as occupational characteristics were considered together. Immigrant and female workers struggled to find jobs matching their educational attainments in 1994. The higher probability of overeducation for these groups indicates that their educational attainment seemed to be undervalued or discriminated in that period. Such disadvantages might be still true for immigrants. In 2012, the probability of overeducation for immigrants was evaluated 1.6 times higher relative to native workers.

Occupational characteristics: The second half of Table 6 for Models 2 and 4 shows the coefficients of occupational characteristics, controlling for other variables in the models. The results are comparable with those of the overutilization models in Table 4, where occupational level, supervisory roles, and training experience were found to significantly increase the odds of overutilization. The same variables were associated with underutilization, but those were estimated to decrease the likelihood of underutilization. Workers holding jobs or positions requiring higher skills had relatively lower risk of being underutilized. Workers with training experience were also less likely to be underutilized. Their odds of underutilization, for example, were 53% for other workers without training experience.

As presented in Table 5, Model 4 showed distinctive results to Model 2. The impact of holding great supervisory role was consistent across all surveys, indicating that workers with this role tended to have higher educational attainment than required. This result suggests that educational attainment might be one of factors determining workers for those positions. Firm size was also found to be related to overeducation, but only in 2012; employees in larger companies were less likely to be overeducated. The difference by firm size in workers' educational mismatch might be a recent trend when we consider the results of Models 2 and 4 in Table 5 together.

4.7. Do Contextual Factors at Labor Market Entry Have an Impact on Job Matching?

In order to understand if some cohorts are more or less impacted by contextual factors, we conducted multinomial logistic regression modelling with the pooled sample of all surveys. In these models, contextual factors were the main interest. Thus, we concentrated on the coefficients of those variables and less on individual and occupational characteristics. Specifically, there were two types of models: (1) odd number models in Table 7 with contextual variables (educational expansion and GDP growth) and (2) even number models in Table 7 with cohorts (seven groups: 1928–1937, 1938–1947, 1948–1957, 1958–1967 (reference group), 1968–1977, 1978–1987, and 1988–1996).

Table 7. Pooled model: cohort variables.

Pooled Model	Literacy Skill Mismatch				Numeracy Skill Mismatch				Educational Mismatch			
	Overutilized		Underutilized		Overutilized		Underutilized		Undereducated		Overeducated	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
% of holding the same degree	0.009 (0.007)		0.000 (0.008)		−0.001 (0.009)		0.004 (0.009)		−0.163 *** (0.011)		−0.174 *** (0.020)	
GDP growth rate	−0.134 (0.087)		−0.190 ** (0.090)		0.047 (0.098)		−0.313 *** (0.084)		−0.200 (0.139)		−0.153 ** (0.069)	
Cohort1928–1937		−1.009 * (0.526)		−0.903 * (0.485)		0.443 (0.481)		−1.215 *** (0.425)		−0.927 ** (0.397)		1.917 *** (0.275)
1938–1947		−0.284 (0.309)		−0.561 * (0.326)		0.505 * (0.284)		−1.096 *** (0.299)		−0.566 ** (0.273)		1.137 *** (0.179)
1948–1957		−0.135 (0.196)		−0.222 (0.239)		0.215 (0.219)		−0.235 (0.224)		−0.160 (0.204)		0.752 *** (0.131)
1968–1977		0.166 (0.196)		0.409 ** (0.203)		−0.036 (0.191)		0.657 *** (0.227)		−0.005 (0.209)		−0.791 *** (0.132)
1978–1987		0.650 *** (0.246)		0.916 *** (0.243)		−0.133 (0.260)		1.313 *** (0.233)		0.264 (0.260)		−1.662 *** (0.175)
1988–1996		0.796 ** (0.372)		0.981 *** (0.370)		−0.433 (0.388)		1.848 *** (0.325)		0.236 (0.393)		−2.231 *** (0.324)
Observations	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552

Note: Standard errors in parentheses. Individual's work hours, skill proficiencies, parental education, and number of living were controlled. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

Models 1, 3, 5, 7, 9, and 11 described how contextual factors are associated with skill and educational mismatch while accounting for various individual and occupational characteristics. In these models, the percent of people who have the same degree when entering into the labor market was found to be related to educational mismatch, but it did not significantly influence the probability of skill mismatch. Specifically, when there were many people with similar academic backgrounds searching for jobs, the probability of educational mismatch (both undereducation and overeducation) diminished by about 15% for each unit increase of this variable. Alternatively, the GDP growth rate was linked to underutilization and overeducation. With a one-unit increase of GDP growth rate around the timing of finding jobs, the odds of literacy and numeracy underutilization and overeducation lowered by 17.3%, 26.9%, and 14.2%, respectively.

Models 2, 4, 6, 8, 10, and 12 demonstrated whether the probability of mismatch differed by cohorts. Between overutilization and undereducation models (Models 2, 6, and 10) and underutilization or overeducation models (Models 4, 8, and 12), the latter models provided an apparent pattern in relationship with dependent variables. In terms of literacy and numeracy skill underutilization (Models 4 and 8), the recent cohorts tended to work at jobs that utilize fewer skills. Conversely, as shown in Model 12, the recent cohorts were less likely to experience overeducation.

4.8. Does the Impact of Contextual Factors Differ by Cohorts?

We analyzed pooled sample data by age in order to understand if the impact of contextual factors at the beginning stage of a career is maintained during its lifetime. As the main interest is on cohort variables, we concentrated on reporting the coefficients of these variables. With respect to literacy skill mismatch, Table 8 suggests that the impact of contextual factors at the time of entering to the labor market may not last.

Table 8. Pooled model by age (literacy skill).

(Ref. Well-Matched)	Literacy Skill Mismatch (Pooled Model)									
	Overutilized					Underutilized				
	24 or Less	25–34	35–44	45–54	55 Plus	24 or Less	25–34	35–44	45–54	55 Plus
Individual backgrounds										
Female	−0.440	0.099	−0.225	0.032	0.164	0.150	−0.064	0.053	0.355	−0.023
	(0.451)	(0.264)	(0.250)	(0.272)	(0.290)	(0.356)	(0.271)	(0.293)	(0.383)	(0.490)
Immigrant	−0.125	−0.510	−0.129	−0.518	−0.179	−0.335	0.296	−0.174	0.101	0.543
	(0.491)	(0.337)	(0.290)	(0.377)	(0.497)	(0.564)	(0.316)	(0.440)	(0.664)	(0.828)
Education	−0.146	0.469 ***	0.319 *	0.196	0.476 **	−0.236	−0.399 **	−0.179	−0.020	−0.614
	(0.389)	(0.171)	(0.173)	(0.187)	(0.223)	(0.296)	(0.173)	(0.222)	(0.302)	(0.393)
Occupational characteristics										
Part-time	0.051	−1.171 **	−0.322	0.417	−0.447	−0.546	−0.111	0.882 *	−0.144	0.769
	(0.568)	(0.575)	(0.743)	(0.597)	(0.733)	(0.543)	(0.481)	(0.530)	(0.700)	(0.924)
Firm size	0.033	0.001	0.179 *	0.040	0.010	−0.066	−0.067	−0.089	−0.001	0.078
	(0.166)	(0.106)	(0.108)	(0.085)	(0.097)	(0.152)	(0.087)	(0.113)	(0.125)	(0.138)
Occupational level	1.008 **	0.817 ***	0.636 ***	0.591 **	0.584 *	−0.372	−0.301	−0.204	−0.688 **	−0.343
	(0.396)	(0.225)	(0.227)	(0.254)	(0.304)	(0.284)	(0.223)	(0.215)	(0.280)	(0.354)
Some supervisory	−0.104	0.808 **	0.370	0.628 *	0.513	−1.054 *	−0.619 **	−0.645 **	−0.852	−0.100
	(0.637)	(0.350)	(0.286)	(0.349)	(0.411)	(0.562)	(0.297)	(0.321)	(0.529)	(0.584)
Great supervisory	−0.308	0.727 **	0.237	0.675 **	0.675	−0.365	−0.797 **	−0.462	−0.464	−0.941
	(0.792)	(0.368)	(0.400)	(0.342)	(0.462)	(0.775)	(0.378)	(0.329)	(0.460)	(0.672)
Training experience	1.271 *	0.658 **	0.791 ***	0.514	0.942 **	−0.368	−0.661 **	−0.806 ***	−0.585	−0.294
	(0.685)	(0.335)	(0.283)	(0.362)	(0.474)	(0.462)	(0.278)	(0.303)	(0.363)	(0.420)
Contextual variables										
% of holding the same degree	0.033	0.069 ***	0.009	−0.007	0.004	−0.031	0.022	−0.004	0.003	0.002
	(0.042)	(0.020)	(0.017)	(0.015)	(0.018)	(0.038)	(0.022)	(0.025)	(0.027)	(0.028)
GDP growth rate	−0.462	−0.297 **	0.264	0.041	−0.218	−0.343	−0.437 ***	0.476 *	−0.269	0.031
	(0.438)	(0.142)	(0.342)	(0.213)	(0.246)	(0.376)	(0.127)	(0.252)	(0.247)	(0.303)
Constant	1.578	5.307 ***	2.077	3.024 ***	4.545 ***	−12.705 ***	−10.462 ***	−13.694 ***	−12.041 ***	−12.952 ***
	(2.227)	(1.173)	(1.693)	(1.162)	(1.682)	(2.381)	(1.418)	(2.084)	(2.702)	(3.841)
Observations	903	1897	1538	1340	874	903	1897	1538	1340	874

Note: Standard errors in parentheses. Individual's work hours, skill proficiencies, parental education, and number of living were controlled. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

Contextual factors were found to play an important role in yielding more or less number of mismatched workers only at the primetime of finding jobs. Educational context seemed to temporarily differentiate the probability of mismatch at the point of job searching. When there were many competitors holding the same degree, the probability of working at jobs overutilizing their literacy skill rose by about 7% for each unit increase in this variable. When economic conditions were favorable for job seekers, the probability of finding well-matching jobs relative to mismatching jobs was higher. A one-unit of increase in GDP growth rate was associated with 26% and 35% decreases in the odds of being overutilized and underutilized, respectively. However, economic conditions at the time of seeking employment were found to be conversely related to the odds of underutilization after 10 years. The cohort that enjoyed economic boom when they entered to the job market tended to be less utilized after 10 years.

The effect of economic conditions was also present in numeracy skill mismatch (Table 9), though it lasted longer. After another 10 years (20 years later after searching for a job), workers who entered to the labor market during good economic conditions tended to experience less numeracy skill surplus. These results indicate that the future economic condition is associated with the probability of underutilization, as the youngest workers tended to be less involved in underutilization if a business cycle was in an upsurge in 10 years. These effects can be interpreted as an extension of the lasting impact of economic conditions, especially considering that some find their jobs when younger than 25 years of age. Alternatively, the GDP growth rate and educational context were found to have minimal effect on the probability of numeracy skill overutilization (see first half in Table 9).

Table 9. Pooled model by age (numeracy skill).

(Ref. Well-Matched)	Numeracy Skill Mismatch (Pooled Model)									
	Overutilized					Underutilized				
	24 or Less	25–34	35–44	45–54	55 Plus	24 or Less	25–34	35–44	45–54	55 Plus
Individual backgrounds										
Female	−0.384 (0.410)	−0.265 (0.240)	−0.569 * (0.295)	−0.307 (0.321)	−0.068 (0.415)	0.082 (0.353)	0.034 (0.265)	0.286 (0.301)	−0.051 (0.296)	0.677 (0.412)
Immigrant	−0.538 (0.515)	0.012 (0.312)	−0.367 (0.341)	−0.508 (0.422)	−0.019 (0.670)	−0.034 (0.558)	0.277 (0.288)	0.205 (0.342)	0.741 (0.455)	−0.358 (0.745)
Education	−0.365 (0.558)	0.214 (0.183)	0.076 (0.178)	−0.021 (0.194)	0.596 ** (0.304)	−0.305 (0.299)	0.036 (0.151)	−0.096 (0.213)	−0.027 (0.295)	−0.137 (0.362)
Occupational characteristics										
Part-time	0.879 * (0.457)	−0.751 (0.600)	0.291 (0.469)	−0.125 (0.814)	0.620 (0.747)	0.017 (0.499)	−0.279 (0.490)	0.408 (0.462)	0.094 (0.534)	0.666 (0.534)
Firm size	−0.103 (0.171)	−0.073 (0.120)	0.056 (0.106)	0.128 (0.104)	−0.032 (0.144)	0.079 (0.173)	0.001 (0.066)	0.162 (0.114)	0.118 (0.092)	0.002 (0.125)
Occupational level	0.962 ** (0.390)	0.780 *** (0.217)	0.723 *** (0.244)	0.891 *** (0.251)	0.529 (0.342)	−0.362 (0.297)	−0.328 (0.212)	−0.346 * (0.190)	−0.696 *** (0.226)	−0.562 * (0.324)
Some supervisory	0.255 (0.475)	0.674 ** (0.337)	0.155 (0.330)	0.500 (0.429)	0.991 * (0.535)	−0.727 (0.618)	−0.765 ** (0.311)	−0.583 * (0.333)	−0.365 (0.386)	−0.296 (0.473)
Great supervisory	−0.522 (0.785)	0.789 *** (0.290)	−0.106 (0.385)	0.175 (0.418)	1.428 *** (0.474)	−0.715 (4.043)	−0.987 ** (0.459)	−0.379 (0.360)	−0.423 (0.370)	−0.576 (0.671)
Training experience	0.799 * (0.448)	0.336 (0.384)	0.516 (0.335)	0.093 (0.295)	0.336 (0.479)	−0.460 (0.564)	−0.415 (0.270)	−0.036 (0.341)	−0.018 (0.376)	0.158 (0.378)
Contextual variables										
% of holding the same degree	0.037 (0.059)	0.021 (0.025)	0.011 (0.017)	−0.028 (0.018)	0.023 (0.025)	0.005 (0.040)	0.024 (0.023)	−0.004 (0.025)	0.014 (0.024)	0.003 (0.032)
GDP growth rate	0.415 (0.400)	−0.115 (0.147)	0.025 (0.317)	−0.002 (0.220)	0.117 (0.245)	−0.820 ** (0.329)	−0.435 *** (0.149)	0.509 ** (0.244)	−0.551 *** (0.206)	−0.281 (0.241)
Constant	−1.155 (1.666)	2.718 ** (1.101)	1.898 (1.615)	1.907 (1.370)	0.044 (2.084)	−6.701 *** (1.904)	−8.473 *** (1.280)	−11.676 *** (1.856)	−8.386 *** (1.881)	−9.924 *** (2.454)
Observations	903	1897	1538	1340	874	903	1897	1538	1340	874

Note: Standard errors in parentheses. Individual's work hours, skill proficiencies, parental education, and number of living were controlled. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

The educational condition was rather closely related to educational mismatch. The probability of working at educationally mismatching jobs was found to decrease when there were many people holding the same degree within their cohort, and its impact was also maintained during most of their careers. Why does educational expansion decrease the probability of belonging to educationally mismatched workers? By definition of educational mismatch, workers with certain levels of education (lowest and highest) cannot be determined as overeducated or undereducated. No matter how many people have the lowest degree, there is no probability they are overeducated, vice versa. Thus, the results from undereducation in Table 10 may reflect an educational context where there are many higher education graduates. In contrast, overeducation in Table 10 (overeducated) may reflect an educational context where there are many people with degrees lower than high school.

The relationship between business cycle and educational mismatch showed a similar pattern that was found in literacy and numeracy skill mismatch. Entering the labor market in good economic conditions reduced the likelihood of finding a job requiring higher educational attainment than previously attained. In such cases, in 10 years, they were more likely to have a higher level of educational attainment than the average worker in the same workplace. Then, another 10 years later, the impact of economic conditions was more likely to return to average, thus decreasing the probability of overeducation.

Table 10. Pooled model by age (educational attainment).

(Ref. Well-Matched)	Educational Mismatch (Pooled Model)									
	Undereducated					Overeducated				
	24 or Less	25–34	35–44	45–54	55 Plus	24 or Less	25–34	35–44	45–54	55 Plus
Individual backgrounds										
Female	−2.197	0.724 *	−0.287	−1.298 **	−0.125	0.371	0.537 **	0.240	−0.078	−0.422
	(3.189)	(0.418)	(0.493)	(0.535)	(1.038)	(0.657)	(0.246)	(0.195)	(0.209)	(0.303)
Immigrant	−0.514	0.364	1.021 **	0.454	−0.087	0.010	0.026	0.957 ***	0.094	0.496
	(1.926)	(0.824)	(0.485)	(0.849)	(1.582)	(0.551)	(0.282)	(0.204)	(0.266)	(0.452)
Education	−43.458	−43.317 ***	−23.312 ***	−25.606 ***	−34.212 **	5.252 ***	3.563 ***	3.639 ***	3.641 ***	3.582 ***
	(39.269)	(6.582)	(1.614)	(5.682)	(14.272)	(0.647)	(0.238)	(0.327)	(0.322)	(0.354)
Occupational characteristics										
Part-time	−1.434	−0.228	0.533	1.473	0.966	1.408 *	0.173	0.314	−0.404	0.727
	(4.350)	(0.751)	(0.637)	(1.060)	(1.000)	(0.782)	(0.394)	(0.354)	(0.491)	(0.565)
Firm size	0.344	0.116	−0.041	0.303 *	0.081	0.117	−0.089	0.011	−0.063	−0.187 *
	(0.654)	(0.175)	(0.165)	(0.181)	(0.246)	(0.145)	(0.065)	(0.077)	(0.082)	(0.107)
Occupational level	85.745	47.941 ***	23.040 ***	23.370 ***	26.956 ***	−3.451 ***	−2.570 ***	−2.411 ***	−2.340 ***	−2.849 ***
	(93.898)	(7.331)	(1.498)	(5.664)	(9.723)	(0.534)	(0.307)	(0.338)	(0.256)	(0.443)
Some supervisory	1.251	0.277	0.526	0.431	0.904	−0.433	−0.606 **	0.041	0.456	1.032 ***
	(5.260)	(0.639)	(0.530)	(0.592)	(0.873)	(0.790)	(0.247)	(0.270)	(0.295)	(0.349)
Great supervisory	−9.031	−0.441	0.416	−0.368	0.158	0.624	0.646 **	0.307	0.965 ***	0.748 **
	(12.825)	(0.700)	(0.708)	(0.860)	(1.177)	(0.826)	(0.268)	(0.252)	(0.279)	(0.379)
Training experience	0.368	1.038 **	−0.191	0.986	0.907	−0.429	−0.296	−0.383	0.129	0.575 *
	(4.570)	(0.498)	(0.453)	(0.833)	(1.045)	(0.655)	(0.281)	(0.292)	(0.338)	(0.345)
Contextual variables										
% of holding the same degree	−5.385	−1.351 ***	−0.258 ***	−0.236 ***	−0.445	−0.172	−0.218 ***	−0.382 ***	−0.193 ***	−0.148 ***
	(7.215)	(0.247)	(0.028)	(0.032)	(0.286)	(0.114)	(0.040)	(0.051)	(0.030)	(0.031)
GDP growth rate	−0.652	−4.513 ***	−0.285	−0.178	−3.001	0.388	0.058	0.800 ***	−1.055 ***	0.172
	(1.985)	(1.157)	(0.446)	(0.380)	(3.997)	(0.428)	(0.170)	(0.301)	(0.184)	(0.229)
Constant	27.660	31.202 ***	6.373 **	9.857 ***	35.568	−6.658 **	−1.375	−1.479	0.846	−5.046 ***
	(37.587)	(6.671)	(2.777)	(2.293)	(28.233)	(2.731)	(1.706)	(1.396)	(1.514)	(1.955)
Observations	903	1897	1538	1340	874	903	1897	1538	1340	874

Note: Standard errors in parentheses. Individual's work hours, skill proficiencies, parental education, and number of living were controlled. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ (two-tailed tests).

5. Discussion

The authors of this study examined trends in educational and skill mismatch in the United States. We showed how the incidence of various types of mismatch has changed over the past 20 years and whether there are different trends by subpopulations. The impact of contextual factors on mismatch has rarely been considered in prior studies. The equilibrium between supply (workers) and demand (occupations) might determine the degree of mismatches in a society, but the context in which workers and jobs are matching differentiates the balance. Thus, to delineate a better representation of the trends in educational and skill mismatch, we employed socioeconomic variables that have not been well-investigated due to the lack of available data for application. The combined repeated-cross-sectional data allowed us to simultaneously incorporate individual, occupational, and contextual factors in models.

With respect to skill mismatch, the determinants constantly observed during the period covered by the data were variables related to the occupation or position of the workers, rather than individual characteristics. The effect of individual characteristics was confined to a specific period or minimal after controlling for job-related variables. Importantly, the less observable gender difference implies that there may have been an enhancement in people's awareness of discrimination or a change in the value of pursuits. The barriers for immigrants may also have lowered according to the increase of employers' understanding of other cultures and educational systems. Alternatively, younger workers may suffer from mismatch more than in the past, as the impact of career trajectory has become more evident. As such, starting with mismatch could be burdensome for these workers as it may prevent them from successfully navigating their careers (Acosta-Ballesteros et al. 2018; Baert et al. 2013).

An individual's educational attainment significantly influences their probability of skill mismatch. Specifically, over the last 20 years, its influence was found to be evident in overutilization, while its impact on underutilization gradually decreased. We suspect that this phenomenon is a result of a combination between the change in skill requirements and an increase in the spectrum of competitiveness of highly educated people due to the expansion of educational opportunities that have been going on for the last 20 years.

Under good economic conditions, we found that job seekers are more likely to find jobs favorable to their skill use. This result generally corresponded to the narratives suggested with the review of literature. Moreover, the results this study are consistent with those of previous research that demonstrated the impact of business cycle on overeducation through unemployment rate (Quintini 2011a; Vaisey 2006). With higher unemployment rates, the incidence of overeducation tended to increase. Vaisey (2006) explained that workers were more likely to accept less demanding jobs due to the difficulties in finding jobs under such conditions. This may appear to contradict the idea put forth by the study that the incidence of overeducation was contingent on the labor force growth rate; in the growing labor market, the incidence of overeducation tended to incline (Groot and van den Brink 2000).

However, several differences in analysis between the present study and Groot and van den Brink (2000) should be considered, as this finding may not be contradictory. First, their study focused on whether labor force growth increases the incidence of overeducation. Instead, we examined whether socioeconomic conditions in the time of entry into the labor market affect the probability of being mismatched. Due to this difference in unit of analysis, the generated results may seem to be divergent, but in certain conditions, the results could be the same. In addition, Groot and van den Brink (2000) did not consider other factors causing mismatch such as individual background and occupational characteristics. Because the labor force growth may not evenly affect all occupations, their findings are difficult to directly compare with those of this study. Finally, how the labor force growth is associated with overeducation was not clearly discussed in their study. Without such discussion, it is challenging to apply their theory in our analysis.

The influence of environmental factors was not often limited to the time of entry into the labor market; instead, it persisted throughout the career depending on the types of skill. The lasting influence seems to change with the accumulation of workers and the stages of their career according to the economy upsurge. Specifically, with respect to numeracy skill, the economic boom in entering the labor market was found to be positive in that it may provide wider options for jobs, which further allows workers to find jobs fully utilizing their skills. However, 10 years later, these workers' numeracy skill tended to be underutilized. This can be interpreted as the accumulation of workers in the boom of the economy limiting the opportunity for promotion, which may require using more of their competencies. Ten years later, the disadvantages of this period were discovered, potentially due to regression to the mean. Because there have been few studies regarding these findings and interpretations, further research is necessary to collect more supporting evidence.

There are evidently some limitations in this study—especially in the data. The authors of this study made special effort to combine cross-sectional data, but there were too few data points, which ultimately hindered this study from drawing clear trends. In addition, the age of participants in the questionnaire was given as a category (10 year bands). Without the precise age of individuals, there were limitations in giving variation to the cohort variables. Furthermore, it could have been better if it was possible to distinguish the cohort into smaller units; however, because the data did not provide the participants' age in specific years, such analysis was not applicable. Importantly, some noise in each cohort was present because the data were collected in nine year intervals. Additionally, some cohorts were only present in certain data because they did not fall within the specific age ranges. This study also solely relied on data drawn from the supply side. Although workers' responses may precisely apply to their workplace, they may simultaneously provide inaccurate information when they overestimate their abilities or have limited understanding of their work. In this regard, the measurement of mismatch in a statistical manner necessarily involves a certain level of inaccuracies.

Additionally, this study focused on the context of the United States. The socioeconomic situation and policies including the industrial structure and education system of each country are very diverse (e.g., Flisi et al. 2017; McGowan and Andrews 2015; Sparreboom and Tarvid 2016). Therefore, the socially recognized meaning of education and the relationship between education and work may differ by country. The results of this study may not be directly applicable to other countries. Additional analysis is essential with the consideration of contextual differences.

In terms of educational mismatch, this study produced less productive information due to the lack of information on elementary levels of occupations. Without such occupations, a low level of educational attainment holders cannot be well-matched or overeducated. It is more problematic in combination with the statistical approach used in measuring educational mismatch. Inherently, people with the highest and lowest schooling are not able to be undereducated and overeducated, respectively. Therefore, further studies need to be conducted with additional data and measurements that complement these limitations.

Nonetheless, the results of this study suggest various policy implications by providing an overview of trends in educational and skill mismatch. Moreover, understanding the impact of socioeconomic conditions at the time of entry into the labor market on mismatches and its persistent influence on careers may encourage policymakers to focus on the transitional period from school to work. By focusing on the association between economic conditions and mismatch, policies in relation to labor market flexibility could be a way to reduce the number of mismatched workers (e.g., Mauriès 2016; McGowan and Andrews 2015). However, giving flexibility in employment and dismissal is likely to have many side effects by reducing job security, which is associated with the contraction of consumption and low economic growth. Rather, well-designed educational policies could reduce the unfavorable circumstance at the beginning of a career. For example, educational frameworks in a country are related to the incidence of mismatches there.

By simultaneously analyzing both proportions of educational and skill mismatches, Flisi et al. (2017) drew a scatterplot and categorized countries into three groups that were closely related to their educational systems—whether they provide general or vocational-focused education. The rate of educational and skill mismatches tended to be less in countries with more stratified educational systems. Regarding educational policy, countries with higher participation rates in lifelong education tended to have fewer number of mismatched workers than their counterparts (McGowan and Andrews 2015). Supporting this finding, Mauriès (2016) further observed that investments in schools such as primary, non-tertiary, and tertiary education were positively correlated to decreasing the incidence of skill mismatch. Thus, policy-makers should provide sufficient opportunities for potential job seekers to find employment that fully utilizes their competencies through diverse policy efforts across the socioeconomic dimension, along with the consideration of educational frameworks.

Author Contributions: Conceptualization, D.-H.S. and D.B.; methodology, D.-H.S.; software, D.-H.S.; validation, D.-H.S. and D.B.; formal analysis, D.-H.S. and D.B.; investigation, D.-H.S.; data curation, D.-H.S.; writing—original draft preparation, D.-H.S. and D.B.; writing—review and editing, D.-H.S.; visualization, D.-H.S.; supervision, D.B.; project administration, D.-H.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Among three data sets, IALS and ALL data sets are available from Statistics Canada on request due to their policy. You may check the guidelines (https://nces.ed.gov/surveys/all/data.asp) in order to request these data. PIAAC data is available in a publicly accessible repository. It can be found at OECD website (https://www.oecd.org/skills/piaac/data/).

Acknowledgments: This manuscript was originally prepared as a part of dissertation of the first author and revised for this journal. The analysis in this study is based on the Statistics Canada International Adult Literacy Survey (IALS), 1994 to 1998, the International Adult Literacy Skills Survey (ALL), and Program for the International Assessment of Adult Competencies (PIAAC). All computations, use and interpretation of these data are entirely that of author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Box A1. The items measuring literacy and numeracy skill use in each survey.

The International Adult Literacy Survey (IALS) in 1994—Reading (e1a–e1g)/Writing (e2a–e2d)

- "The following questions refer to the job at which you worked the most hours in the last 12 months."
- "How often (do/did) you read or use information from each of the following as part of your main job? Would you say every day, a few times a week, once a week, less than once a week, rarely or never?" (Letters or memos/Reports, articles, magazines or journals/Manuals or reference books, including catalogs or part lists/Diagrams or schematics/Bills, invoices, spreadsheets or budgets/Materials written in a language other than English/Directions or instructions for medicines, recipes, or other products)
- "How often (do/did) you write or fill out each of the following as part of your (current/most recent) job? Would you say every day, a few times a week, once a week, less than once a week, rarely or never?" (Letters or memos/Forms or things such as bills, invoices, or budgets/Reports or articles/Estimates or technical specifications)

The Adult Literacy and Life-skills (ALL) survey in 2003—Reading (e1a–e1f)/Writing (e2a–e2e)

- "The next questions are about your reading, writing and mathematics activities at your main job -whether these activities are done on paper or on computer"
- "How often <do/did> you read or use information from each of the following as part of your main job? Would you say at least once a week, less than once a week, rarely or never" (Letters, memos or e-mails/Reports, articles, magazines, or journals/Manuals or reference books including catalogues/Diagrams or schematics/Directions or instructions/Bills, invoices, spreadsheets or budget tables)
- "How often <do/did> you write or fill out each of the following as part of your main job? Would you say at least once a week, less than once a week, rarely or never." (Letters, memos or e-mails/Reports, articles, magazines, or journals/Manuals or reference books including catalogues/Directions or instructions/Bills, invoices, spreadsheets or budget tables)

Program for the International Assessment of Adult Competencies (PIAAC) in 2012—Reading (G_Q01a-G_Q01h)/Writing (G_Q02a-G_Q02d)

- "The following questions are about reading activities that you (Undertake/Undertook) as part of your (Job/Last job). Please only report reading that (Is/was) part of your (Job/Last job), not reading you (Do/Did) in your non-work time. Include any reading you might do on computer screens or other electronic displays." (Never, less than once a month, less than once a week but at least once a month, at least once a week but not every day, every day) // (Directions or instructions/Letters, memos or e-mails/Articles in newspapers, magazines or newsletters/Articles in professional journals or scholarly publications/Books/Manuals or reference materials/Bills, invoices, bank statements or other financial statements/Diagrams, maps or schematics)
- "The following questions are about writing activities that you (Undertake/Undertook) as part of your (Job/Last job). Include any writing you might do on computers or other electronic devices." (Letters, memos or e-mails/Articles for newspapers, magazines or newsletters/Reports/Forms)

Box A2. The measurement of skill mismatch (Allen et al. 2013, p. 10).

Step 1. We restrict the analysis to respondents who are currently in paid employment and who do not describe their own current status as "Pupil, student" or "Apprentice, internship".

Step 2. For this restricted group, we standardize the relevant measure of skill level and skill use (that is, compute the z-score) for the skill domains of literacy and numeracy:

a. For skill level we take the first plausible value of each skill measure;
b. We construct a scale consisting of the mean of the seven reading use items and four writing use items included in the background questionnaire to indicate literacy use. For numeracy use, we construct a scale consisting of the mean of the six numeracy use items included in the background questionnaire.

Step 3. We subtract each standardized measure of skill use from the corresponding standardized measure of skill level.

Step 4. We define all individuals with a value of no more than 1.5 points above or below zero on this difference variable as "well-matched". We define all individuals with a value less than −1.5 as "overutilized" and all individuals with a value greater than 1.5 as "underutilized".

Table A1. The incidence and change of literacy skill mismatch.

Well–Matched										
	1994	2003	2012	Intracohort–Change				Within–Age–Change		
Cohort	Percent	Percent	Percent	1994–2003	2003–2012	1994–2012	Age	1994–2003	2003–2012	1994–2012
(7)	-	-	69.89	-	-	-	16 to 24	−8.13	3.09	−5.04
(6)	-	66.80	71.53	-	4.73	-	25 to 34	−7.32	−4.83	−12.15
(5)	74.93	76.36	75.11	1.43	−1.25	0.18	35 to 44	−2.42	−0.69	−3.11
(4)	83.68	75.80	75.03	−7.88	−0.77	−8.65	45 to 54	−1.02	−4.33	−5.35
(3)	78.22	79.36	72.18	1.14	−7.18	−6.04	55 to 65	−5.68	−4.31	−9.99
(2)	80.38	76.49	-	−3.89	-	-				
(1)	82.17	-	-	-	-	-				
All	80.06	75.70	73.12	−4.36	−2.58	−6.94				
Overutilization										
	1994	2003	2012	Intracohort–Change				Within–Age–Change		
Cohort	Percent	Percent	Percent	1994–2003	2003–2012	1994–2012		1994–2003	2003–2012	1994–2012
(7)	-	-	12.28	-	-	-	16 to 24	6.72	−0.24	6.48
(6)	-	12.52	12.78	-	0.26	-	25 to 34	5.16	0.50	5.66
(5)	5.80	12.28	12.90	6.48	0.62	7.10	35 to 44	2.93	−0.03	2.90
(4)	7.12	12.93	16.48	5.81	3.55	9.36	45 to 54	1.32	5.05	6.37
(3)	10.00	11.43	21.43	1.43	10.00	11.43	55 to 65	6.56	7.97	14.53
(2)	10.11	13.46	-	3.35	-	-				
(1)	6.90	-	-	-	-	-				
All	8.36	12.43	15.11	4.07	2.68	6.75				
Underutilization										
	1994	2003	2012	Intracohort–Change				Within–Age–Change		
Cohort	Percent	Percent	Percent	1994–2003	2003–2012	1994–2012		1994–2003	2003–2012	1994–2012
(7)	-	-	17.83	-	-	-	16 to 24	1.42	−2.85	−1.43
(6)	-	20.68	15.69	-	−4.99	-	25 to 34	2.16	4.33	6.49
(5)	19.26	11.36	11.99	−7.90	0.63	−7.27	35 to 44	−0.51	0.72	0.21
(4)	9.20	11.27	8.49	2.07	−2.78	−0.71	45 to 54	−0.32	−0.71	−1.03
(3)	11.78	9.20	6.39	−2.58	−2.81	−5.39	55 to 65	−0.87	−3.66	−4.53
(2)	9.52	10.05	-	0.53	-	-				
(1)	10.92	-	-	-	-	-				
All	11.58	11.87	11.77	0.29	−0.10	0.19				

Note: Cohort (1) 1928–1937, (2) 1938–1947, (3) 1948–1957, (4) 1958–1967, (5) 1968–1977, (6) 1978–1987, and (7) 1988–1996.

Table A2. The incidence and change of numeracy skill mismatch.

Well–Matched										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**	**Age**	**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	71.57	-	-	-	16 to 24	0.37	−2.70	−2.33
(6)	-	74.27	71.79	-	−2.48	-	25 to 34	−6.26	−4.13	−10.39
(5)	73.90	75.92	77.66	2.02	1.74	3.76	35 to 44	3.79	−2.00	1.79
(4)	82.18	79.66	77.60	−2.52	−2.06	−4.58	45 to 54	−2.85	0.21	−2.64
(3)	75.87	77.39	78.70	1.52	1.31	2.83	55 to 65	5.42	−6.87	−1.45
(2)	80.24	85.57	-	5.33	-	-				
(1)	80.15	-	-	-	-	-				
All	78.62	78.26	75.70	−0.36	−2.56	−2.92				
Overutilization										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**		**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	12.82	-	-	-	16 to 24	4.22	1.62	5.84
(6)	-	11.20	13.08	-	1.88	-	25 to 34	1.20	2.54	3.74
(5)	6.98	10.54	10.01	3.56	−0.53	3.03	35 to 44	4.65	−1.39	3.26
(4)	9.34	11.40	12.90	2.06	1.50	3.56	45 to 54	3.22	2.32	5.54
(3)	6.75	10.58	11.09	3.83	0.51	4.34	55 to 65	−6.75	4.97	−1.78
(2)	7.36	6.12	-	−1.24	-	-				
(1)	12.87	-	-	-	-	-				
All	8.34	10.34	11.94	2.00	1.60	3.60				
Underutilization										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**		**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	15.61	-	-	-	16 to 24	1.30	1.07	2.37
(6)	-	14.54	15.13	-	0.59	-	25 to 34	3.10	1.58	4.68
(5)	13.24	13.55	12.33	0.31	−1.22	−0.91	35 to 44	−8.43	3.38	−5.05
(4)	10.45	8.95	9.50	−1.50	0.55	−0.95	45 to 54	1.61	−2.53	−0.92
(3)	17.38	12.03	10.21	−5.35	−1.82	−7.17	55 to 65	−4.56	1.90	−2.66
(2)	10.42	8.31	-	−2.11	-	-				
(1)	12.87	-	-	-	-	-				
All	13.04	11.40	12.36	−1.64	0.96	−0.68				

Note: Cohort (1) 1928–1937, (2) 1938–1947, (3) 1948–1957, (4) 1958–1967, (5) 1968–1977, (6) 1978–1987, and (7) 1988–1996.

Table A3. The incidence and change of educational mismatch.

Well–Matched										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**	**Age**	**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	62.72	-	-	-	16 to 24	−5.30	9.60	4.30
(6)	-	53.12	58.15	-	5.03	-	25 to 34	2.09	8.49	10.58
(5)	58.42	49.66	63.11	−8.76	13.45	4.69	35 to 44	−10.32	18.59	8.27
(4)	47.57	44.52	60.17	−3.05	15.65	12.60	45 to 54	−12.40	14.61	2.21
(3)	54.84	45.56	58.27	−9.28	12.71	3.43	55 to 65	−5.58	11.48	5.90
(2)	57.96	46.79	-	−11.17	-	-				
(1)	52.37	-	-	-	-	-				
All	53.91	47.34	60.31	−6.57	12.97	6.40				

Table A3. *Cont.*

Undereducation										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**		**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	23.76	-	-	-	16 to 24	14.36	−12.13	2.23
(6)	-	35.89	20.94	-	−14.95	-	25 to 34	3.14	−2.07	1.07
(5)	21.53	23.01	18.85	1.48	−4.16	−2.68	35 to 44	6.75	−5.59	1.16
(4)	19.87	24.44	22.71	4.57	−1.73	2.84	45 to 54	8.96	−1.51	7.45
(3)	17.69	24.22	23.62	6.53	−0.60	5.93	55 to 65	5.34	0.29	5.63
(2)	15.26	23.33	-	8.07	-	-				
(1)	17.99	-	-	-	-	-				
All	18.27	25.42	21.63	7.15	−3.79	3.36				
Overeducation										
	1994	**2003**	**2012**	**Intracohort–Change**				**Within–Age–Change**		
Cohort	**Percent**	**Percent**	**Percent**	**1994–2003**	**2003–2012**	**1994–2012**		**1994–2003**	**2003–2012**	**1994–2012**
(7)	-	-	13.52	-	-	-	16 to 24	−9.06	2.53	−6.53
(6)	-	10.99	20.90	-	9.91	-	25 to 34	−5.22	−6.44	−11.66
(5)	20.05	27.34	18.04	7.29	−9.30	−2.01	35 to 44	3.57	−13.00	−9.43
(4)	32.56	31.04	17.12	−1.52	−13.92	−15.44	45 to 54	3.44	−13.10	−9.66
(3)	27.47	30.22	18.11	2.75	−12.11	−9.36	55 to 65	0.24	−11.77	−11.53
(2)	26.78	29.88	-	3.10	-	-				
(1)	29.64	-	-	-	-	-				
All	27.82	27.24	18.05	−0.58	−9.19	−9.77				

Note: Cohort (1) 1928–1937, (2) 1938–1947, (3) 1948–1957, (4) 1958–1967, (5) 1968–1977, (6) 1978–1987, and (7) 1988–1996.

Note

[1] The authors of this study have made their best efforts to appropriately measure skill mismatch, but the measurement of skill may have a fundamental limitation. Since skills are complex constructs, a certain level of inaccuracy in measurement is inevitable. This means that an analysis with different skill mismatch measurements may generate different results.

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