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ABSTRACT

The Magnitude and Predictors of Overeducation and Overskilling in Latin America: Evidence from PIAAC*

Occupational mismatch, defined as a discrepancy between workers' qualifications or skills and those required by their job, is a highly debated phenomenon in developed countries, but rarely addressed in developing economies from a comparative perspective. This study investigates the magnitudes of overeducation and overskilling, and their correlates, in four developing Latin American countries that have undergone a rapid and unregulated expansion of tertiary education participation (i.e. Chile, Ecuador, Mexico and Peru). Using a variety of measures derived from PIAAC data, we find that the magnitudes of subjective overeducation, and objective and subjective overskilling are sizable (particularly in Chile and Mexico), albeit lower than OECD estimates. Differences in objective overskilling between the OECD and LAC countries are largely explained by workforce skill levels. We also find that overeducation, overskilling and credential inflation affect those occupations which arguably require less qualifications. Potential supply and demand side explanations for these patterns are discussed.

JEL Classification: O54, I26, J24

Keywords: Latin America, PIAAC, occupational mismatch, overeducation, overqualification, overschooling, overskilling

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1. Introduction

An occupational mismatch can be defined as a discrepancy between workers' qualifications or skills and those required by their jobs. This phenomenon has received significant attention from the academic literature in different disciplines, such as economics, psychology and sociology, due to its relevance for both individual returns (e.g. wages, job satisfaction, career prospects, unemployment and job mobility) and country outcomes (e.g. efficiency, productivity growth and equity) (Brynin, 2002; Hartog, 2000; Quintini, 2011; Rubb, 2003; Tsang et al., 1991). However, the topic has received comparatively little research and policy attention in developing economies (Battu & Bender, 2020; Mehta et al., 2011; Quinn & Rubb, 2006).

Indeed, single-country studies on the incidence of occupational mismatches, their predictors and effects are frequent for developed countries but have only recently been carried out in Latin America (e.g. Cortez, 2017; Pearlman & Rubb, 2020; Rodríguez Lozano, 2016; Sevilla & Farías, 2020). Furthermore, previous comparative research on occupational mismatches has been conducted mostly considering European and North American countries (e.g. Allen et al., 2013; Di Stasio et al., 2016; Flisi et al., 2017; McGuinness, Bergin, et al., 2018; Verhaest & Van der Velden, 2013).

Cross-country analyses have not been conducted for the Latin American region due to previous lack of suitable and comparable data. However, nowadays, the Program for the International Assessment of Adult Competencies (PIAAC), led by the Organization for Economic Co-operation and Development (OECD), provides rich representative individual-level data that allows one to calculate multiple objective and subjective measures of occupational mismatches, based on both qualifications and skills, for an increasing number of systems, including four Latin American countries: Chile, Ecuador, Mexico and Peru.

Massive and unregulated growth in tertiary education participation in Latin American countries in recent decades has triggered fears of the phenomena of overeducation and overskilling in their adult population (Battu & Bender, 2020; Mehta et al., 2011; Quinn & Rubb, 2006). This study aims at estimating the incidences of overeducation and overskilling in Chile, Ecuador, Mexico and Peru, and comparing between them and with OECD averages, through five selected measures calculated using recently available data from PIAAC. We also explore the extent to which the differences with respect to the OECD averages are predicted by differences in the average educational and skill attainment of workers. Further, we investigate the predictors of overeducation and overskilling to understand how occupational mismatches affect different population groups, with a focus on the role of the workers' area of study and occupation.

Our main results can be summarized as follows. We find a high incidence of overeducation in the four LAC countries under analysis, which is significantly higher when one relies on the subjective rather than on the objective indicator. This is indicative of credential inflation present in all four countries. We find some variation in the incidence of subjective overeducation, with higher rates in Mexico (43%) and Chile (37%) than in Peru (31%) and Ecuador (29%). Subjective overeducation is also significantly higher (between 45% and 65%) in certain occupations (Service and Sales Workers, Agricultural and Fishery Workers, Craft Workers, Operators and Assemblers, and Elementary Occupations). Furthermore, in these occupations the differences between objective and subjective overeducation are also the largest, indicating that they are affected by a high degree of credential inflation.

Differences between objective and subjective measures of overskilling are less pronounced. We find higher subjective overskilling rates in Chile (36%) and Mexico (39%) than in Ecuador (18%) and Peru (18%). Comparison between overeducation and overskilling rates reveals that these are similar in Chile and Mexico, but overeducation is higher than overskilling in Peru and Ecuador. This means that the perceived excess of years of education that some workers bring to their job does not translate into a perceived excess of skills, and suggests that workers in Peru and Ecuador end-up in low qualification jobs relative to their educational attainment because of their relatively low skill development.

Overeducation and overskilling rates are higher in the OECD than in our four LAC countries, especially for overskilling. Differences in objective overskilling in favor of the OECD are largely explained by the additional average skill attainment of the OECD workforce. Differences in subjective overskilling, however, are unrelated to the average skill composition of the workforce. This suggests that workers' perceptions about their skill attainment comprise elements beyond the basic numeracy and literacy skills considered in this type of studies.

In relation to the predictors of overeducation and overskilling, the area of study chosen by the worker plays a significant role in predicting the probability of being overskilled, after controlling for their educational attainment, basic skills and sociodemographic characteristics. Interestingly, choosing Social Sciences and Law, Science Math and Computing, or Engineering predicts important reductions in the probability of being objectively overskilled (with respect to choosing Humanities), but predicts an increase in the probability of being subjectively overskilled. This also suggests that other skills beyond basic numeracy and literacy can be relevant when judging one's abilities, so the perception of being overskilled can rise despite holding constant workers' basic skills.

In addition, it is possible to identify a subgroup of occupations that consistently predict a reduction in the probability of being overqualified across all indicators. In particular, workers in occupations described as Legislators, Senior Officials and Managers, Professionals, and Technicians, are less likely to be overeducated and overskilled (both objectively and subjectively) than those working in Elementary Occupations, after controlling for their educational and basic skill attainment, and their sociodemographic characteristics.

Finally, we find that increases in workers' educational attainment predict significant reductions in the probability of being objectively overskilled, for the same level of basic skills, area of study and occupation. This implies that more education reduces the probability of having a low skill engagement at work, within the same area of study and occupation.

This study contributes to the field in three ways. First, we provide a comparative account of the magnitudes and predictors of occupational mismatches in four understudied countries with similar educational and job market developments and challenges. Second, we estimate and compare results from a wide range of overeducation and overskilling indicators. Third, we shed light on the reasons behind the differences in overeducation and overskilling rates between four developing countries and a developed economy benchmark (the OECD average), and find important distinctions between objective and subjective indicators.

The rest of the paper is organized as follows. In Section 2, we present the definition of occupational mismatch, with a focus on distinguishing between the constructs of overeducation and overskilling, and between objective and subjective measures of these constructs. We also review the literature regarding the predictors of occupational mismatch and relevant studies conducted in the region. In Section 3, we present the context of this study and highlight common features of the education systems and job markets in the countries considered. In Section 4, we present the secondary data, sample, indicators and predictors used, as well as the analytical approach implemented. In Section 5, we report the main results regarding the incidence and predictors of overeducation and overskilling in the region, and the differences across measures. The article concludes with a discussion of results and their policy implications, limitations of the study, and promising areas for future research.

2. Conceptual Framework and Literature Review

2.1 Occupational mismatch: Definition, trends and relevance

Occupational mismatch, at the individual level, refers to the degree to which workers possess education levels or skills that are above, below or poorly connected to those required in their current job (Desjardins & Rubenson, 2011; Green & McIntosh, 2007; McGuinness, Pouliakas, et al., 2018). This notion was first introduced by Freeman (1976) and later addressed and popularized by Duncan and Hoffman (1981), who extended the popular Mincer earnings equation to provide a measure of overeducation and its relation to wages.

Different theoretical models provide different predictions about the incidence of occupational mismatch. From a human capital theory approach, the value of education is absolute (Becker, 2009; Mincer, 1974) and there is no need for individuals to overinvest in education. Under this perspective, the aggregate level of overeducation should be low, as overeducation is regarded as a temporary phenomenon. However, the job competition (queuing) model, under the signaling framework, sees education as a positional good with relative value in the labor market (Bills, 2016). This is, the value of qualifications in the labor market depends on the distribution of educational attainment for a given population of interest (Thurow, 1975), leading to incentives for individuals to overinvest in education as a defensive strategy, which in turn results in credential inflation (Hansson, 2007). Under this perspective, the aggregate level of overeducation should be high and persistent.

The two models discussed above are not mutually exclusive and previous studies suggest that the job competition (queuing) model does not apply, to the same degree, to all countries and labor market sectors (Bills, 2003; Di Stasio et al., 2016; Van de Werfhorst, 2011). However, consensus has been achieved in the literature regarding the widespread and persistent nature of overeducation, suggesting that it is not merely an indicator of an individual, temporary, life-course phenomenon, but rather an issue of structural causation (Brynin, 2002; Korpi & T\aahlin, 2009).

Further, longitudinal studies in Western economies show important differences across countries regarding the stability, growth or decline of overeducation over time, with trends generally varying by geographical country blocks (Groot & Van Den Brink, 2000; McGuinness, Bergin, et al., 2018; McGuinness, Pouliakas, et al., 2018). Thus, variation in the incidence of overeducation has been found across countries, with estimates typically ranging from 10% to more than 40% of the working population, depending on the system studied and the measure used (Groot & Van Den Brink, 2000). Further, a recent review of overeducation research in developing countries suggests that its incidence in these contexts tends to be larger, due to the lower capacity of their labor markets to absorb the increasing supply of educated labor (Battu & Bender, 2020).

Cross-country studies of occupational mismatch have increased in the last decade, elicited by the availability of comparable data, such as those derived from the PIAAC study, which has been particularly useful in their contribution to the previously elusive study of skill mismatches (Choi et al., 2020). However, comparative analyses in this field have mostly focused on developed economies.

Despite the methodological challenges of its measurement and estimation (which will be discussed below), studying occupational mismatches is relevant due to their associations with both individual returns and country outcomes. For example, in relation to individual wages, it has been generally found that returns to overeducation are positive, but smaller than returns to required education (Brynin, 2002; Daly et al., 2000; Groot & Van Den Brink, 2000; Hartog, 2000; Rubb, 2003; Sloane et al., 1999). Some studies have also found a negative association between overeducation and job satisfaction, and have linked this to an indirect negative effect on worker productivity (Mateos-Romero & del Mar Salinas-Jiménez, 2018;

McGowan & Andrews, 2015; Ortiz, 2010; Tsang, 1987; Tsang et al., 1991). Implications at the system level relate to losses in efficiency and productivity growth (McGuinness, 2006). It has also been stressed that changes in the dispersion of attained and required education relate to changes in earnings inequality (R. B. Freeman & Katz, 2007; Hartog, 2000). Further, differences in overeducation rates across population groups can be indicative of discrimination in the labour market (for example, by gender or immigrant status).

Further, evidence from single-country studies in Latin America suggests that overeducation is a relevant phenomenon in the region, that returns to education are lower among the overeducated, and that overeducation disproportionately affects certain population groups (e.g. Castro Ramirez, 2019; Rodríguez Lozano, 2016; Sevilla & Farías, 2020).

Important policy implications can be derived from the study of occupational mismatches and its predictors. For example, a situation where overeducation is relatively large compared to overskilling suggests that the investment in schooling is not contributing proportionally to the skill formation process. In fact, overeducation can be the consequence of this low productivity of schooling, as workers nominally qualified in terms of years of education can end-up working in low qualification jobs because they lack the skills to perform in more highly qualified jobs. In such a context, policy makers would be prompted to ensure education quality and pertinence, promote proper labor market assignments, and reduce the impact of education-occupation mismatches.

2.2 Operationalizations of occupational mismatch

The most common approaches to the study of occupational mismatch have been estimating overeducation (i.e. the situation where workers have higher qualifications than those required for their occupation) and, more recently, overskilling (i.e. the situation where workers present higher skills than those required for their job) (Choi et al., 2020;

McGuinness, Pouliakas, et al., 2018). It is important to note that education mismatch and skill mismatch do not measure the same phenomenon, as individuals with the same education level can vary in their skills due to, for example, differences in experience, quality of education and ability (Green & McIntosh, 2007; Verhaest & Omey, 2006a). Furthermore, a weak and sometimes negative correlation between the incidence of education and skill mismatches has been found at the country level (Flisi et al., 2017; McGuinness, Pouliakas, et al., 2018). Thus, efforts have been made in previous studies to disentangle, and separately study, both phenomena.

There is a long and ongoing debate on how to best measure occupational mismatches (Capsada-Munsech, 2019; Choi et al., 2020; Leuven & Oosterbeek, 2011; Perry et al., 2014). In this field, an important distinction is established between objective and subjective approaches. On one hand, objective overeducation measures typically rely on the actual level of education (usually measured using the number of years of education or the International Standard Classification of Education, ISCED) attained by individuals and assess how much (e.g. more than one standard deviation) it deviates from the mean or mode of the distribution of education attained by peers working in the same occupation (under the statistical/realized matches RM method) or from the level of education considered appropriate for a job, based on evaluation by professional job analysts (under the normative/job analysis JA method). In some studies (see, for example, Desjardins & Rubenson, 2011), objective measures of overskilling are built by comparing the skill score obtained by the worker in some ability test with the degree of engagement that the worker reports having in tasks related to the skill measured by the test. High scores combined with a low skill engagement are interpreted as evidence of overskilling.

On the other hand, subjective measures typically rely on information provided by workers, by either asking them whether they think their job matches their level of education or skills (under the direct self-assessment DSA method) or asking them about the education/skill requirements of their current job (either to do or to get the job) (under the indirect self-assessment ISA method) (Capsada-Munsech, 2019; Verhaest & Omey, 2006b).

As stressed by previous methodological studies, each of these measures have their own advantages and drawbacks (Capsada-Munsech, 2019; Choi et al., 2020; Dolton & Vignoles, 2000; Hartog, 2000; Verhaest & Omey, 2010). Overall, JA indicators are regarded as the most rigorous and accurate measures, but their use is limited as they are costly to construct and difficult to keep up-to-date. Further, they are usually nationally targeted, which prevents cross-country comparisons. RM measures can be calculated using standard indicators of education/skills and occupation, available in most labor force surveys, but they do not capture credential inflation, as the reference point for determining if an individual is overeducated/overskilled is the rest of workers in the same occupation category, instead of the objective requirements to successfully perform the job tasks. Thus, they provide only an indication of the non-structural part of overeducation within occupations (Capsada-Munsech, 2019; Verhaest & Omey, 2010) and are recommended in single-country studies and in contexts where credential inflation is not pervasive. Also, objective measures require the use of arbitrary cut-off points, and can be prone to measurement error due to heterogeneity of education/skills requirements within occupational codes (Verhaest & Omey, 2010).

All in all, subjective measures are considered the most flexible indicators in taking into account job and/or local specificities, and they are usually the best empirically available choice. However, they may be prone to measurement error due to differences in perceptions of overeducation and expectations across groups, to social desirability bias, and to stereotype threat (Hartog, 2000; Steele, 1997; Verhaest & Omey, 2010). Further, the ISA approach that is based only on the respondents' assessments of the required credentials to get the job will tend to underestimate overeducation under widespread credential inflation (Verhaest &

Omey, 2010). However, if the respondents' assessments of the required credentials to do the job are taken into account, the estimation of overeducation can capture credential inflation perceptions.

An extensive range of measures have been proposed within each approach to examine occupational mismatch, and previous research shows that the estimation of overeducation and overskilling incidence is very sensitive to different specifications (Groot & Van Den Brink, 2000; Hartog, 2000; Verhaest & Omey, 2006a). For example, Flisi et al. (2017) propose 18 measures of occupational mismatch, including overeducation and overskilling indicators, based on PIAAC data, and they reveal very different pictures, both within and across countries. Similarly, Choi et al. (2020) map overeducation and overskilling across countries participating in the first waves of the PIAAC study and provide a critical stance by demonstrating that countries rank very differently, in both their incidence of overeducation and overskilling, depending on the indicator of choice. Further, the degree of correlation and overlap of individuals identified as overeducated/overskilled among measures tends to be limited (Capsada-Munsech, 2019; McGuinness, 2006; Verhaest & Omey, 2006b).

Previous studies have also found that overeducation and overskilling estimates are generally larger when measured through subjective indicators (Battu et al., 2000; Choi et al., 2020; Groot & Van Den Brink, 2000; Verhaest & Omey, 2006b). Thus, while ISA indicators are usually recommended for comparative studies, it is also advised to use multiple indicators when possible, and particularly when occupational mismatches are analyzed as a dependent variable. This, because different measures can complement each other and provide more nuanced insights on the occupational mismatch phenomenon, as they tend to measure related but different concepts (Capsada-Munsech, 2019; Verhaest & Omey, 2010). Indeed, objective and subjective indicators tackle different dimensions of overeducation, especially as objective indicators tend to reflect employers' points of view, whereas subjective measures evidence workers' perspectives.

Finally, previous studies have also stressed that individual-level predictors of occupational mismatch can differ across measures, as they label different subsets of the population as being occupationally mismatched (Verhaest & Omey, 2010), with subjective measures generally providing more conservative results regarding the predictive power of common correlates of overeducation (Capsada-Munsech, 2019; Verhaest & Omey, 2006a). Thus, some variation on the identification of significant predictors of overeducation and overskilling is expected between estimation methods (Battu et al., 2000; Choi et al., 2020).

2.3 Predictors of overeducation and overskilling

The literature stresses that processes of job matching vary over the life course and that the higher the age and experience of an individual, the lower the incidence of overeducation (Groot, 1996; Hartog, 2000). Also, while the evidence on the association between gender and overeducation is mixed (Groot & Van Den Brink, 2000; Verhaest & Omey, 2010), previous studies have found overeducation to be more frequent among female workers than among male workers in some national contexts (e.g. Di Stasio et al., 2016; McGuinness, Bergin, et al., 2018). With regard to the predictive power of social origin, usually measured through the effect of parental educational level, results are also inconclusive and context-specific (Argentin & Triventi, 2011; Barone & Ortiz, 2011; Capsada-Munsech, 2015; Verhaest & Omey, 2010). Further, within countries, it has generally been found that the likelihood of being overeducated is higher the greater the workers' educational level and his/her occupation's social status (Battu & Sloane, 2000; Dolton & Vignoles, 2000). These associations have also been confirmed in studies conducted in low- and middle-income countries (Comyn et al., 2019).

In Chile, Sevilla and Farías (2020) found that overeducation has increased over time, and that it disproportionately affects younger, highly educated and female workers. Also, Rodríguez (2016) analyzed the predictors of overeducation in Peru and found that living in rural areas and working at very small companies are positively associated with the probability of being overeducated, which in turn predicts lower salaries. Similarly, evidence from the Ecuadorian labor market suggests that education mismatch decreases as the size of the company and the individual’s experience increase (Botello Peñaloza, 2016). In line with these studies, in Mexico, a negative association was found with work experience and residence in large metropolitan areas (Quinn & Rubb, 2006).

The international literature on predictors of overskilling, in turn, is relatively scant. Previous studies show that the level of education is a key predictor of overskilling (Mavromaras & McGuinness, 2012; Morsy & Mukasa, 2020). Sevilla and Farías (2020) show that, in Chile, the rates of overskilling are larger among males, young workers and those with tertiary education degrees.

The variables mentioned above (namely, sex, age, parental education, education level, employment sector and company size) are used as control variables in the present study, which focuses on the role of area of study and occupation in predicting overeducation and overskilling, and the consistency of these associations across types of measures.

With regard to area of study, overeducation and overskilling have been found to be more frequent among graduates from certain fields of study, such as the humanities, the social sciences and vocational fields (Barone & Ortiz, 2011; Mavromaras & McGuinness, 2012; Morsy & Mukasa, 2020; Ortiz & Kucel, 2008; Robst, 2007). Also, Sevilla and Farías (2020) show that, in Chile, graduates from science, technology, engineering and mathematics (STEM) fields are particularly likely to be both overqualified (under the ISA method) and overskilled in numeracy. In relation to occupation, there are fewer studies, but focusing on

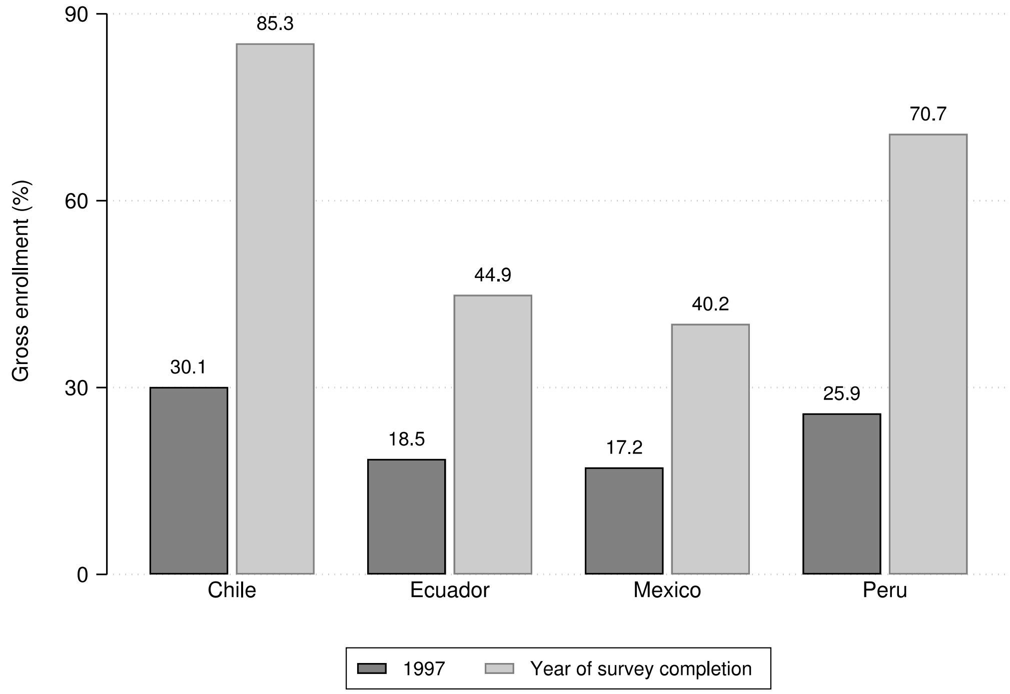
Chilean tertiary education graduates, Castro (2019) finds that workers in technical occupations are significantly more likely to be overeducated.

3. Context and its potential effect on overeducation and overskilling

Massification of tertiary education has become a general trend worldwide in the past decades (Schofer & Meyer, 2005), and enrollment growth has been particularly accelerated in some Latin American countries (Marginson, 2016). Further, the countries under study (Chile, Ecuador, Mexico and Peru) have not only seen a rapid expansion of tertiary education, but this has occurred, to different extents, in contexts of widespread privatization and deregulation of education systems, which in turn has led to a heterogeneous and socio-economically segregated provision (Ferreyra et al., 2017; PNUD, 2017; Schwartzman, 2020; Sverdlick et al., 2005).

According to Figure 1, enrollment rates in tertiary education more than doubled in these four countries in the last two decades. Chile's enrollment went from 30% in 1997 to 85% in 2015. Ecuador's rate increased from 19% to 45%. This proportion grew in Mexico from 17% to 40%, and in Peru from 26% to 71%.

Figure 1. Gross enrollment ratio in tertiary education, 1997 and year of survey completion.



Source: World Development Indicators (UNESCO Institute for Statistics).
Notes: The gross enrollment ratio for tertiary education is calculated by dividing the number of students enrolled in tertiary education, regardless of age, by the population of the age group which officially corresponds to tertiary education and multiplying by 100. In Ecuador, Mexico and Peru, PIAAC data collection was completed in 2017; in Chile, in 2015. As there is no data on Ecuador's gross enrollment in 2017, we report the information from the nearest available year (2015).

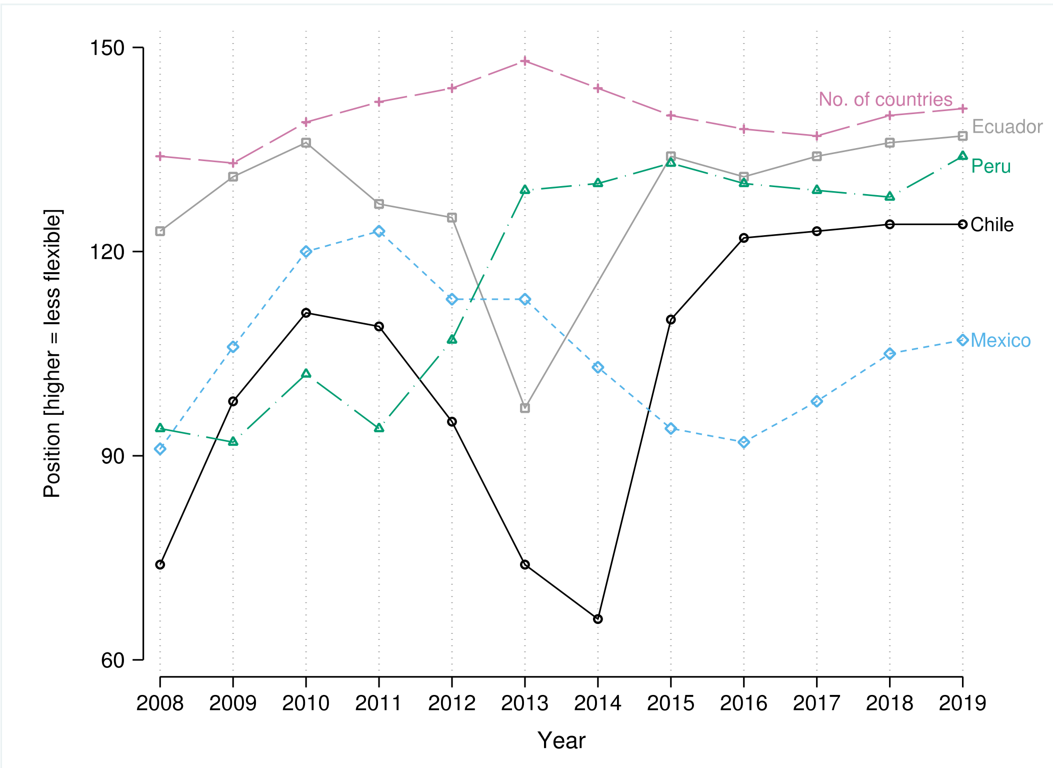
The capacity to absorb the massive waves of new professionals produced by these education systems has been supported by only moderate and rather volatile rates of economic growth in the four countries (Table 1). Likewise, labor protection codes in these economies are considered by employers to be relatively rigid, restraining their labor demand: international rankings place the four countries in the bottom third of economies in terms of labor flexibility (Figure 2).

Table 1. Average real GDP growth rate by five-year period (%).

Country \ Period	2000-2004	2005-2009	2010-2014	2015-2019
Chile	4.61	3.79	4.62	2.04
Ecuador	4.03	3.76	5.15	0.52
Mexico	1.97	0.99	3.33	2.04
Peru	3.58	6.51	5.81	3.17

Source: World Development Indicators (World Bank and OECD).
Note: The annual percentage growth rate of GDP is calculated at constant 2010 U.S. dollars.

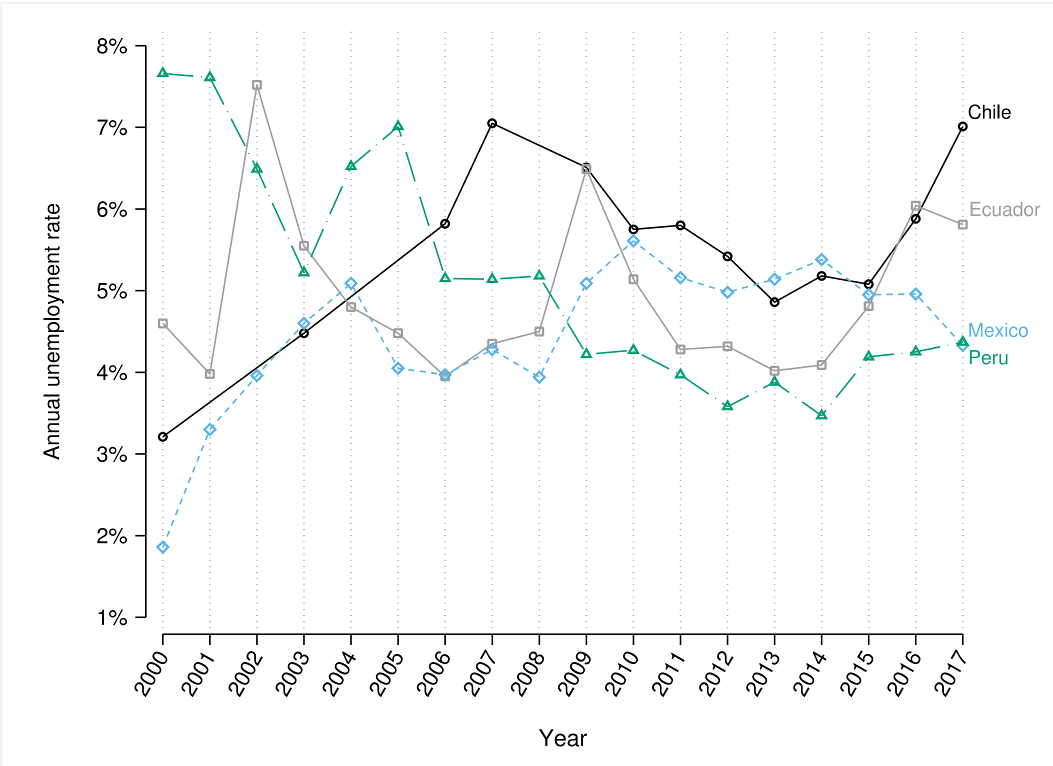
Figure 2. Evolution of the hiring and firing practices ranking, 2008-2019.



Source: The Global Competitiveness Report, 2008-2019 (World Economic Forum).
Notes: No. of countries represents the total number of countries included in each year's ranking. A higher position in the ranking reflects a lower value for the hiring and firing practices indicator, which is calculated from business executives' responses to the question "In your country, to what extent do regulations allow for the flexible hiring and firing of workers?" [1 = not at all, 7 = to a great extent]. Therefore, a higher position in the ranking implies less flexibility in hiring and firing workers.

Despite the combination of massive tertiary education enrollment and moderate economic growth, open unemployment rates for professionals have not raised significantly in the period (Figure 3), fluctuating around 5% of the labor force in the four countries. These statistics likely mask substantial underemployment situations, which are a form of occupational mismatch that can manifest through high rates of overeducation or overskilling.

Figure 3. Annual unemployment rate of the population with tertiary education, 2000-2017.



Source: World Development Indicators (International Labour Organization, ILOSTAT database).
Note: The annual unemployment rate describes the percentage of the labor force with an advanced level of education who are unemployed. Advanced education comprises short-cycle tertiary education, a bachelor's degree or equivalent education level, a master's degree or equivalent education level, or a doctoral degree or equivalent education level, according to the International Standard Classification of Education 2011 (ISCED 2011).

Based on the evidence surveyed above, our hypothesis regarding the incidence of overeducation is that it should be high in the four LAC countries under analysis, reflecting the effect of rapid massification in tertiary education and only moderate economic growth, combined with relatively low flexibility in the labor market.

The manner in which this process has affected overskilling, however, is less clear and will depend on the extent to which the additional years of education translated into more skills and on the complexity of the occupations that have accommodated tertiary education graduates. One can expect overskilling to be comparatively lower than overeducation if access to tertiary education has failed to translate into more skills among the workforce. This supply side phenomenon is likely to happen in the LAC countries under analysis because of the lack of regulation and heterogeneity that has characterized the expansion of tertiary education in these countries, and the comparatively low skills achieved by secondary education students (OECD, 2019), which are likely to be carried forward after compulsory schooling. On the demand side, the low complexity of these economies -concentrated in primary sectors of extractive industries and basic services- (Hausmann et al., 2014)[2] and their slow technological change (Crespi et al., 2010; Katz, 2001) could have meant that these tertiary education graduates were absorbed in jobs with a significantly low skill use. This demand side of the story predicts higher overskilling.

4. Method

In this study, we seek to document the incidences of overeducation and overskilling in Chile, Ecuador, Mexico and Peru, considering both objective and subjective measures. In doing so, we will compare these incidences with respect to the average rates observed in the group of OECD countries[3], and estimate how much of these differences can be predicted by differences in the educational and skill attainment of their workers. In addition, we will document the incidence of overeducation and overskilling across areas of study and occupations and evaluate their role as predictors of these phenomena after controlling for individual characteristics.

[2] Although this is not the case for Mexico, according to Hausmann et al. (2014) Economic Complexity Index.
[3] In this paper, the calculation of OECD averages does not consider Chile and Mexico, despite the fact that both countries are OECD members, to avoid confounded samples.

4.1 Data

The Survey of Adult Skills is an international survey conducted as part of PIAAC. This survey is carried out by interviewing a representative sample of adults in each participating country, collecting a broad range of information through a background questionnaire and assessing skills in literacy, numeracy and problem solving in technology-rich environments. PIAAC participant countries are mainly OECD members. In recent waves, some Latin American countries have joined, and data from Chile (that joined in round 2: 2014-2015), Ecuador, Mexico and Peru (that joined in round 3: 2017) are now available (OECD, 2019).[4]

After removing cases with incomplete data, individuals without secondary education and those who are self-employed or who, despite being formally in employment (objective status), are self-reportedly pupils/students or apprentices/interns (subjective status),[5] the resulting sample consisted of 1,751 individuals for Chile, 970 for Ecuador, 1,025 for Mexico, and 2,077 for Peru.

4.2 Variables

As highlighted by several authors (e.g. Capsada-Munsech, 2019; Flisi et al., 2017), PIAAC data provides opportunities for deriving more nuanced measures of occupational mismatch, by allowing the estimation of both educational and skill mismatches. Given the sensitivity of results to the use of different occupational mismatch definitions and indicators (Capsada-Munsech, 2019; Choi et al., 2020; Groot & Van Den Brink, 2000), a variety of measures are considered in this study.

[4] As data collection took place earlier for Chile, differences with other countries can, in part, be due to historical/cohort effects (Elias & Purcell, 2004). However, as shown by Sevilla and Farías (2019), overeducation has recently increased in Chile. Thus, in this case, the estimates for this country are likely to be conservative.
[5] This, to allow valid comparisons with results reported in Flisi et al. (2016), and as recommended in other studies using PIAAC data (e.g. Pellizzari & Fichen, 2017).

In particular, we 1) calculated 18 measures proposed by Flisi et al. (2017), which are described in Table A1 in Appendix A, and 2) classified them into five groups of indicators: (i) objective overeducation; (ii) subjective overeducation; (iii) objective overskilling in numeracy; (iv) objective overskilling in literacy; and (v) subjective overskilling. Since some of the computed indicators are, by design, very similar, we 3) applied Principal Component Analysis (PCA) within groups (i) and (iii) to select representative measures (see Table A2 in Appendix A for the detailed results). Further, we also 4) privileged consistency across indicators and, therefore, within group (iv) we chose SKILL_LIT2 (the second objective literacy overskilling indicator with the greatest factor loading) because of its similarity with SKILL_NUM2 (the objective numeracy overskilling indicator with the greatest factor loading); and within groups (ii) and (v), we selected SUB_EDU2 and SUB_SKILL1, respectively, because both are based on two analogous conditions (see Table A1 for definitions of occupational mismatch measures).

The selected occupational mismatch measures are as follows:

- Objective overeducation (EDU_YEAR2): An individual is overeducated if his/her years of education are one standard deviation higher than the average years of education in his/her occupation (ISCO 1-digit) and country. This is, thus, an objective indicator calculated using the RM method.
- Subjective overeducation (SUB_EDU2): An individual is overeducated if, in his/her opinion, his/her level of education is higher than the level of education he/she thinks is required to get his/her job or if he/she responds that 'a lower level (of education) would be sufficient' to perform his/her job satisfactorily.
- Objective overskilling in literacy (SKILL_LIT2): An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC proficiency level

scale), and if he/she has a low/medium-low level of literacy engagement in his/her job (engaging in literacy-related tasks less than or once a week).

- Objective overskilling in numeracy (SKILL_NUM2): An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC proficiency level scale), and if he/she has a low/medium-low level of numeracy engagement in his/her job (engaging in numeracy-related tasks less than or once a week).
- Subjective overskill (SUB_SKILL1): An individual is overskilled if, in his/her opinion, he/she has the capabilities to cope with more demanding tasks than those required of him/her in his/her job, and he/she does not need further training in order to cope well with his/her present duties.

Control and predictor variables

Based on our review of the literature and data availability, the following variables were considered in the analysis of predictors of overeducation and overskilling:

Socio-demographic characteristics: Sex, age, parental education (a binary variable indicating if at least one of the parents has graduated from secondary education, or not) and fixed effects for countries.

Employment characteristics: Sector (a binary variable indicating if the person works in the public sector, on one hand, or in a non-profit organization or in the private sector, on the other); and, company size (a set of dummy variables indicating the number of people working for current employer: 1 to 10, 11 to 50, 51 to 250, 251 to 1000 or more than 1000).

Literacy and numeracy skill scores: Standardized scores in the PIAAC test for literacy (defined as the ability to understand, use, and respond appropriately to written texts) and numeracy (understood as the ability to use basic mathematical and computational skills).

Level of education: A set of dummy variables indicating the highest level of education attained, from the following categories: Secondary (used as reference category), Post-secondary non-tertiary, Short-cycle tertiary, Bachelor's degree, and Master's degree/PhD.

Area of study: A set of dummy variables indicating the area of study of the highest degree attained, with the following possible categories: General programmes; Education (teacher training and education science); Humanities (humanities, languages and arts; used as reference category); Social sciences, business and law; Science, maths and computing; Engineering (engineering, manufacturing and construction); Agriculture and veterinary; Health (health and welfare); and, Services. Respondents classified themselves into one of these categories.

Occupation (ISCO 1-digit): A set of dummy variables indicating membership to the following occupational categories: Armed forces occupations; Legislators, senior officials and managers; Professionals; Technicians and associate professionals; Clerks (clerical support workers); Service and sales workers; Skilled agricultural, forestry and fishery workers; Craft and related trades workers; Plant and machine operators, and assemblers; and, Elementary occupations (used as reference category).

Table 2 indicates the distribution of the sample by sex, age group, educational level, area of study, and occupation categories, in the four LAC countries and in the aggregate of OECD countries. Moreover, the third and fourth rows show the average literacy and numeracy scores obtained by adults in these countries and in OECD countries as a whole. Indeed, Chilean, Ecuadorian, Mexican, and Peruvian adult populations have much lower literacy and numeracy skills, as measured by PIAAC, than the OECD aggregate adult population (the gap ranges from 63.4 to 151.8% of a standard deviation), as stressed in previous studies (e.g. Arroyo & Valenzuela, 2018). In terms of educational attainment, all LAC countries show a larger share of the adult population with secondary education only, compared to OECD countries. With respect to areas of study, there is relative concentration of General Studies in Chile and Peru, and of Social Sciences, Law, Science and Math in Ecuador and Mexico. Regarding occupations, LAC countries have a much higher share of elementary occupations compared to OECD aggregates, and a somewhat higher share of Services and sales workers and Clerks.

Table 2. Distribution of the sample according to sex, numeracy and literacy proficiency, age group, educational level, area of study and occupation type (ISCO 1-digit).

		Chile	Ecuador	Mexico	Peru	OECD
	Observations	1,751	970	1,025	2,077	83,605
Literacy proficiency	Mean	239.9	212.8	248.4	217.1	287.6
	SD	44.8	47.4	40.0	47.0	42.6
Numeracy proficiency	Mean	231.0	209.1	241.3	210.6	280.4
	SD	51.9	48.6	42.5	54.0	47.3
Sex	Male	0.58	0.57	0.57	0.58	0.51
	Female	0.42	0.43	0.43	0.42	0.49
Age group	16-24	0.16	0.20	0.23	0.29	0.11
	25-34	0.34	0.35	0.35	0.33	0.26
	35-44	0.23	0.25	0.22	0.20	0.26
	45-54	0.18	0.15	0.15	0.12	0.23
	55-65	0.10	0.06	0.06	0.07	0.14
Highest level of education attained	Secondary	0.58	0.44	0.57	0.58	0.36
	Post-secondary non-tertiary	0.00	0.08	0.00	0.00	0.08
	Short-cycle tertiary	0.25	0.00	0.04	0.19	0.16
	Bachelor's degree	0.15	0.42	0.34	0.19	0.25
	Master's degree/PhD	0.03	0.06	0.05	0.04	0.15
Area of study	General programmes	0.22	0.07	0.13	0.55	0.14
	Education	0.09	0.14	0.10	0.09	0.09
	Humanities	0.11	0.04	0.05	0.02	0.08
	Social sciences and law	0.10	0.27	0.31	0.11	0.20
	Science, maths and computing	0.11	0.22	0.16	0.05	0.11
	Engineering	0.18	0.14	0.13	0.09	0.18
	Agriculture and veterinary	0.02	0.04	0.02	0.01	0.02
	Health	0.07	0.08	0.07	0.05	0.12
	Services	0.09	0.02	0.02	0.02	0.06
Occupation (ISCO 1-digit)	Armed forces	0.01	0.00	0.00	0.01	0.01
	Legislators, senior officials and managers	0.03	0.04	0.12	0.03	0.10
	Professionals	0.16	0.29	0.23	0.19	0.25
	Technicians	0.17	0.11	0.13	0.13	0.19
	Clerks	0.14	0.10	0.12	0.12	0.10
	Service and sales workers	0.20	0.19	0.18	0.22	0.17
	Agricultural and fishery workers	0.02	0.03	0.00	0.01	0.01
	Craft workers	0.12	0.09	0.05	0.10	0.07
	Operators and assemblers	0.07	0.06	0.08	0.06	0.05
	Elementary occupations	0.09	0.10	0.09	0.13	0.05

4.3 Empirical strategy

As discussed in Section 2, overeducation and overskilling are based on the existence of a mismatch between one's educational or skill level and the educational or skill level required at one's job. Therefore, differences in the incidence of this mismatch can be due to differences in either of these two variables.

In this study, we rely on a variety of indicators that approximate the educational or skill level required at the workplace in different ways. In fact, the objective measure of overeducation captures this requirement through the educational attainment of colleagues. The subjective measure of overeducation captures this through the worker's perception about the education required to get or perform the job. In the case of overskilling, and depending on whether one relies on the objective or subjective measure, the skill requirements of the job are captured through the level of skill engagement at the workplace or the perceived degree of difficulty of the tasks performed at the workplace, respectively.

In the next section we will document and compare the incidence of overeducation and overskilling between LAC countries and the OECD average, and between different areas of study and occupations. An interesting question is how much of the differences we encounter can be related to differences in the average educational and skill attainment of workers, and how much to the differences in the educational and skill requirements of their jobs. To shed light on this matter, we seek to: 1) explore how much of the differences in overeducation and overskilling between our four LAC countries and the OECD average are predicted by differences in the educational and skill attainment of workers; and 2) investigate how changes in the area of study of the worker or in his/her occupation predict a change in the likelihood of being overeducated or overskilled, after holding his/her levels of education and skills constant.

To implement 1), we estimate raw and controlled differences between each LAC country and the OECD average for every indicator. The raw difference is simply the difference in the incidence of overeducation and overskilling between the LAC country and the OECD. The controlled differences refer to the difference that remains after controlling for the educational or skill attainment of the workers and a set of basic socio-demographic characteristics. We run the following OLS regressions to obtain these estimates:

$$m_i = \alpha_1 + \sigma_{1C}C_i + \sigma_{1E}E_i + \sigma_{1M}M_i + \sigma_{1P}P_i + \varepsilon_{1i} \quad (1)$$

$$m_i = \alpha_2 + \sigma_{2C}C_i + \sigma_{2E}E_i + \sigma_{2M}M_i + \sigma_{2P}P_i + \theta_2{}'t_i + \varepsilon_{2i} \quad (2)$$

$$m_i = \alpha_3 + \sigma_{3C}C_i + \sigma_{3E}E_i + \sigma_{3M}M_i + \sigma_{3P}P_i + \theta_3{}'t_i + \mu_3{}'s_i + \varepsilon_{3i} \quad (3)$$

Where m_i indicates whether individual i is overeducated or overskilled according to the occupational mismatch indicator m; α_1, α_2 and α_3 are the intercepts; C_i, E_i, M_i and P_i are variables that take the value of 1 if the individual i lives in Chile, Ecuador, Mexico or Peru, respectively, and 0 otherwise (country fixed effects); t_i is a vector that contains one or two individual characteristics depending on the particular mismatch indicator used (years of education if EDU_YEAR2 or SUB_EDU2 are used, a variable that indicates if the individual is medium-low or high skilled in literacy if SKILL_LIT2 is used, a variable that indicates if the individual is medium-low or high skilled in numeracy if SKILL_NUM2 is used, or these last two variables if SUB_SKILL1 is used); s_i is a vector containing a set of sociodemographic control variables of the individual i (i.e. sex, age and parental education); and ε_{1i}, ε_{2i} and ε_{3i} are the error terms.

Coefficients σ_{1C}, σ_{1E}, σ_{1M}, σ_{1P} in equation (1) provide the raw differences. Coefficients σ_{2C}, σ_{2E}, σ_{2M}, σ_{2P} in equation (2) provide the controlled difference considering the educational or skill attainment of the workers. Coefficients σ_{3C}, σ_{3E}, σ_{3M}, σ_{3P} in equation (3) provide the controlled difference considering the educational or skill attainment of the workers and his/her sex, age group and parental education.

To implement 2), we run the following OLS regressions:

$$m_i = \alpha_4 + \sigma_{4E}E_i + \sigma_{4M}M_i + \sigma_{4P}P_i + \sum_{j=1}^{9} \beta_j\, a_{ji} + \sum_{j=1}^{5} \delta_{4j}\, e_{ji} + \theta_4 ns_i + \vartheta_4 ls_i + \mu_4{}'s_i + \varepsilon_{4i} \quad (4)$$

$$m_i = \alpha_5 + \sigma_{5E}E_i + \sigma_{5M}M_i + \sigma_{5P}P_i + \sum_{j=1}^{10} \tau_j\, o_{ji} + \sum_{j=1}^{5} \delta_{5j}\, e_{ji} + \theta_5 ns_i + \vartheta_5 ls_i + \mu_5{}'s_i + \omega_5{}'l_i + \varepsilon_{5i} \quad (5)$$

Where α_4 and α_5 are the intercepts, a_{ji} is a variable that takes the value of 1 if individual i attained his highest level of education in the area of study j, o_{ji} is a variable that takes the value of 1 if individual i works in the occupation j, e_{ji} is a variable that takes the value of 1 if level j is individual i's highest level of education, ns_i is the standardized numeracy skills score of the individual i, ls_i is the standardized literacy skills score of the individual i, l_i is a vector containing the employment characteristics of individual i (i.e. public or private sector and company size), and ε_{4i} and ε_{5i} are the error terms. All data manipulation and analysis were conducted in the software *Stata*.

5. Results

Results are presented in four sections. First, we describe and compare the incidence of overeducation and overskilling across countries and measures. Then, we discuss differences with respect to the OECD average, and how much of these differences are predicted by differences in the educational and skill attainment of workers. In a third section, we explore the incidence of overeducation and overskilling across areas of study and occupations.

Finally, we evaluate the role of areas of study and occupations as predictors after controlling for individual characteristics.

5.1 Incidence of overeducation and overskilling

Figures 4 and 5, show the incidence of overeducation and overskilling, respectively, in Chile, Ecuador, Mexico, Peru and OECD countries (average), according to the five selected indicators described in Section 3.

Figure 4. Overeducation mismatch by country (%).

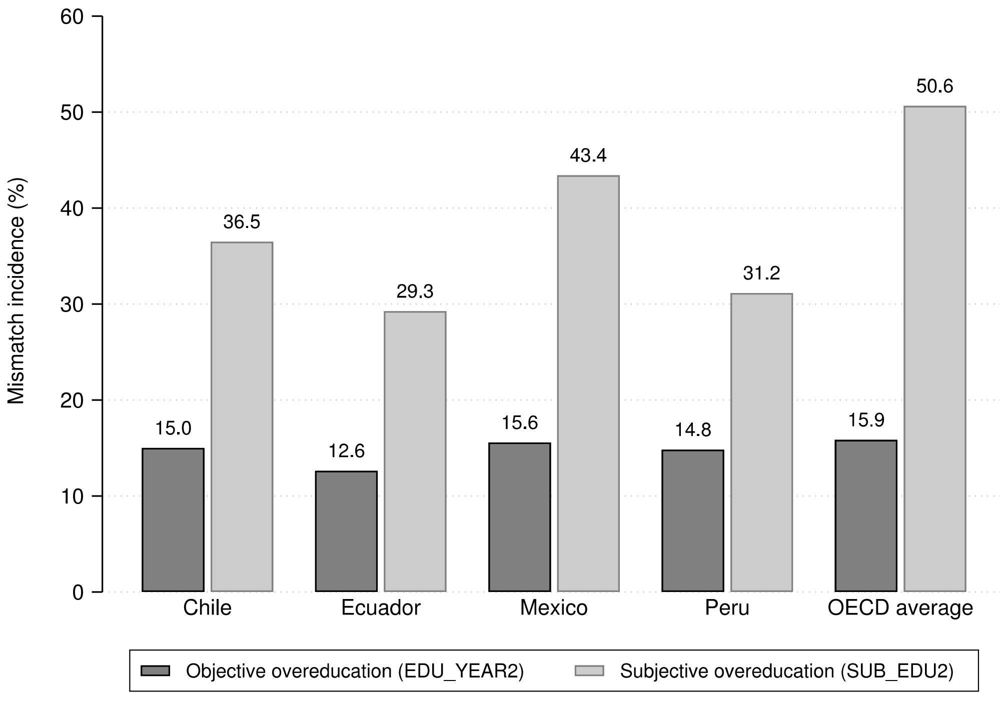
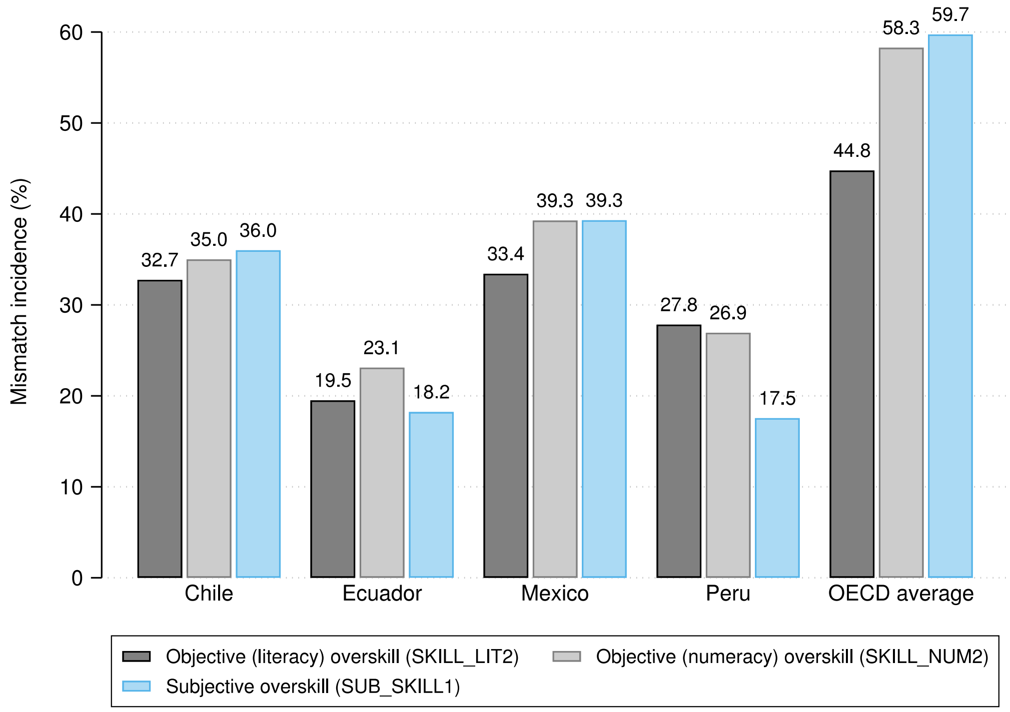


Figure 5. Overskill mismatch by country (%).



As discussed above, our objective overeducation indicator (EDU_YEAR2) is a relative measure of overeducation within the distribution of each country. Its incidence does not vary substantially across countries, ranging from 12.6% in Ecuador to 15.6% in Mexico. The subjective overeducation indicator (SUB_EDU2), in turn, is based on the assessment of workers regarding the level of education required to get and perform their job. This indicator is better suited for cross-country comparisons (Capsada-Munsech, 2019). The incidence of overeducation according to this measure is significantly higher than that estimated using the objective indicator, and ranges from 29.3% in Ecuador to 43.4% in Mexico.

The fact that subjective overeducation figures are significantly higher than the results for the objective indicator (with differences ranging between 16.4 percentage points (pp) in Peru and 27.8 pp in Mexico) is consistent with the evidence reported in the literature and surveyed above. In fact, a plausible explanation for this difference is that our objective measure does not capture credential inflation, as the reference educational attainment is the average schooling of the workforce in the same occupation. As discussed above, the higher incidence of overeducation revealed by the subjective indicator (which is particularly high in Mexico and Chile, and somewhat lower in Ecuador and Peru), is consistent with a labor force with increased nominal years of education and academic degrees, that has been absorbed by economies that do not appear to demand or recognize those additional investments.

But, to what extent do these additional years of education translate into or predict more skills? Workers are being allocated to jobs that seem to require a lower educational attainment than the one they have. Is this happening despite or because of the skill levels that they have? Figure 5 presents the results obtained for the three overskilling indicators. As highlighted in Section 2, these results are rather novel for developing countries and can be used to shed light on the questions raised above. In particular, a situation where overeducation and overskilling figures are similar is consistent with more years of education predicting more skills. In contrast, a situation where overeducation is significantly larger than overskilling is consistent with more nominal years of education failing to predict further skill development.

In literacy, objective overskilling (SKILL_LIT2) ranges from 19.5% in Ecuador to 33.4% in Mexico. In the case of numeracy, objective overskilling (SKILL_NUM2) ranges from 23.1% in Ecuador to 39.3% in Mexico. In relation to the incidence of subjective overskilling (SUB_SKILL1), it ranges from 17.5% in Peru to 39.3% in Mexico. Interestingly, overskilling tends to be consistently higher for Mexico and Chile, and somewhat lower in Ecuador and Peru.

We will rely on the subjective measures to compare the overeducation and overskilling figures because, as explained above, the objective overeducation indicator is likely underestimating this phenomenon due to credential inflation. Comparison of the subjective overeducation and overskilling figures reveals mixed results. In fact, overeducation and overskilling rates are similar in Chile and Mexico, while overeducation is larger than overskilling in Ecuador (by 11.1 pp) and Peru (by 13.7 pp). This evidence indicates that in Ecuador and Peru, the perceived excess of years of education that some workers bring to their job does not translate into a perceived excess of skills. This, in turn, suggests that these workers ended-up in low qualification jobs relative to their educational attainment, at least in part, because of their relatively low skill development.

5.2 Differences with the OECD, and the role of workers' educational attainment and skill levels

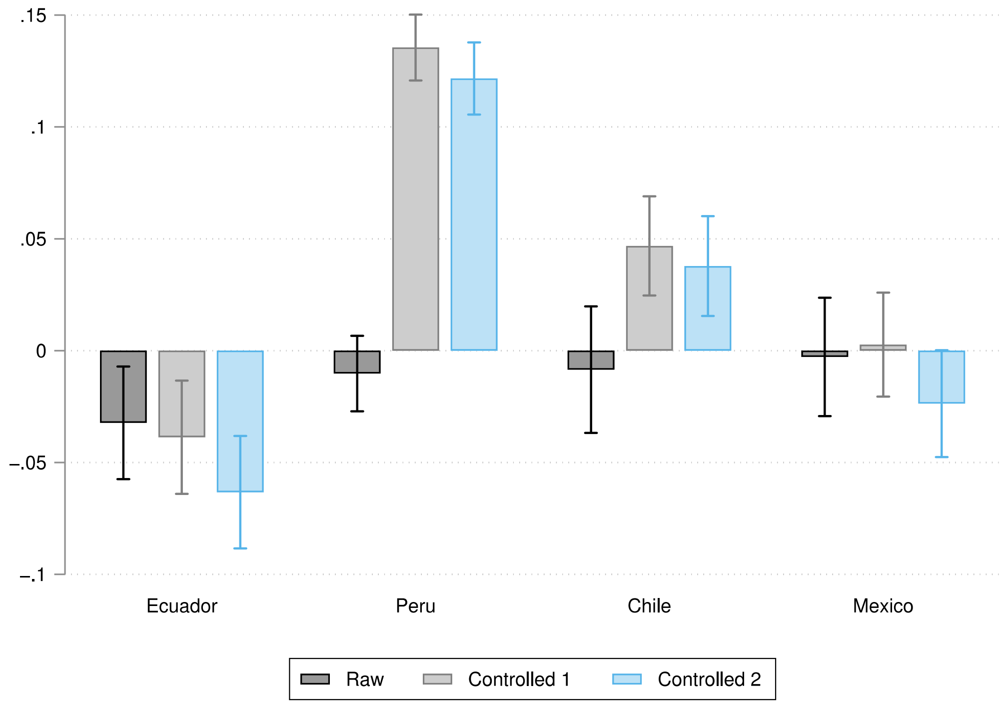
In this section, we focus on comparing overeducation and overskilling rates between the four LAC countries and the OECD average. As shown in Figure 4, on average, OECD countries have similar incidences of objective overeducation to those observed in Ecuador, Peru, Chile and Mexico. In terms of subjective overeducation, the OECD average remains above the incidence observed in all four LAC countries.

Differences between the OECD and LAC are much more significant in terms of overskilling. As revealed by Figure 5, the incidence of overskilling is significantly higher in OECD economies, with differences that can be as large as 42.2 pp in the case of subjective overskilling when compared with the estimate for Peru.

An interesting question is how much of these differences can be related to differences in the average educational and skill attainment of workers, and how much to the differences in the qualification and skill requirements of the jobs. On the supply side, in our sample (that excludes individuals that did not complete secondary education), LAC countries have lower skills and educational attainment than OECD countries, according to the descriptives shown in Table 2. On the demand side, LAC countries also arguably require less skills in their jobs because of their lower level of economic development and complexity. A sign of this latter fact is the higher share of elementary occupations in LAC, shown in Table 2.

To shed light on the question above, in what follows we present raw and controlled differences between each LAC country and the OECD for every indicator, estimated using the empirical strategy described in Section 4.3. Figures 6 to 10 depict the results of this exercise. In every figure and for each LAC country, we present the raw difference first, followed by the controlled differences after holding constant: 1) the educational or skill attainment of workers; and 2) the educational or skill attainment of workers and his/her sex, age group and parental education.

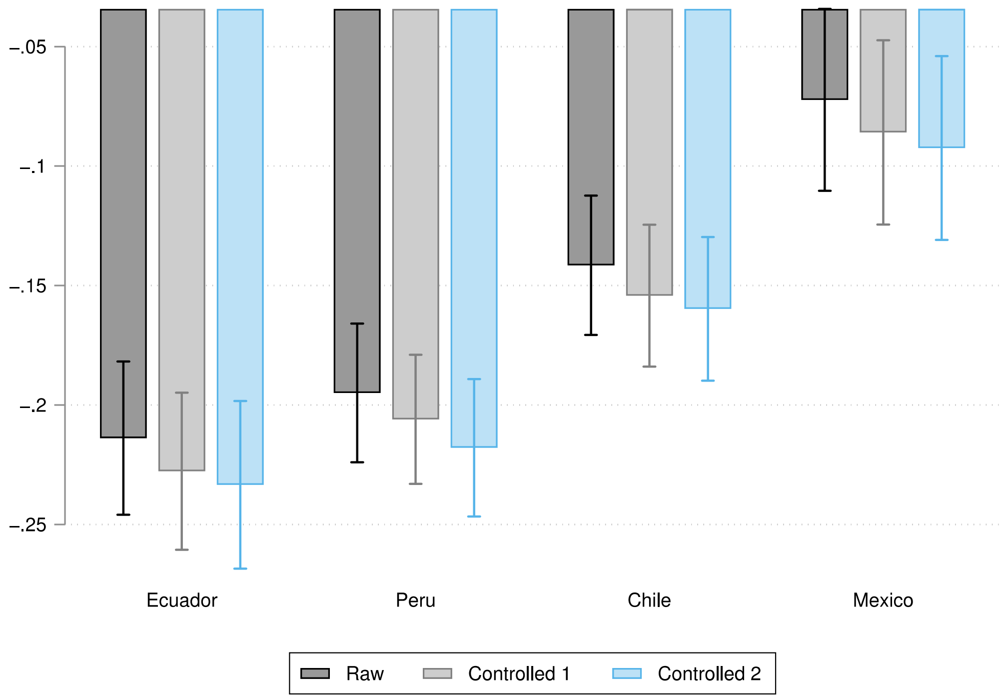
Figure 6. Raw and controlled differences in the incidence of objective overeducation (EDU_YEAR2) between the selected countries and the OECD average.



Notes: “Raw” corresponds to the difference in incidence between the LAC country and the OECD average. “Controlled 1” corresponds to the difference after controlling for the workers’ years of education. “Controlled 2” corresponds to the difference after controlling for the workers’ years of education, sex, age group and parental education. Vertical lines indicate 95% confidence intervals.

Figure 6 confirms that objective overeducation rates across the four LAC countries are not significantly different from the average rate for the OECD countries. Differences range between -0.3 pp for Mexico and -3.2 pp for Ecuador. Controlled differences, however, are larger and more heterogeneous. In the case of Ecuador and Mexico, the probability of being objectively overeducated grows in favor of the OECD after controlling for the workers' educational attainment and socio-demographic characteristics. The opposite happens for Peru and Chile, where the probability of being overeducated grows in favor of these countries after holding constant workers' education.

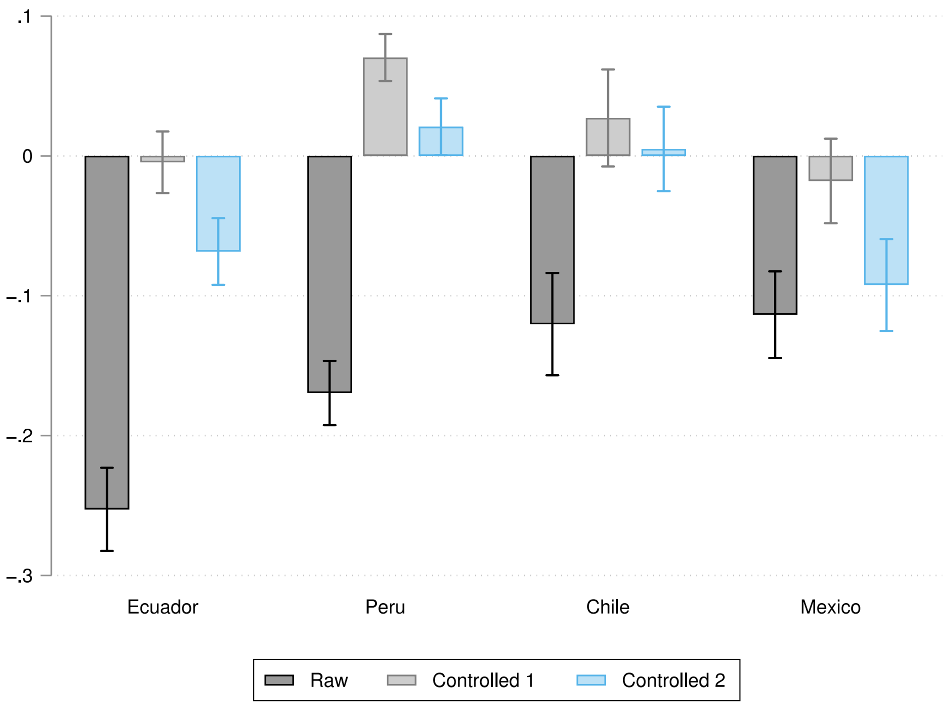
Figure 7. Raw and controlled differences in the incidence of subjective overeducation (SUB_EDU2) between the selected countries and the OECD average.



Notes: "Raw" corresponds to the difference in incidence between the LAC country and the OECD average. "Controlled 1" corresponds to the difference after controlling for the workers' years of education. "Controlled 2" corresponds to the difference after controlling for the workers' years of education, sex, age group and parental education. Vertical lines indicate 95% confidence intervals.

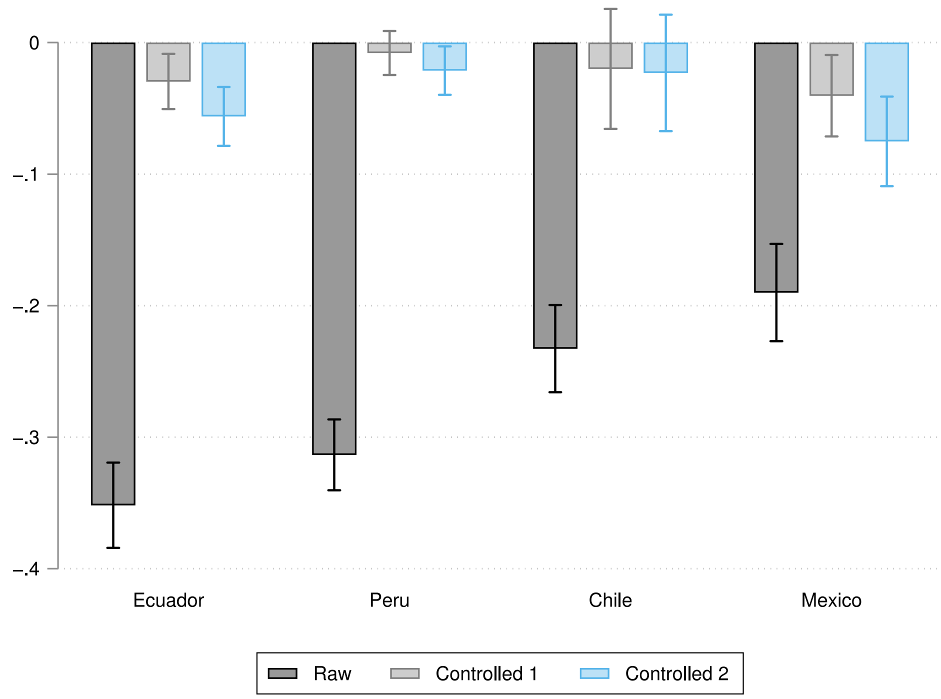
Figure 7 depicts the raw and controlled differences in the incidence of subjective overeducation between the selected countries and the OECD average. Raw differences confirm that subjective overeducation rates are larger in the OECD than in the four LAC countries considered. Differences range between -7.2 pp for Mexico and -21.4 pp for Ecuador. Controlling for the educational attainment and sociodemographic characteristics of workers does not affect these differences by a significant amount, although they tend to marginally increase in all four cases.

Figure 8. Raw and controlled differences in the incidence of objective overskilling in literacy (SKILL_LIT2) between the selected countries and the OECD average.



Notes: "Raw" corresponds to the difference in incidence between the LAC country and the OECD average. "Controlled 1" corresponds to the difference after controlling for the workers' skill level (a dummy variable indicating if the individual is medium-high skilled in literacy or not). "Controlled 2" corresponds to the difference after controlling for the workers' skill level, sex, age group and parents 'education. Vertical lines indicate 95% confidence intervals.

Figure 9. Raw and controlled differences in the incidence of objective overskilling in numeracy (SKILL_NUM2) between the selected countries and the OECD average.

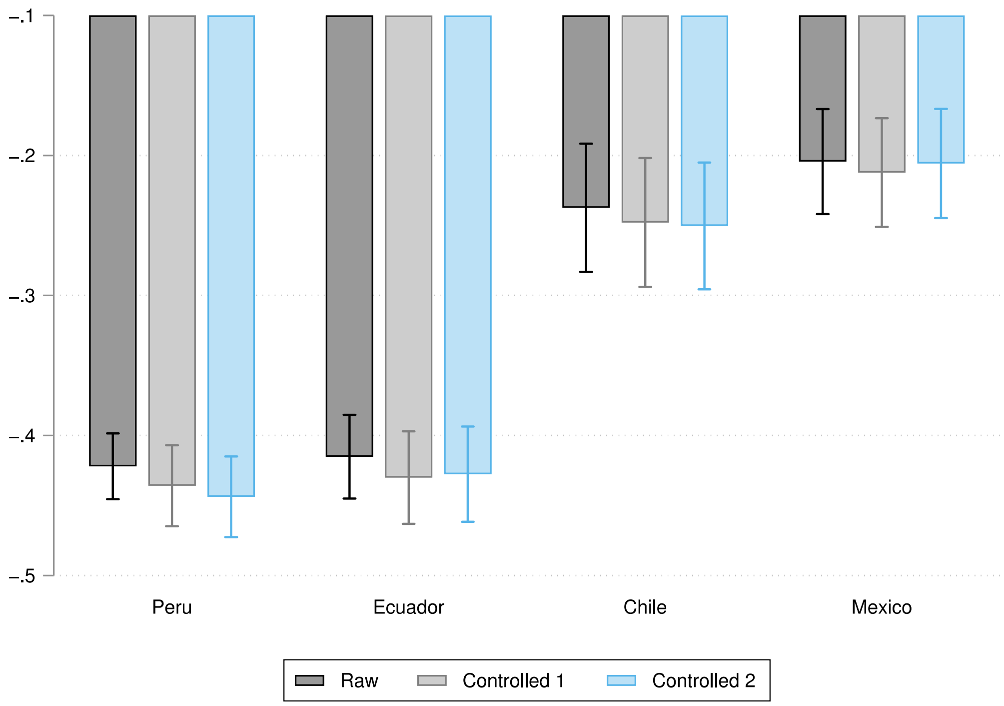


Notes: "Raw" corresponds to the difference in incidence between the LAC country and the OECD average. "Controlled 1" corresponds to the difference after controlling for the workers' skill level (a dummy variable indicating if the individual is medium-high skilled in numeracy or not). "Controlled 2" corresponds to the difference after controlling for the workers' skill level, sex, age group and parents' education. Vertical lines indicate 95% confidence intervals.

Raw differences in Figures 8 and 9 confirm that objective and subjective overskilling rates are significantly higher in the OECD than in the four LAC countries considered. Differences in terms of objective overskilling in literacy range between -11.4 pp (Mexico) and -25.3 pp (Ecuador). In terms of numeracy, differences range between -19.0 pp (Mexico) and -35.2 pp (Ecuador). Most of these differences, however, can be predicted by the differences in the skill composition of the workforce. Indeed, once one controls for workers' skills and sociodemographic characteristics, all differences fall below 7.8 pp (in absolute terms) and several of them are no longer statistically significant. Therefore, most of the difference in objective overskilling in favor of the OECD can be related to the fact that these economies have, on average, a more skilled workforce.

The incidence of subjective overskilling is also significantly larger for the OECD average than for the selected Latin American countries, with differences that range between -20.4 pp (Mexico) and -42.2 pp (Peru). However, unlike the results obtained for the objective indicator, these differences remain practically unchanged after controlling for the workers' skill attainment and sociodemographic characteristics (see Figure 10).

Figure 10. Raw and controlled differences in the incidence of subjective overskilling (SUB_SKILL1) between the selected countries and the OECD average.



Notes: "Raw" corresponds to the difference in incidence between the LAC country and the OECD average. "Controlled 1" corresponds to the difference after controlling for the workers' skill level (a dummy variable indicating if the individual is medium-high skilled in numeracy or not). "Controlled 2" corresponds to the difference after controlling for the workers' skill level, sex, age group and parents' education. Vertical lines indicate 95% confidence intervals.

If we focus on the results for the subjective overeducation and overskilling indicators, we observe that workers in the OECD are more likely than workers in the LAC economies to perceive that they have more education and skills than those required by their jobs. Interestingly, the evidence presented above shows that this phenomenon is unrelated to the educational and skill composition of the workforce. One way of explaining this is by postulating that the average job has lower education and skill requirements in the OECD than in the four LAC countries. Another possibility is that, for a given average job requirement, the OECD has less efficient job markets in terms of matching the supply and demand for qualifications. None of these explanations, however, is consistent with the evidence indicating that LAC economies have lower levels of economic development and complexity than the average OECD country.

A more plausible explanation is that workers' perceptions about their educational and skill attainment comprise elements beyond their years of schooling and their basic numeracy and literacy skills. Notice that this is especially relevant for the subjective overskilling indicator as a worker's perception about his/her skills in relation to the tasks that he/she has to perform at work likely involves more than just basic numeracy and literacy skills. This implies that, for a given skill requirement, a worker in the OECD can be more likely to perceive that he/she can perform more demanding tasks than a worker in the LAC sample, even after holding constant their basic numeracy and literacy skills.

5.3 Incidence of overeducation and overskilling across areas of study and occupations

Figures 11 and 12 show the incidence of occupational mismatches by area of study across the Latin American sample. Interestingly, the magnitudes of overeducation in each area of study vary somewhat by measure. When considering objective overeducation, the incidences are particularly high among those who studied Health (24.5%), Engineering (21.7%), Services (20.9%), and Social Sciences and law (20.7%), and extremely low among those trained in General programmes (1.8%). However, the incidence of subjective overeducation is higher for those with qualifications in Services (44.8%), Humanities and arts (42.4%), Social Sciences and law (42.1%), and Agriculture and veterinary (41.4%), and considerably lower for those who studied Education (30.1%).

Figure 11. Overeducation mismatch (%) by area of study in the sample.

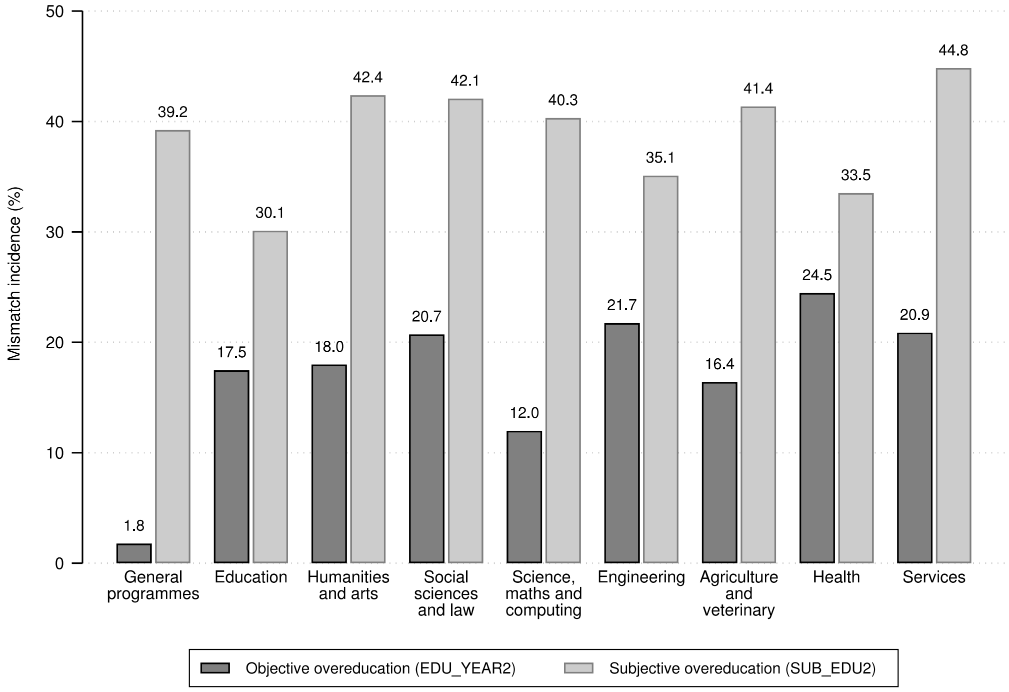
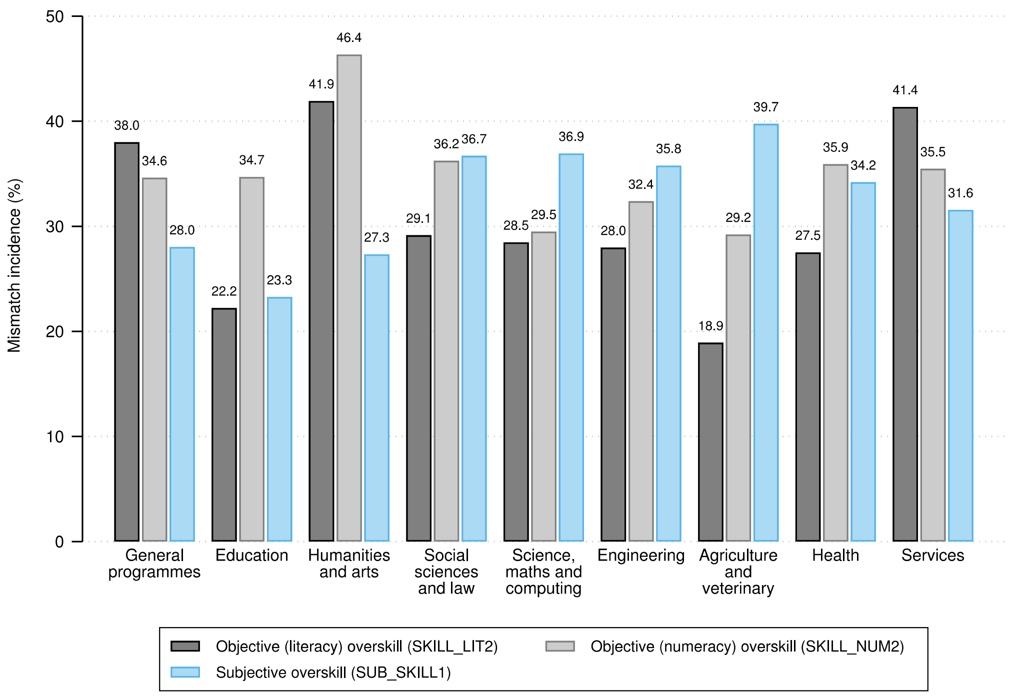


Figure 12. Overskill mismatch (%) by area of study in the sample.



Further, in relation to overskilling, there is substantive variation across study areas. Those with the highest incidence of objective overskilling in literacy are Humanities and arts (41.9%) and Services (41.4%), and this is much lower in Agriculture and veterinary (18.9%). Similarly, the incidence of objective overskilling in numeracy is high in Humanities and arts (46.4%), and somewhat lower in Science, math and computing (29.5%); and in Agriculture and veterinary (29.2%).

These patterns are, to some extent, contrary to the one observed for the incidences of subjective overskilling, which are particularly large among those who studied Agriculture and veterinary (39.7%), and lower in Education (23.3%), Humanities and arts (27.3%) and General programmes (28.0%).

Now, we turn to the analysis of the incidence of overeducation and overskilling across occupations. Figures 13 and 14 present the incidence of occupational mismatches by occupation across the sample. Those occupations with the largest incidence of objective overeducation are Technicians (24.7%) and Clerks (23.2%), and the lowest is found among Skilled agricultural and fishery workers (3.3%). Patterns of subjective overeducation incidence, in turn, differ, as they are higher for Elementary occupations (65.3%) and Skilled agricultural and fishery workers (57.3%), and significantly lower for the Armed forces (19.8%) and Professionals (21.6%). Here, the differences between objective and subjective overeducation in the occupations of Service and sales workers, Skilled agricultural and fishery workers, Craft workers, Operators and assemblers, and Elementary occupations, are particularly striking, with the workers' perceptions of mismatch being significantly higher (by more than 28 pp).

In relation to overskilling, those occupied in Elementary occupations and as Service and sales workers show the highest incidences of objective overskilling in literacy (44.9 and 44.2%, respectively), while those in the Armed forces show the lowest (16.8%). Further, those occupied as Plant and machine operators and assemblers and in the Armed forces, show the highest incidences of objective overskilling in numeracy (45.1 and 41.5%, respectively), while Technicians; Clerks; and Legislators, senior officials and managers show the lowest (30.4, 28.7 and 28.4%, respectively). Finally, when considering subjective overskilling, those occupied as Plant and machine operators and assemblers and Clerks show the highest incidences (45.2 and 40.8%, respectively), and those occupied as Craft and related trades workers, the lowest (23.6%). With some exceptions (i.e. Clerks and Skilled agricultural and fishery workers), here we find more coherence across objective and subjective indicators.

Figure 13. Overeducation mismatch (%) by occupation across the sample.

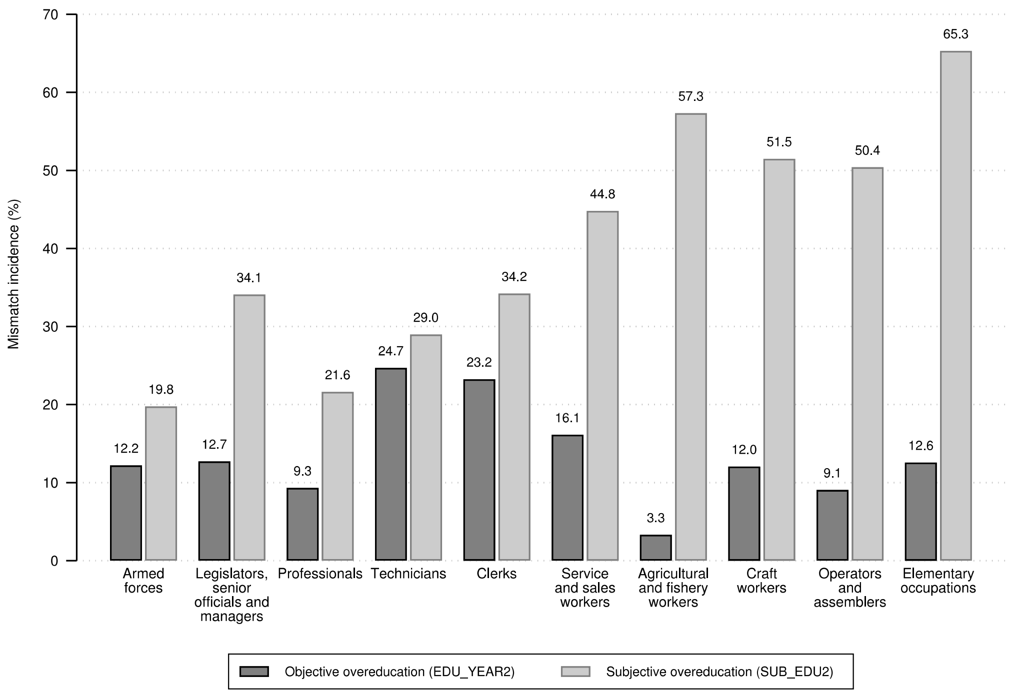
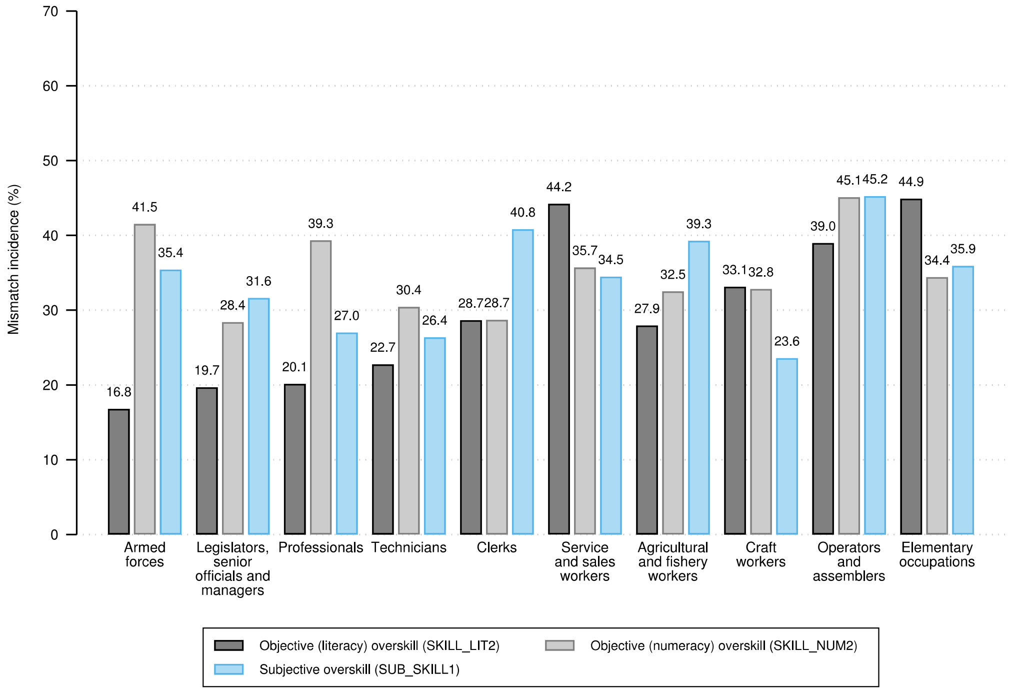


Figure 14. Overskill mismatch (%) by occupation across the sample.



5.4 Predictors of overeducation and overskilling

In this section, we present results on the identification of significant correlates of overeducation and overskilling across the sample of Latin American countries, with focus on the role of area of study and occupation. In particular, we analyze whether, after holding individual characteristics constant, changes in the area of study chosen by the individual or his/her occupation predict changes in the probability of being overeducated and overskilled, both objectively and subjectively. We also explore whether increases in skill or education predict a change in the probability of being overeducated or overskilled, within the same area of study or occupation.

This analysis relies on the empirical strategy described in Section 4.3, and the results are presented in Table 3. Each pair of columns in this table correspond to the results for one of the overeducation or overskilling indicators considered. The first column of each pair presents the results corresponding to areas of study. Notice that these regressions have

Humanities as the reference area. This means that reported coefficients should be interpreted as the predicted change in the probability of being overeducated or overskilled if the worker shifts from Humanities to the corresponding area of study. The second column of each pair presents the results corresponding to occupations. Notice that the reference is Elementary occupations so the coefficients should be interpreted as the change in the probability of being overeducated or overskilling predicted by a shift from Elementary occupations to the corresponding occupation.

5.4.1 The role of area of study

We find that the area of study has no significant role in predicting differences in the probability of being either objectively or subjectively overeducated (except for Education[6]) once we control for the worker's educational and skill attainment and the rest of covariates described in Section 4.3 (see columns 2 and 4 in Table 3).

[6] Studying Education predicts a reduction of 13 pp in the probability of being overeducated, both objectively and subjectively. This is, for a given educational attainment, studying Education predicts an increase in the educational attainment of colleagues and the perceived educational attainment required to get or perform the job.

Table 3. Predictors of occupational mismatch indicators across the sample.

	EDU_YEAR2		SUB_EDU2		SKILL_LIT2		SKILL_NUM2		SUB_SKILL1	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Literacy proficiency	-0.03**	-0.01	-0.03	-0.02	0.15***	0.17***	-0.02	-0.00	-0.03*	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Numeracy proficiency	-0.01	0.00	0.01	0.02	0.05***	0.05***	0.26***	0.25***	0.05***	0.06***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Level of education (Reference: Secondary)										
Post-secondary non-tertiary	0.06***	0.20***	0.11*	0.22***	-0.07	0.01	-0.02	-0.02	-0.07	-0.03
	(0.02)	(0.03)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Tertiary (no university)	0.33***	0.41***	0.09***	0.19***	-0.11***	-0.06**	-0.07**	-0.07**	-0.07*	-0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Tertiary (university)	0.34***	0.60***	-0.01	0.19***	-0.22***	-0.11***	-0.12***	-0.12***	-0.03	0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Master's degree/PhD	0.89***	1.22***	0.37***	0.60***	-0.27***	-0.13**	-0.15***	-0.13**	-0.01	0.07
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Area of study (Reference: Humanities)										
General programmes	-0.02		0.02		-0.04		-0.09**		0.07	
	(0.03)		(0.05)		(0.05)		(0.04)		(0.05)	
Education	-0.15***		-0.12**		-0.09*		-0.07		0.00	
	(0.04)		(0.06)		(0.05)		(0.05)		(0.05)	
Social sciences and law	-0.00		-0.01		-0.14***		-0.16***		0.10**	
	(0.04)		(0.05)		(0.05)		(0.04)		(0.04)	
Science, maths and computing	-0.04		-0.05		-0.14***		-0.19***		0.10*	
	(0.03)		(0.05)		(0.05)		(0.04)		(0.05)	
Engineering	-0.02		-0.06		-0.14***		-0.24***		0.10*	
	(0.04)		(0.05)		(0.05)		(0.05)		(0.05)	
Agriculture and veterinary	-0.02		-0.01		-0.21***		-0.21**		0.14	
	(0.07)		(0.09)		(0.07)		(0.09)		(0.09)	
Health	-0.05		-0.10*		-0.11**		-0.08		0.10*	
	(0.04)		(0.06)		(0.06)		(0.05)		(0.05)	
Services	0.06		0.02		-0.02		-0.12		0.05	
	(0.04)		(0.06)		(0.06)		(0.07)		(0.05)	
Occupation (ISCO 1-digit) (Reference: Elementary occupations)										
Armed forces		-0.34***		-0.38***		-0.29***		-0.11		0.04
		(0.07)		(0.11)		(0.10)		(0.11)		(0.15)
Legislators, senior officials and managers		-0.43***		-0.45***		-0.32***		-0.21***		-0.12**
		(0.03)		(0.06)		(0.06)		(0.05)		(0.06)
Professionals		-0.55***		-0.56***		-0.28***		-0.06		-0.13***
		(0.03)		(0.04)		(0.05)		(0.05)		(0.04)
Technicians		-0.08***		-0.39***		-0.25***		-0.13***		-0.12**
		(0.02)		(0.04)		(0.04)		(0.04)		(0.05)
Clerks		-0.01		-0.33***		-0.20***		-0.14***		0.02
		(0.02)		(0.04)		(0.04)		(0.04)		(0.05)
Service and sales workers		0.02		-0.22***		-0.03		-0.02		-0.03
		(0.01)		(0.04)		(0.03)		(0.03)		(0.04)
Skilled agricultural and fishery workers		-0.02		-0.04		-0.11*		0.04		0.07
		(0.02)		(0.09)		(0.06)		(0.06)		(0.09)
Craft and related trades workers		-0.06**		-0.14***		-0.09*		-0.05		-0.12**
		(0.03)		(0.04)		(0.05)		(0.05)		(0.05)
Plant and machine operators and assemblers		-0.01		-0.12**		-0.02		0.07*		0.08
		(0.02)		(0.05)		(0.05)		(0.04)		(0.06)
R^2	0.35	0.58	0.06	0.17	0.17	0.22	0.21	0.22	0.06	0.08
Observations	5823	5823	5819	5819	5823	5823	5823	5823	5815	5815

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Models 1 and 2 include country fixed effects and variables that control for sociodemographic characteristics (i.e. sex, age and parents' education). In addition, Model 2 includes variables that control for current employment characteristics (i.e., sector, company size). Sample sizes differ slightly across measures due to minor missing data in variables used to calculate occupational mismatch indicators. Elementary occupations include Cleaners and helpers; Agricultural, forestry and fishery laborers; Laborers in mining, construction, manufacturing and transport; Food preparation assistants; Street and related sales and service workers; and, Refuse workers and other elementary workers.

The area of study chosen by the individual plays a much more significant role in predicting differences in the probability of being overskilled. These predictions, however, differ between objective and subjective indicators. In fact, studying Social sciences and law, Science, math and computing, or Engineering, predicts important reductions in the probability of being objectively overskilled with respect to studying Humanities, but predicts an increase in the probability of being subjectively overskilled. These results suggest that moving from Humanities to one of these areas of study, with a given educational and basic skill attainment, can decrease the likelihood of having a low skill use (and therefore reduce the likelihood of being objectively overskilled) but, at the same time, other skills beyond basic numeracy and literacy become relevant when judging one's ability, so perceptions about being able to perform more demanding tasks can rise. This explanation is similar to the one suggested above when analyzing why the differences in subjective oveskilling rates between the OECD and the four LAC countries are unrelated to the average basic skill attainment of their workers.

5.4.2 The role of occupation type

We find that the worker's occupation has a significant role in predicting changes in the probability of being both objectively and subjectively overeducated and overskilled, once we control for the covariates described in Section 3. In fact, one can identify a group of occupations (Legislators, Senior officials and managers, Professionals and Technicians) that exhibit fairly consistent results between objective and subjective measures of overeducation and overskilling. Workers in these occupations are less likely to be overeducated and overskilled, than those working in Elementary occupations, both objectively and subjectively. Therefore, if one shifts from an Elementary occupation to one of these occupations, there is an increase in the educational level of colleagues (reflected in a reduction in the probability of being objectively overeducated) that is accompanied by a positive shift in the degree of skill engagement (reflected in a reduction in the probability of being objectively overskilled) and the perceived education and skill requirements of the job (reflected in a reduction in the probability of being subjectively overeducated and overskilled).

4.2.3 The role of skills and educational level

Finally, we also analyze whether changes in the skill level of the individual (holding his/her educational attainment, and area of study or occupation, constant) predict changes in the probability of being overeducated, and whether changes in the educational level of the individual (holding his/her skill attainment and area of study or occupation constant) predict changes in the probability of being overskilled. This will reveal whether, within the same area of study or occupation, increases in skills/education provide a means to increase the probability of finding a job better suited for the education/skills one has.[7]

Results presented in Table 3 show that changes in skills (both in terms of literacy and numeracy proficiency) do not predict changes in the probability of being overeducated (for the same level of education and within the same area of study or occupation). However, increases in educational attainment predict significant reductions in the probability of being objectively overskilled. Because we are holding the level of skill constant, this implies that more education reduces the probability of having a low skill engagement at work, within the same area of study or occupation.

6. Discussion and conclusions

Massive investments in tertiary education in Latin American countries in recent decades have been accompanied by only moderate and volatile economic growth episodes, rigid labor codes, low complexity and slow technological change. This combination triggered fears of overeducation in their workforce. Consequences in terms of overskilling were less clear because this tertiary education expansion occurred in a context of widespread privatization and deregulation, which led to a

[7] Notice that increasing one's education/skill within the same area of study or occupation will predict an increase in the probability of being overeducated/overskilled in a rather mechanical way. This is because by controlling for area of study or occupation we are, at least up to a certain point, holding the educational and skill requirements of the job constant. This is why we do not focus our analysis on these changes.

heterogeneous and socially stratified quality of education. More years of education, thus, probably failed to produce or predict more skills for many workers in these economies.

The present study aimed at estimating the incidences of overeducation and overskilling in Chile, Ecuador, Mexico and Peru, using objective and subjective indicators. We compared our results between countries and measures, and against the average OECD estimates. We also explored the role of area of study and occupation on the likelihood of being overeducated and overskilled across all four Latin American economies.

We found that the fears of overeducation were warranted. Our results show that overeducation affects between 29% and 43% of the workforce of these countries, and is particularly high in certain occupations (Service and Sales Workers, Agricultural and Fishery Workers, Craft Workers, Operators and Assemblers, and Elementary Occupations). We also found strong evidence of credential inflation disproportionately affecting these occupation groups.

Results in terms of overskilling were mixed. In Chile and Mexico overskilling rates are high and comparable to overeducation rates. In Ecuador and Peru, however, we found smaller overskilling rates. We consider this as evidence that, in these two countries, the additional years of education that workers bring to the labor market fail to fully translate into, or predict, additional skills. As noted above, this is likely the consequence of a significant expansion in tertiary education services with heterogeneous quality and pertinence.

Comparison against the OECD average revealed that overeducation and overskilling rates are smaller in the four LAC economies, but the phenomena driving these differences is not the same for objective and subjective indicators. Differences in objective indicators (especially for overskilling) are largely predicted by the additional average skill of the OECD workforce. Differences in subjective indicators, however, are unrelated to the educational or skill composition of the workforce. We argue that this is evidence of workers taking into account characteristics beyond their years of education and basic numeracy and literacy skills when judging their qualifications.

Furthermore, our regression analysis identified significant differences in the probability of falling into overeducation or overkilling for workers choosing different areas of study or occupations. In fact, the probability of being objectively overskilled is significantly larger for workers who studied Humanities (compared to Social sciences and Law, Science, Math and Computing, or Engineering) and the probability of being both overeducated and overskilled is significantly larger for workers in Elementary Occupations (compared to Legislators, Senior officials and managers, Professionals and Technicians).

The investment in human capital, through general education and skill formation, is a costly process for the individuals and the society. The presence of high levels of overeducation or overskilling in developing countries is a symptom of inefficient investment of scarce resources. As suggested by Comyn et al. (2019, p. 17), "mismatch between education/skills offered and education/skills wanted results from an interplay of supply and demand, and so requires both supply- and demand-side policy measures". Based on the results presented in this study, policymakers in Latin America need to promote more quality and pertinence in education on the supply side, and more economic growth and complexity, with high skill activities on the demand side, in order to reduce overeducation and overskilling levels, while achieving higher standards of economic and human development.

Also, policy in these unregulated and expansive education systems faces the need of monitoring equity and reducing heterogeneity in the quality of education provision. In particular, it is important to assess to what extent access to higher education of previously excluded groups actually translates into social mobility by allowing access to prestigious and socially advantageous occupations.

Some limitations of the present study are worth highlighting. First, the measurement and estimation of occupational mismatch remain controversial topics (Capsada-Munsech, 2019; Choi et al., 2020; Leuven & Oosterbeek, 2011; Perry et al., 2014). As recommended in the literature (Verhaest &

Omey, 2010), overeducation and overskilling were measured in various ways and comparisons across measures were made. However, results are sensitive to the definition of occupational mismatch selected. Second, as stressed by the literature, occupation mismatches are dynamic, and the cross-sectional design of PIAAC data does not allow us to capture relevant trends. Third, the present study did not consider macro variables that may affect the incidence of overeducation and overskilling and that can explain, at least in part, the results, such as, unemployment rate, educational quality, cost of higher education, structure and orientation of educational provision (e.g. relative availability of academic versus vocational and general versus specific education), economic cycles and labor force growth and composition (Comyn et al., 2019; Di Stasio et al., 2016; Groot & Van Den Brink, 2000; McGuinness, Bergin, et al., 2018; McGuinness, Pouliakas, et al., 2018; Verhaest & Van der Velden, 2013).

Promising areas for future research include longitudinal follow-ups, to monitor change in qualification mismatches in the region. Expanding these analyses to other understudied countries in Latin America would also be desirable. Also, the differences in occupational mismatches across occupations found in this study, point to the need for an in-depth study that takes into consideration the composition and trajectories of the working force by occupation. Finally, our results also highlight the need for a better understanding of the qualifications and skills that workers take into account when judging their abilities against those demanded by their jobs.

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Appendix

Table A1. Overeducation and overskill measures.

Indicator	Definition
OVEREDUCATION	
Objective measures	
EDU1	An individual is overeducated if his/her level of education is higher than the modal level of education in his/her occupation (ISCO 2-digit) and country.
EDU2	An individual is overeducated if his/her level of education is higher than the modal level of education in his/her occupation (ISCO 1-digit) and country.
EDU3	An individual is overeducated if his/her level of education is higher than the modal level of education in his/her occupation (ISCO 1-digit), country and age cohort (*ageg10lfs*).
EDU_YEAR1	An individual is overeducated if his/her years of education are 1 standard deviation higher than the average years of education in his/her occupation (ISCO 2-digit) and country.
EDU_YEAR2	An individual is overeducated if his/her years of education are 1 standard deviation higher than the average years of education in his/her occupation (ISCO 1-digit) and country.
EDU_YEAR3	An individual is overeducated if his/her years of education are 1 standard deviation higher than the average years of education in his/her occupation (ISCO 1-digit) and country, and age cohort (*ageg10lfs*).
Subjective measures	
SUB_EDU1	An individual is overeducated if, in his/her opinion, his/her level of education is higher than the level of education he/she thinks is required to get his/her job.
SUB_EDU2	An individual is overeducated if, in his/her opinion, his/her level of education is higher than the level of education he/she thinks is required to get his/her job or if he/she respond that 'a lower level (of education) would be sufficient' (*d_q12b*) to perform his/her job satisfactorily.
SUB_EDU3	An individual is overeducated if, in his/her opinion, 'a lower level (of education) would be sufficient' (*d_q12b*) to perform his/her job satisfactorily.
OVERSKILL	
Objective measures	
SKILL_NUM2	An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC numeracy proficiency level scale), and if he/she has a low/medium-low level of numeracy engagement in his/her job (engaging in numeracy-related tasks less than or at least once a week).
SKILL_NUM3	An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC numeracy proficiency level scale), and if he/she has a low/medium-low level of numeracy engagement in his/her job (engaging in numeracy-related tasks less than median level in his/her occupation (ISCO 2-digit) and country).
SKILL_NUM4	An individual is overskilled ('underutilized') if the difference between their standardized measures of numeracy skill level and numeracy skill use (the numeracy engagement score is defined as the mean of numeracy related tasks scores) is higher than 1.5.
SKILL_NUM5	An individual is overskilled if their numeracy skill level is more than 0.5 standard deviations higher than the average level in their occupation (ISCO 2-digit) and country.
SKILL_LIT2	An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC literacy proficiency level scale), and if he/she has a low/medium-low level of literacy engagement in his/her job (engaging in literacy-related tasks less than or at least once a week).
SKILL_LIT3	An individual is overskilled if he/she is medium-low/high skilled (levels 2 to 5 in the PIAAC literacy proficiency level scale), and if he/she has a low/medium-low level of literacy engagement in his/her job (engaging in literacy-related tasks more than median level in his/her occupation (ISCO 2-digit) and country).
SKILL_LIT4	An individual is overskilled ('underutilized') if the difference between their standardized measures of literacy skill level and literacy skill use (the literacy engagement score is defined as the mean of literacy related tasks scores) is higher than 1.5.
SKILL_LIT5	An individual is overskilled if their literacy skill level is more than 0.5 standard deviations higher than the average level in their occupation (ISCO 2-digit) and country.
Subjective measures	
SUB_SKILL1	An individual is overskilled if, in his/her opinion, he/she has the capabilities to cope with more demanding tasks than those required of him/her in his/her job (*f_q07a*) and he/she doesn't need further training in order to cope well with his/her present duties (*f_q07b*).

Note: The first numeracy and literacy plausible values (*pvnum1* and *pvlit1*, respectively) were used to define individual skill levels (proficiency scores).

Table A2. Factor loadings from the Principal Component Analysis.

Group of indicators	Indicator	Factor 1
Objective overeducation	EDU1	0.408
	EDU2	0.409
	EDU3	0.409
	EDU_YEAR1	0.407
	EDU_YEAR2	**0.411**
	EDU_YEAR3	0.406
Objective literacy overskill	**SKILL_LIT2**	**0.521**
	SKILL_LIT3	0.495
	SKILL_LIT4	0.526
	SKILL_LIT5	0.454
Objective numeracy overskill	**SKILL_NUM2**	**0.545**
	SKILL_NUM3	0.487
	SKILL_NUM4	0.523
	SKILL_NUM5	0.439

Notes: Selected indicators in bold. Considering the binary nature of the variables, we calculate tetrachoric correlations within each group of indicators. Next, we use the correlation matrices as inputs in the computation of eigenvalues and eigenvectors and apply the Kaiser criterion (i.e., choosing a number of components equal to the number of eigenvalues greater than 1).

Table A3. Percentage of overeducated or overskilled individuals (according to different measures of occupational mismatch).

No.	Measure	Chile	Ecuador	Mexico	Peru	OECD average
1	EDU1	15.6	18.1	16.9	25.3	26.9
2	EDU2	15.1	17.2	18.5	26.5	28.5
3	EDU3	15.8	17.2	17.8	23.0	25.1
4	EDU_YEAR1	14.7	14.1	15.1	15.8	15.7
5	**EDU_YEAR2**	**15.0**	**12.6**	**15.6**	**14.8**	**15.9**
6	EDU_YEAR3	14.9	15.0	16.2	15.5	15.2
7	SUB_EDU1	25.6	24.2	33.9	24.6	35.6
8	**SUB_EDU2**	**36.5**	**29.3**	**43.4**	**31.2**	**50.6**
9	SUB_EDU3	15.3	7.0	16.7	9.6	24.4
10	**SKILL_LIT2**	**32.7**	**19.5**	**33.4**	**27.8**	**44.8**
11	SKILL_LIT3	33.1	21.9	38.7	22.1	48.6
12	SKILL_LIT4	3.7	1.5	4.0	2.4	11.5
13	SKILL_LIT5	33.2	34.0	31.4	32.4	32.0
14	**SKILL_NUM2**	**35.0**	**23.1**	**39.3**	**26.9**	**58.3**
15	SKILL_NUM3	26.9	20.0	33.2	19.2	45.1
16	SKILL_NUM4	2.8	0.5	2.2	1.0	11.0
17	SKILL_NUM5	33.2	33.0	31.9	32.2	31.8
18	**SUB_SKILL1**	**36.0**	**18.2**	**39.3**	**17.5**	**59.7**