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The Effect of Educational-job Mismatch on Company's Productivity: A Panel Data Approach (Case study from Afghanistan)

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ABSTRACT: The mismatch of education, especially over-education, leads to inefficient allocation of scarce resources and becomes a public policy problem. The purpose of this study is to analyze the impact of educational-job mismatch on firm productivity. For this, we used a panel dataset for the period 2010-2016 obtained from the Central Statistical Organization (CSO) of Afghanistan, the World Bank database, and the Ministry of Labor and social welfare. Methodologically, we aggregated at the company level using the ORU (Overeducation, Required Education. and Undereducation) criteria. We also applied the OLS model, a fixed effects model, and a GMM estimator for dynamic systems. We investigate the significantly positive impact of university-level demands on company productivity while attempting to control for simultaneity concerns, unobserved work values that do not change over time, peer group consequences, and the interplay of the production process of adjustment; additional or longer periods of over-education or over-skilling (for younger as well as older workers) are detrimental to company productivity; additional years of under-education and under-skilling (for young employees) are not good (bad) for enterprises productivity. Governments should use greater levels of education and over-education of young and elderly employees as a policy instrument to boost productivity. The Generalized method of moments (GMM) approach is used in this work, which adds to the Afghan literature.

KEYWORDS: Educational-job mismatch, Over-education/over-schooling, productivity, Panel data, GMM estimator, Afghanistan

JEL Classification: A20, I21, J24

1. INTRODUCTION

In recent decades, emerging economies have emphasized the growth and development of education and the improvement of the educational level of people and citizens as a tool for economic growth, progress, and development. Despite the rapid increase in academic achievement and educational attainment, the successful growth of skilled employment has often lagged behind. The combination of a rapidly educated workforce (skilled labor) and slow growth in skilled employment can also contribute to the problem of "overeducation" in developing countries-also known as "vertical mismatch"-meaning that jobs filled by well-educated professionals require more formal education than they achieve. The discrepancy between a worker's degree of education and what the job market demands is referred to as overeducation and undereducation (educational mismatch). This significant marvel, initially emphasized by Freeman (1976), has been intensively investigated, particularly since the 1980s, to assess the effect of the constant growth in higher education enrollment in industrialized countries (McGuinness, 2006). For several decades, developed economies have pushed programs aimed at improving worker education.

In the world of Freeman (1976), the education mismatch appears to be a lack of coordination and alignment between improvements in educational attainment and jobs that require more skills. This highlights an incongruity between the degree of education achieved by workers and the education degree needed for their professions. Workforces are taking into account overeducated if their degree of education is more than that obligatory and needed for their profession and work, and undereducated otherwise. Thus, there are two variables of educational imbalance: overeducation and undereducation (Farooq, 2015).

Concerns about increasing over-education are fueled in part by widespread informal work in emerging economies. In the words of the International Labor Organization (ILO), self-employed workers in informal enterprises/firms and workers in "employment relationships that are not subject in law or in practice to national labor laws are not subject to income tax, social protection, or the privilege of certain labor benefits" such as informal employment (ILO, 2003). Informal employment is often associated with low skills and low wages, and the growth of formal employment tends to attract and retain -skilled workers, which may exacerbate overqualification and wage losses According to Union data (2012), the educational and occupational mismatch is an important factor affecting 36% of workers in the EU-27 during the year, with significant differences between European countries. In addition, about

30% of highly qualified workers were overqualified in 2009. Overeducation can also be costly to three economic agents: to individuals when the overeducated labor force receives a reduced amount than their previous age group when they take jobs that match their degree of education; to the economy as a whole when education levels are too high to be productive when overeducated workers are less productive than well-skilled labors. Overeducated or schooling, laborers are less creative than companies with adequately educated workforces; when funding too much education leads to inefficiencies, the entire economy suffers. Academic mismatch thus appears to be an important issue whose consequences need to be explored (Mavromaras and McGuinness, 2012). While the outcomes about the effects of education disparity (mismatch) on wages are fairly dependable, the current suggestion on the effects of education disparity on the productivity of company points in a distinct way (Hartog, 2000).

The primary axis of the study is based on human capital theory, which deduces the influences of overeducation and undereducation on productivity through the impacts of wages (Battu et al., 1999). A second trend and research topics are the influence of inadequate education on occupation fulfillment and another indicator of the productivity of workers (Büchel, 2002). Nevertheless, these two tendencies and hotspots show a certain outcome. The first one is that the employees who have a high degree of education(overeducated) have better than the laborers that have a low level of education(undereducated) in the same workplace. labors are much better than their three equally educated matching parts in similar occupations and workplaces, while the second offers an ambiguous prediction. Moreover, the first two approaches are harmful and have many methodological restrictions. From the human capital theory perspective, it is thought that the effects of education on salaries might be reflected in productivity overall (Mortensen, 2003). To our knowledge, Campman and Reix (2012) and Gronau (2014) first directly identify the effects of overeducation and undereducation on the productivity of the firm.

These findings, however, allow the potential for future growth and advancement. Identifying the situations in which educational mismatch is favorable and negative is an important field of research. It is more likely that the link between the education mismatch variable and company productivity is impacted by firm-specific work conditions and sectors. As an example, it's easy to envisage a well-educated individual with a Ph.D. in mathematics adding value to the finance department of a bank or a high-tech company functioning in a changing environment. On the contrary, an overeducated employee working in a traditional retail store or cleaning company may have lower job satisfaction) The discrepancy between education and employment in different countries around the world has been well studied. To date, no such study has been conducted on a similar topic in Afghanistan. Thus, this is a search initiative. The main objective of this study is to investigate and understand the impact of education-job mismatch on business productivity in Afghanistan. Due to a lack of time and limited budgets, it was not possible to cover all firms operating in Afghanistan. Therefore, this study includes only 1621 firms. Data for this study were collected over 7 years (2010-2016). To achieve the research objective, the following research question was answered.

✓ Does education-job mismatch affect firm productivity?

This study is divided into the following sections. Section 2 deals with the literature review, section 3 deals with the research methodology and data set, section 4 deals with the research findings, and the last section deals with the discussion and conclusions.

2. LITERATURE REVIEW

The term "educational mismatch" (also known as "over-educated" and "under-educated") describes the gap between a worker's educational level and the demands of the labor market. Freeman (1976) was the first to draw attention to this important and central phenomenon, and since the 1980s numerous studies have been conducted to determine the impact of ever-increasing labor force participation rates in developed economies (McGuinness, 2006). The educational attainment of the labor force in advanced economies has been improving for years. In addition, the study examines the "education mismatch" (Freeman, 1976) or the discrepancy and mismatch between rising education levels and jobs that require higher skills. This highlights and illustrates the mismatch between a worker's education level and the degree of education needed for their profession. Workers can be classified as over-educated or under-educated if they have further education than is required for their job. Thus, the two variables of educational incongruence discussed in this article are overeducation and undereducation (Farooq, 2015).

The lack of skills and knowledge is a cause of concern and worry for policymakers. It has been gradually and increasingly addressed by the European Union, which considers it threatening and detrimental to competitiveness (European Commission, 2009). At the same time, the term "overeducation", first coined by Richard Freeman in 1976, became prominent in the literature. It is known that up to 40% of the working population belongs to this group and that they often suffer huge wage losses compared to educated workers. In the long run, the existence of overeducation remains a conundrum as returns to college degrees also stabilize or increase. Moreover, per capita investment in higher education remains the highest of any schooling(education) group. The decision to graduate or enter the labor market is not relevant for all participants; the impact on efficiency comes from the availability and presence of overeducation. Although much attention has been paid to the phenomenon of overeducation and the educational miracle, its explanation is far from straightforward. First, the various ways in which overeducation can be predicted raise further measurement issues, as described and explained above. Second, some jobs require minimum education rather than a certain level of education, as other aspects of human capital may be as important as skills and qualifications. Third, in most cases, educational requirements increase over time as occupations (jobs) become more diverse. Fourth, as mentioned earlier, a person may be overqualified simply because he or she has a low skill level. However, this can be difficult to determine in the absence of data measuring individual skills (Allen, 2001).

The literature on education-occupation mismatch in economics is largely inspired by the context and structure of three classical theories of labor markets: human capital theory, occupational competition, and employment models. Baker (1964) proposed that a worker be paid according to his marginal product (MP), which depends on the level of human capital he has acquired through education, on-the-job training, or experience. In other words, suppose that the characteristics of the workers or the supply determine the distribution of income. Thus, overeducation will only occur as a temporary consequence of market imbalances, as the wage adjustment mechanism restores any imbalance (imbalance) between supply and demand (ACAR, 2017). In contrast, the job competition theory (Thurow, 1975) adopts and prefers a demand-driven approach. These models are based on the assumption that wages (compensation) are job-specific and independent of an employee's human capital. In this scenario, workers compete for higher-paying occupations and jobs and rank companies based on the relative cost of training them. Workers with a high school diploma are assigned to highly skilled employment due to the assumption that education and training are complementary in the workplace.

Overqualification occurs when the supply of highly skilled workers exceeds the supply of high-paying jobs, with some workers choosing occupations that involve a low level of education for which they are paid (Linsley, 2005). Distribution theory (Stinger, 1993) reconciles and corrects two extreme theoretical and hypothetical structures, assuming that salaries are strongminded by the appearance and features of careers. Productivity and wages are assumed to be positive, but not specifically related to human capital in this context and structure. Instead, the actual level of recorded productivity is limited by the availability and quality of work. Overqualification occurs in assignment models when employees are not assigned to careers effectively and efficiently based on their comparative advantage (Sicherman and Galor, 1990). With the growth and development

of the educated workforce around the world and the illegitimate and unintended consequences of the vertical mismatch between education and work, numerous empirical studies on the prevalence and impact of the mismatch between the results have been conducted and published in recent years and required levels. One of the difficulties in studying the wage effects of vertical maldistribution is how to quantify it. Hartog (2000) summarizes the three possible options as follows:

- ✓ Analysis of the job. This technique is used after a methodical and systematic assessment by professional job analysts.
- ✓ Employee self-assessment. The mismatch is assessed directly by the workers themselves. Studies and surveys ask workers their opinions about the minimum education required to perform their duties (e.g., Duncan and Hoffman 1981, Sicherman 1991, Dolton and Vignoles, 2000).
- ✓ Perceived or realized matches. This technique was first introduced by Verdugo (1989). In this research and study, the mean educational level plus 1 standard deviation was used to define and determine the educational level required to complete the task. This value is then compared to the actual educational level of each employee/worker to determine if the employee has education equivalent to that required for employment. Other studies apply this approach but use the model value instead of the mean value (Mendes de Oliveira, Santos, and Kiker, 2000).

Green and Zhu (2010) distinguish between 'real' and 'formal' overeducation, depending on whether or not it is associated with the underutilization of skills and abilities. They found that those who fall into the real overeducation category are harmed and suffer higher salary losses than those who fall into the formal overeducation cluster, with only prior demonstration and significantly lower and lower job satisfaction. An alternative approach is to treat overeducation and overqualification separately (Green and Zhu, 2010). Thus, Alan and Van der Welden (2001) examine the relationship between educational mismatch and skill mismatch and find that the former has a significant negative effect on wages (salaries), but the latter does not. In comparison, they estimate levels of job satisfaction and job search are far superior to overqualification (Alan and Van der Welden, 2001).

Overeducation refers to a surplus of education that exceeds the level required for a particular activity (Rumberger, 1981; Hartog, 2000). In addition, there is a horizontal mismatch between overeducation and training when workers' jobs do not match their areas of education (Robst, 2007). The presence of these mismatches raises concerns about their impact on individual labor market outcomes, such as their influence and impact on job satisfaction. From a sociological perspective, education-job mismatches negatively affect job satisfaction because the worker's expectations of social status and type of work are not met as they thought they would be when they invested in their higher education (Capsada-Monsic, 2017). The effect of educational-job mismatch on a firm's productivity has been addressed using two different approaches from a microeconomics perspective. The first deals with the theory of human capital (Baker, 1964). It points out that education allows for the labor force to gain more knowledge and skills that make them more creative and that the salary hole indicates various levels of productivity. Thus, the impact of the education-occupation disparity on output can be predicted by its effect on salaries.

Remberger (1987) discovered, using cross-sectional data from the United States, that the effect of one year of overeducation on earnings (pay) is positive but lower than the effect of one year of the required education. Hence, he contends that "extra education is not utterly and completely worthless, but rather occupations hinder workers' capacity to fully exploit the talents and abilities acquired in school" (Rumberger, 1987). Several research, some of which adjust for firm, unobserved labor force heterogeneity, and/or educational attainment, have indicated that over-(under-)educated employees earn more (less) than sufficiently trained and educated counterparts. According to human capital theory, a workforce that is over- (under-)skilled and educated raises (declines) employee productivity (Battu et al., 1999). The second research component looks at the detrimental outcomes of education misalliance on work satisfaction as well as other worker productivity metrics (such as turnover, absenteeism, or shirking). The conventional theory here is that unhappy workers with advanced degrees (overeducated workers) are less pleased, more likely to be absent, and sicker than their appropriately educated counterparts (Vroom, 1964). As a possible consequence of the detrimental effect on company productivity, employers will be hesitant to hire highly educated (overeducated) staff (Mahy, & Vermeylen, 2015). in the world of Hersh (1991), Overeducated (higher educated) workers are less content and satisfied than that other worker, and more-educated male workers are more inclined and ready to quit their occupations.

Tsang et al. (1991) confirmed this without predicting relationships for college-educated female employees (with overeducation). For instance, the "The Strategic Structure of European for Education" seeks to increase the percentage of persons in the European Union (EU) aged 30 to 34 who have completed a university education to an average of 40% by 2020. This approach implicitly and firmly presupposes either there is an additional demand for high degree of education in other words, that businesses hiring more educated employees would expand and enhance their output methods to consider of these extra talents and skilling (McGuinness, 2006). In contrast, tertiary-educated individuals' risk being employed for positions for which they are overqualified if these expectations and presumptions are not realized. Additionally, there may be some "crowding out" during the era of increased employment (oversupply of labor), in which employees with tertiary education occupies that might be held by others with less education.

For instance, among the 27 EU nations, the rate of people with college degrees climbed from 22.4 percent in 2000 to 34.6 percent in 2011 (European Commission, 2012). Verhaest and Omey (2006) discovered that highly educated employees in Belgium have greater incomes (turnover) but cannot demonstrate the expected effect of higher education (overeducation) on job satisfaction using Belgian data from 1999 to 2002. Nonetheless, they discovered a significant negative impact of overeducation (high education) on job satisfaction in 2009 using the same (but expanded) data set for Belgium, but they also discovered that the negative impact of overeducation (high education) on job satisfaction decreased with the number of years of experience. Excessive learning as a result of dissatisfaction with one's employment has a bad influence on one's age (Verhaest, Omey, 2006).

Tsang (1987) investigates the effect of over-education on job satisfaction but also creates a company-level job-satisfaction index and calculates its influence on company productivity using a Cobb-Douglas production function in his study. He discovers that over-education has a negative influence on job happiness, but that job satisfaction is also positively and strongly associated to production, implying that over-education has a negative impact on labor productivity". According to Büchel's (2002) findings, "Overeducation has no substantial relationship with work satisfaction. He even discovers that overeducated people are healthier, more work- and career-oriented, and stay with the same company for a longer period of time " (Mahy, Rycx, & Vermeylen, 2015). So, these two methodologies yield distinct outcomes and conclusions: Though the theory of human capital predicts that highly qualified (overeducated) people are more efficient, work satisfaction research does not always support this. Spence (1973) refers to the signaling theory (screening model), which holds that productivity is influenced by characteristics like as the worker's family background, job experience, or even talents (Spence, 1973).

Education, according to this idea, just acts as a signal for the candidate to demonstrate his ability to the company. Moreover, earnings (salaries) can never be directly tied to productivity. That is, salaries do not have to represent marginal productivity under noncompetitive pay selection models such as rent-sharing, group dealing (collective bargaining), discrimination, or monopoly models, where individuals with equivalent productivity characteristics are paid differently (Blanchflower and Bryson 2010; Manning 2003; Mortensen, 2003). In terms of work happiness theory, much research appears to overlook the fact that job satisfaction is not the only element that influences productivity via education (Judge et al., 2001). Even if you are overeducated. The fundamental limitation of this research is that they all look at the influence of educational mismatch on production in a roundabout approach.

Hartog (2000) has indeed brought up this topic, stating that it would be fascinating to investigate the direct effect of overeducation (undereducation) on productivity rather than the indirect influence through salaries, job satisfaction, or other worker characteristics. As far as we know, Kampelmann and Rycx (2012) and Grunau (2013) conducted direct estimations of the influence of ORU variables (more required/overeducation and undereducation) on business productivity (measured by value added per capita) (2014). Although both studies find that under-skilled individuals reduce firm-level production, they disagree on the effect of over-education (significantly positive in the first study, not significant in the second). As a result, further research is required to better our understanding of this link and association.

Many studies have been conducted on the educational jobs mismatch in different countries in the world. For example, in Indonesia, India, Pakistan, Turkey, Germany, Thailand, Cambodia, Iran, etc. Until now, there was no such research conducted regarding the relevant issue in Afghanistan. So, it was initiative research. The study contributes to the body of knowledge in the following ways: First, it provides empirical evidence on the impact of educational-jobs mismatch on firms' productivity in Afghanistan that can be used in short-term and long-term interventions, particularly in poverty reduction. In general, research findings can help inform the formulation of strategies and policies to promote growth in education and business productivity.

3. DATA AND METHOD

From 2010 to 2016, data for this study were acquired from Afghanistan's Central Statistics Office (CSO), the Ministry of Labor and Social Affairs, and the Macrotrends and World Bank databases. The study includes at least ten NACE agriculture, forestry, and fishing (A), mining and quarrying (B), manufacturing (C), energy supply (D), building (F), transportation and storage (H), information and communication (J), and real estate activities (L). The poll includes a wealth of information supplied by company management, such as the characteristics of the company (such as industry, amount of labor, and shared bargaining) and those employed there (such as age, education, length of service, total income, hours worked, gender, occupation). Our final sample is an imbalanced panel of 5686 observations from 1621 distinct companies. With the exception of the energy supply sector, it represents all small, medium, and large companies in the Afghanistan private sector.

In the literature, there are three basic ways for quantifying and assessing the education necessary for a job and the frequency of mismatches between training and employment. The first technique, known as job analysis or objective measurement, is based on occupational analysts' assessments and the sort of education necessary for a certain position. The self-assessment approach, also known as the subjective method, demands the worker to specify the category and amount of proper training essential to accomplish duties connected to a certain job/task. Thus, this metric is based on interviews with employees and/or employers. The empirical or learning matching strategy is used in the third way to assess the degree of education necessary for a job based on information normally supplied by employees for that profession/occupation. The educational level necessary is then often computed based on the educational level required for a certain occupation or job. Each of the preceding criteria has advantages and cons (Hartog, 2000). The job analysis technique, for example, is attractive since it is based on indistinct explanations and precise assessment parameters. Unfortunately, due to the high expense and complexity of this technique, postal classifications are only issued on a limited basis.

Moreover, categories can rapidly become obsolete as technology improvements impact the substance and complexity of the activity. Based on current local facts, the second technique is based on worker self-assessments. Yet, it has the drawback of not being founded on rigorous criteria. Respondents, in particular, may overestimate and inflate their employment needs. Furthermore, it usually results in a decline in the share of less-educated workers (uneducated workers).

Finally, empirical or realized correction processes have the advantage of being easy to execute and consistent. Additionally, unlike self-assessment methods, they can foresee and estimate the degree to which personnel is over- or under-qualified. The relationship between perception and implementation, on the other hand, has been questioned for its endogenous definition. Indeed, the degree of over- and under-education is likely to impact the quantity of training required. In general, it is incredible to say that one approach is obviously and unequivocally better than another, and in fact, the method of choice is frequently determined through the availability of data (McGuinness, 2006). So, to determine the education necessary for a job, we analyzed the type and years of schooling of employees in each of the two-digit ISCO jobs (22 categories)[1].

A worker is termed overqualified or underqualified if his years of education are lesser (greater) than the years of schooling necessary for the job, i.e., observed. To investigate the effect of the education discrepancy variable on the productivity of the company, we use the aggregate firm-level norm for overeducation, required education, and undereducation (ORU). We estimate the model used by Stephan Kampelmann and François Rycx (2012) using the "firm-level productivity'' equation:

$$Ln\,VAPL_{j,t} = \beta_0 + \beta_1(ln\,VAPL_{j,t-1}) + \beta_2\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} REQ_{i,j,t}\right) + \beta_3\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} OVER_{i,j,t}\right) + \beta_4\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} UNDER_{i,j,t}\right) + X_{j,t}\beta_5 + Z_{j,t}\beta_6 + \gamma_t + \upsilon_{j,t}$$

,

The variables that are used in the above equation are as follows.

Dependent variable:

$VAPL_{j,t}$ Is the productivity of firm j at year t, measured via the average value added per worker.

Explanatory (dependent) variables:

I. $m_{j,t}$ is the number of employees hired in the firm j at year t.
II. $REQ_{i,j,t}$ The number of years of schooling required for employment in a business in year t, at the two-digit International Standard Classification of Occupations (ISCO) level (in the whole economy) at time t.
III. $\mathrm{OVER}_{i,j,t} = (\mathrm{Attained\_education}_{i,j,t} - \mathrm{REQ}_{i,j,t})$
IV. $\mathrm{UNDER}_{i,j,t} = (\mathrm{Attained\_education}_{i,j,t} - \mathrm{REQ}_{i,j,t})$

[1] Our dataset categorizes worker education levels into six groups. Years of research were spurred by this information, which was reported by the company's human resources department (according to its record). To that goal, we have established the following guidelines: (j) elementary education lasts 6 years; (ii) lower secondary education lasts 9 years; (iii-iv) general, technical, and artistic secondary education lasts 12 years; (v) non-university higher education lasts 14 years; and (vi) university and non-university education lasts 16 years.

V. $\text{Attained_education}_{i,j,t}$The number of years correspoindng to the high level of education obtained through labor i hired in firm j at time t.
VI. the vector comprising
VII. $X_{j,t}$ Is a vector comprising amassed and aggregated physiognomies[2] and features of labors in firm j at year t: the share of the labor force that has at least 10 years of tenancy/tenure, the portion of workforces correspondingly and respectively younger than 25 and older than 49 years, and the share of women, blue-collar and part-time workers.
VIII. $Z_{j,t}$ is a vector comprising firm j physiognomies at year t, i.e., the sectorial affiliation (8 dummies), age and size (number of workers) of the firm, conditional spreading in hourly wages (salaries)[3] 11 and level of wage bargaining (1 dummy)[4].
IX. $\gamma_t$is set of 7 years dummies.
X. $\upsilon_{j,t}$is the error term

The equation above illustrates the link between the average number of years of overeducation and undereducation on company productivity when year dummy variables and average prevalence rates for employees and companies are controlled for. Including a lagged dependent variable (DV) between suppressors accounts for emergent and latent dependencies on firm productivity, growth, and skill development goals, as well as the fit of the relevant parameters in our system GMM (see discussion below). The aforementioned equations are estimated by using pooled, fixed effects methods, and GMM estimators devised by Arellano and Bover (1995) and Blundell and Bond (1998).
The basic regression embraces a pooled ordinary least squares (OLS) technique with standard errors that are robust to heteroscedasticity and serial correlation. These estimates are based on the cross-sectional variation between companies and longitudinal variation within enterprises over time. The pooled OLS estimator has been rejected and critiqued for its possible "heterogeneity bias" because business productivity is strongly dependent on firm-specific factors that develop over time and are not quantified in mini-polls. Therefore, the pooled OLS estimation technique may be biased in favor of the ORU variable, because unobserved company factors might affect the company's level of value-added, mean level of education inequality, and worker occupation.
This is known as a separation problem, and it can be created by variables such as a desirable location, company-particular assets such as patent ownership, or other types of assets. In order to account for heteroskedasticity across businesses, we re-estimate the above equation using a fixed-effects estimator with robust and resilient standard errors and serial correlation. The fixed effects model predicts productivity changes rather than firm i's productivity level. Time-invariant heterogeneity, by definition, is unrelated to productivity change and is thus included. Separate consideration should be given to the possible relationship between company productivity and education-occupation mismatch. We use a GMM to estimate the above equation to account for exogenous variables, establish company productivity dependence, and illustrate the existence of company fixed effects. We estimate equation one using Arellano and Bover's (1995) and Blundell and Bond's (1998) GMM estimators for dynamic systems in addition to availability.
The conventional technique used to predict and analyze the impacts of workforce heterogeneity on productivity in the literature (Göbel and Zwick, 2012; van Ours and Stoeldraijer, 2011) entails simultaneously assessing two equation systems (a level and first-order difference method) and using "internal tools" to stabilize endogeneity. In differential equations, ORU variables are discovered by their delay levels, but in horizontal equations, ORU variables are recognized by their delay difference. The implicit assumption and implication are the change (level) of productivity over a period, but this may be connected to the current change (level) in (the) variable (ORU), regardless of the level of delay (difference) of the latter. Moreover, changes in variable levels (ORU) are supposed to be correctly and fairly connected to these changes (changes). Unlike differential GMMs, the Generalized Method of Moments (GMM) system allows for the insertion of time-independent independent variables between suppressors. Interpolation and variable inclusion have no effect on other estimates regression because education-level instruments (such as lagged differences in ORU variables) are orthogonal to time-invariant variables (Roodman, 2000).
We use Hansen's (1982) over-identification and identifiability borderline tests to assess the reliability and validity of various techniques. Moreover, Arellano-Bond (1991) explored the sequence connection (e.g., second-order autocorrelation in first-

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[2] $\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} REQ_{i,j,t} + \frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} OVER_{i,j,t} + \frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} UNDER_{i,j,t}\right) = \frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} Attained_{i,j,t}$, i.e.
The sum of the average years of over-schooling and under-schooling required by company j at time t equals the average volume of schooling years acquired through laborers employed by company j at time t.
[3] In the wage equation developed by Winter-Ebmer and Zweimüller (1999), the distribution of hourly wages after adjusting for human capital factors and employee characteristics is shown (i.e., the standard deviation of the wage regression residuals, which are carried out separately for each company and each year). As more research emphasizes the influence of salary disparity within enterprises on productivity, this variable is accounted for. Until now, there is no conceptual unanimity on the features of this relation. For instance, the "tournament model" developed by Lazear and Rosen (1981) emphasizes that a more diverse compensation framework increases worker attempts by generating an inducement by offering the highest price to the valued employee. Furthermore, their approach reveals that the larger the wage discrepancy, the larger the optimum effort.
[4] Regrettably, we cannot determine company capital stocks directly from our data. Excluding the actual capital stock has no influence on the assessment of the production function at the company level, according to Van Ours and Stoeldraijer (2011), because the corresponding impact on productivity is small. This explanation is consistent with the findings of Doucouliagos and Laroche's conceptual investigation (2003). Moreover, it is important to mention that the regressors in our work statement are quite identical to those utilized in earlier research on the influence of ethnicity and pay schemes on company output.

difference error) to assess the honesty and dependability of a forecast or estimate. In practice, we chose the model with the least lag (smallest lag change) that passes the Hansen and Arellano-Bond tests to optimize the sample size. The use or acceptability of a spontaneous or dynamic structure is intended to expand the specification of the parameters of curiosity (although the LDV coefficient (taking the response variable into account) is unimportant for the assessment). In reality, as demonstrated by Bon (2002), dynamic models are required to produce credible results when estimating productivity equations with serially linked productivity shocks and independent variables associated with these shocks. For instance, the mentioned endogeneity problem may be used to illustrate how to input components' response to productivity shocks, even when the impacts of the demand shocks are lone substantially reflected by business-particular regressors. It is crucial to highlight that by integrating lagged dependent variables (LDVs) in the specification of GMM, fixed effects (FE), and OLS models, a reasonable ad hoc test is also provided for the latter. According to Roodman (2009), the test is if the LDV regression coefficient obtained by the systematic GMM falls between the OLS and fixed-effect estimations. A series of robustness checks will be performed on the pooled OLS, fixed effects, and GMM estimators of the dynamic system. We will focus on the robustness of these results to various overemployment and underemployment indicators that take into consideration labor age ranges. We also explore whether the influence of education misalignment on company productivity varies with the age of highly educated vs less educated (overqualified versus undereducated) workers.

Table 1: Summary statistics

Variables:	Mean	Std. Dev.
Added value per labor in Afghani (Annually)	1532,578	487,232
Lagged added value per labor (annually)	10.03	0.58
Required degree of education (REQ) in years	10.53	5.09
Over-education/ schooling (OVERE):		
% Of employees	24.45	23.3
Years	0.61	0.67
Under-education/ schooling (UNDERE):		
% Of employees	28.52	27.45
Years	-0.82	1.03
Wage disparities within companies:	0.15	0.07
Employees having a tenure of 10 years or more (%)	36.09	25.42
Females (%)	13.99	10.14
Labor force participation of less than 25 years	4.72	1.70
Proportion of workers aged 25 to 45 years	57.55	8.76
Labor force participation rate of persons beyond (more than) 45 years	18.72	7.00
Blue-collar workers[5] (%)	53.8	7.23
Working part-time (less than 25 hours per week (%)	10.53	5.09
The size of the company (number of labors)	97.73	34.02
Sector (%):		
Agriculture, forestry and fisheries(A)	9.34	
Mining and quarrying (B)	2.62	
Manufacturing industry(C)	31.65	
Energy supply(D)	22.29	
Construction(F)	8.36	
Transport and storage(H)	6.19	
Information and communication(J)	7.31	
Real estate activities(L)	10.03	
The overall number of observations	5686	5686
The total number of companies	1621	1621

Source: Authors' Analysis based on Central Statistics Organization (CSO), World Bank database

[5] Use the International Standard Classification of Occupations to differentiate between blue-collar and white-collar employees (ISCO-88). White collar workers are those in groups 1 to 5 (legislators, senior civil servants, and executives; professionals; technicians and related professions; clerks; groups 4 and 5 are service workers; groups 7 and 9 are shop and market salespeople) (7: workers in crafts and allied trades; 8: factory and machine operators and mechanics; 9: service workers and suppliers of shops and markets).

The mean and standard deviations of the chosen variables are shown in Table 1. This demonstrates that an average of 10.53 years of schooling/education is required at the enterprise level. In the firm, the proportions of overeducated and undereducated workers were 24% and 29%, respectively. To put it another way, the mean years of over-education and under-education in the company are 0.61 and -0.82, respectively. Furthermore, we discovered that the company's average annual added value per worker was around 153300 AFG, that 14% of the employees were women, that 53% of the employed people were blue collar, that 58% of those are prime-age employees (between 25 and 45 years old), that 36% of employees have worked for the company for at least 10 years, and that 11% of employees are part-time (i.e., working not as much of than 25 hours in a workweek).

The majority of these businesses, which employ an average of 98 people, are engaged in manufacturing (32%), energy supply (22%), real estate operations (10%), agriculture, forestry, and fisheries (9%), construction (8%), transport and storage (6%) and information and communication (7%).

4. RESULTS OF THE STUDY

Table 2. depicts the relationship between educational misalliance and company productivity (Pooled OLS, Fixed-effects and Generalized method of movements (GMM) estimator, 2010-2016)

Dependent variable: *lnValue-added per labor*

	(1) OLS	(2) Fixed effect (FE)	(3) GMM-SYS[6]
LnValue-added per labor (VAL)	0.328*** (0.006)	0.101*** (0.025)	0.253*** (0.005)
RQE (In years, one year lagged)	0.016** (0.005)	0.008 (0.012)	0.045*** (0.015)
OVER (In years, one year lagged)	0.014*** (0.007)	0.230*** (0.009)	0.032*** (0.0009)
UNDER ((In years, one year lagged)	0.007** (0.010)	0.336*** (0.014)	0.0177 (0.0152)
Characteristics of labor[7]:	Yes	Yes	Yes
Characteristics of firm[8]:	Yes	Yes	Yes
Years dummies (7):	Yes	Yes	Yes
P-value	0.00	0.00	0.00
P- value (Hansen statistic)			482.7 0.42
Arellano-Bond statistic (AR2)[9] p- value			1.46 0.12
Number of observations	5686	5686	5686
Number of firms	1621	1621	1621
R-squared	0.665		
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Source: Authors' Analysis based on Central Statistics Organization (CSO), World Bank database

The regression coefficient for minimum time spent in school (education) is 0.016. This coefficient illustrates that if the degree of education demanded by a company increases by one year[10], the company's productivity increases by 1.6% each year on average. In terms of education disparity (mismatch), we indicate that years of overeducation have a considerable positive impact on company productivity, but years of undereducation[11] have the reverse effect. The results show that when the average over-education (under-education) of the previous year rises by one unit the year before, the company's productivity increases on average by 1.4%,

*** significant at 10%
** significant at 5%
* Significant at 10%
Robust standard errors are given in parentheses.

[6] The first and second lags of the explanatory variables (excluding time dummies) are used as instruments in the GMM specification.

[7] Proportion of employees who i) have been with the company for at least ten years and (ii) are under the age of 25 and above the age of 49. Women's, blue-collar, and part-time worker proportions, as well as the conditional allocation of hourly pay, are also included.

[8] Sector identification (8 dummy variables), employee count, firm age, and collective bargaining level (1 dummy variable).

[9] AR2 depicts the test for second-order autocorrelation in first-differenced errors.

[10] This might be due to changes in i) the careers framework of the workforce into companies and/or ii) the careers division of educational attainment throughout the economy.

[11] In our data analysis, the average years of undereducation are, by definition, negative (see equation (1), Table 1). Thus, we can interpret the positive coefficient of regression as follows: as the average years of undereducation -education rise (fall), it becomes more (less) negativity, and productivity increases (less).

and decreases on average by 0.7%. Nevertheless, we used a fixed effects technique to re-estimate equation (1). The results are presented in the third pillar of Table 2, proving once again that productivity is significantly strongly associated with its lagged value. Despite this, after controlling for constant variables, the relative elasticity decreases from 0.328 to 0.101, and the estimated quantity of schooling required decreases from 0.016 to 0.0080 (p-value=0.12). When firm-level variation across time is taken into account, the relationship between tenure and low educational attainment appears to be statistically insignificant. These estimations remain imprecise due to the existence of ORU variables. This problem (along with output dependencies and fixed effects) is solved by re-estimating equation (1) with the GMM estimator for dynamic systems introduced by Arellano and Bover (1995) and Blundell and Bond (1998). As a consequence, the lag of the variable's level in the horizontal equation and the lag of the variable's difference in the differential equation serve as instruments. The 1st and 2nd intervals of the other independent variables were utilized as the mean of the dummy variable time, presuming it was exogenous. Table 2's final column contains the findings. At first, we examined its dependability using Hanson's (1982) threshold identification test and Arellano-(1991) Bond's second-order autocorrelation test at first differenced.

They do not reject the null hypothesis of the instrument's absence of autocorrelation (see Table 2). We also show that present productivity is substantially associated with its prior value, as one might predict. Surprisingly, the extent of the logarithmic (Ln) variable decreases amongst the OLS and fixed effects estimation methods. This conclusion, as observed by Rodman (2009), offers adequate support for our GMM definition for dynamic systems. The coefficient of the mean number of years of education required by a firm is now 0.045 and statistically significant at the 1% level, indicating that as the degree of education necessary for a company increase by one year, the firm's productivity increase by 4.5%. The productivity findings for educational inequality deviate from the fixed effects estimator as well. They now show, as in the OLS standard, that greater levels of education greatly boost business value. They find that increasing average yearly levels of education by one unit enhances business production by 3.2% on average. The opposite impact is produced by a low degree of education (undereducation).

Table 3. Mismatches between educational attainment and company productivity (GMM estimates, controlling for cohort effects, 2010-2016)

Dependent variable: Ln *Value-added per labor*

	(1) GMM-SYS[12]	(2) GMM-SYS[13]
LnValue-added per worker (VAL)	0.101** (0.003)	0.017** (0.004)
RQE (In years, one year lagged)	0.259*** (0.006)	
OVER (In years, one year lagged)	0.078** (0.001)	
UNDER (In years, one year lagged)	0.014 (0.008)	
Over-education among young employees (In years, one year lagged)		0.030* 0.001
Over-education among older employees (In years, one year lagged)		0.056*** (0.011)
Under-education among young workers**13** (In years, one year lagged)		0.089*** (0.003)
Under-education among older workers (Lagged on One year, in years)		0.017 (0.015)
Characteristics of labor[14]:	Yes	Yes
Characteristics of firm[15]:	Yes	Yes

*** significant at 10%
** significant at 5%
* Significant at 10%
Robust standard errors are given in parentheses.

[13] First and second lags of independent variables, not including time dummies, are used as instruments.

[14] According to our dataset's definition, the mean years of undereducation must have negative values (see equation (1), table 1). Thus, the following explanation should be used to understand a positive regression coefficient: Productivity rises when mean years of undereducation rise (fall), that is, become less (more) negative.

[14] Proportion of workers with (i) at least 10 years of service and (ii) less than 25 years old or above 49 age. The proportion of female, blue-collar, and part-time jobs and conditional allowances of hourly wages are also included.

[15] Membership of department (8 dummy variables), employees' number, company's age, and level of wage bargaining (1 dummy variable).

Year dummies (7):	Yes	Yes
Significance (p-value)	0.000	0.000
Hansen statistic p- value	323.5 0.16	344.2 0.16
Arellano-Bond statistic (AR2) p- value	1.42 0.13	1.46 0.12
Number of observations	5686	5686
Number of firms	1621	1621
Standard errors in parentheses		

Source: Authors' Analysis based on Central Statistics Organization (CSO), World Bank database

The results presented so far can still be misleading, as our ORU measures do not take into account the birth cohort of employees, although they do take into account some measures of productivity and the problems related to work requirements. education. It may be more useful to compare the education level of workers with the education patterns of their cohort of workers in the same occupation to determine whether they are over-educated or under-educated, meanwhile a substantial rise in the number of education years over time can mean formal education. In other words, since the education and age of the employees (i.e., for example, have a similar experience). In practice, we take into account two groups of age and set a threshold for young and old employees at 35[16] years. The amount of education necessary for younger and older employees was then calculated individually, and a worker was characterized as overqualified or underqualified if their degree of education was above (below) the obligatory for workforces in the similar age category and career at the 2-digit level ISCO. In conclusion, the first equation is adjusted so that i) the average number of years of schooling/education years essential through company j at time t equals the total number of years of schooling necessary for the whole professions held by young and elderly labor force in company j at time t; (ii) At time t, the mean number of years of over-schooling (under-schooling) in company j equals the overall number of over-education years of young and old workforce in company j at time t. This new specification is estimated using a dynamic system GMM estimator that controls for firm fixed effects, concurrency problems, and the dynamics of the firm's productivity adjustment process. The outcomes are exposed in the 2nd pillar of Table 3. In addition, we used the Hansen test (1982) for the overidentification constraint and the Arellano-Bond test (1991) for the second-order autocorrelation in the first difference error to assess their dependability. These confirm the reliability of our estimations. We also discover that present productivity is strongly tied to its historical worth. As seen in Table 3, this confirms the consistency of our estimates. We also observe that present productivity is significantly related to previous value. The results for the ORU variable expose that i) productivity is statistically significantly and positively correlated with the mean number of schooling years required by companies, ii) the average number of years of overtraining/overeducation has positive and significant impact on company value-added, and iii) the average number of education years is negative and not statistically significant to the company productivity, with corresponding p-values exceeding significance level by 1%, 5%, and 10%. The magnitudes of the estimated coefficients correlated with the ORU variable are especially intriguing because they do not differ much from those obtained using equation one. Overall, the effect of the ORU variable on firm production does not appear to be influenced by worker birth cohort. Another thing to look at is if the influence of educational mismatch on business output changes based on the age of over-educated and under-educated employees. Because our measures of over-education and under-education are more likely to identify actual skill discrepancies among new labor market entrants, the connection between schooling disparity and output should be stronger for young employees. Indeed, it may be claimed that old employees can more readily reimburse for their absence of proper education (i.e., their "under-education") by greater job skill and training.

Furthermore, employees who don't have the skills necessary for their career and are unable to catch up (via training and professional experience) are more likely to be employed in less demanding professions (within the same company or elsewhere) or in jobs they aspire to acquire as they age. Education-based abilities, on the other hand, deteriorate and grow stale with time, rendering older employees less likely to have talents beyond what is necessary for their employment. Another argument is that employees who boost their company's productivity by "over-education" are more likely to be promoted and placed in jobs that are a suitable fit for their abilities and skills as they age. These projections, however, could not be substantiated. Indeed, it may still have a negative impact on company productivity if less-educated older workers lack the labor market experience to substitute formal education, and if less-educated individuals who are unable to catch up continue to maintain their post. Overtrained professionals, on the other hand, may gain additional talents over their careers. Employees with greater levels of education, for example, maybe more creative and autonomous, better able to adapt to changing settings, learn new skills more rapidly, manage difficult jobs, and collaborate with colleagues' education.

[16] Employees are deemed young (older) when they reach the age of 35. (at least 36).

Nevertheless, the favorable effect of overeducation on the productivity of the company may persist beyond the retirement age of overeducated employees. To investigate the influence of educational mismatch on worker productivity, we add the average number of years of over-education and under-education of younger and older employees per company as an explanatory variable in our benchmark equations (by controlling effects). The result of the GMM estimator for dynamic system is displayed in the 3rd pillar of Table 3. The null hypotheses of valid instruments and no autocorrelation are not rejected by statistical testing. Furthermore, we discover that the coefficient of lagged productivity has a confident and positive effect on its present worth. In terms of the ORU variables, the findings demonstrate that when the amount of education/training required by enterprises increases by one year, productivity increases by 1.7% the following year on average. Second, they demonstrate that the average number of years of overeducation, for both young and senior personnel, has a positive effect on the company's added value.

More specifically, when the average number of years of overeducation among young and senior workers increases by one unit over the preceding years, company productivity improves by 5.6% and 3%, respectively. Lastly, the data reveal that the average number of years of undereducation among young workers has a negative and insignificant influence on the company productivity. In fact, a one-year increase in employee undereducation results in an 8.9% decrease in production. Yet, the data show that the number of years of undereducation of older workers has little influence on business output. According to the standard t-statistics, the effects of undereducation and overeducation on the production of an additional year are not statistically significant (for both young and old labors). Compounding this outcome with the conventional result that over-educated employees receive more (and less) than properly coordinated and matched people with the identical degree of education (such as people in the same job), one would expect firms to gain proportionally more educated (overeducated) salaried employees to be further profitable. To answer this question, we predict again our fundamental equations with the GMM estimator of dynamic systems, adjusting for group effects and utilizing firm profitability or total operating surplus per employee as dependent variables. The gap between the company's value added at factor cost and its payroll costs is represented by this variable (including employee social charges). It is split by the company's total staff count.

According to the findings, postponed profitability greatly boosts the value of existing enterprises. Variables associated to over-education, needs-based education, and under-education, on the other hand, have no influence on the productivity of company (even when the over-education and under-education variables are fragmented by worker age). Though attentiveness is suggested owing to potential profit measurement mistakes, the data do not appear to support the idea that business profitability is positively related to the average number of years of over-education. However, the study finds that a compensatory higher trend in salaries cancels the positive affect of overeducation on productivity, resulting in unaltered profitability. The findings further support the notion that punishing ignorant young workers compensates for their detrimental impact on company productivity while having no impact on profits.

DISCUSSION AND CONCLUSION REMARKS

Mismatch (inequality) in education, especially overeducation, leads to inefficient allocation of scarce resources and is therefore a public policy problem. This article aims to analyze the direct impact of educational inequality (mismatch) on firm productivity. It also draws on previous research to examine whether the effects of educational inequality on firm productivity differ by the age of overeducated and undereducated workers. Methodologically, we aggregated ORU (Above, Required, and Below School) standards at the company level; the structuring (dependent) variable was average value added per worker (AVL) at the firm level. For dynamic systems, we also use a mixed form of OLS, a fixed effects model, and a GMM estimator. The databases of the Afghan Central Statistics Organization (CSO), the Ministry of Labor and Social Affairs, Macrotrends, and Word Bank are the data sources for this study, which covers the period 2010-2016. The survey included detailed data provided by management, including characteristics of the firm (such as industry, number of employees, and the amount of communal pay bartering) and the employees there (such as education, age, length of service, gross income, hours worked, gender, occupation). With us, the sample size of this study is an imbalanced panel of 5686 firm-year data from 1621 distinct enterprises. excluding the energy supply sector, it represents all small, medium, and large enterprises in the Afghan private industry (NACE D). We also examine how the mean number of years of over-education and under-education within company (young and old labors) affects company productivity, according to the average number of years of schooling required.

Taking current problems, unobserved job characteristics that do not change over time, peer group effects, and the interplay of the production process of adjustment into account, we find that: (ii) years of over-education are beneficial for firm productivity of both young and older workers, and (iii) years of under- schooling (undereducation) are detrimental to young worker productivity. These findings imply that (i) more qualified employees are more productive throughout their careers as they gain additional knowledge and skills, and (ii) less educated workers obtain more jobs due to their experience to compensate for their low productivity; they continue their education or take fewer demanding jobs as they age. Furthermore, our findings are effortlessly acquiescent with the literature on the impact of insufficient schooling on salaries. They tend to support the notion that more educated people earn more (less) than less educated individuals because they are more productive (less productive) than the latter. The findings of study, however, do not support the notion that overeducated persons are less productive due to melancholy and job dissatisfaction. We cannot rule out the potential that job-specific educational mismatches cause workers' attitudes and actions to be less linked with their job performance and job satisfaction. Over-education, on the other hand, appears to have had a beneficial and large influence on productivity.

This result is not surprising, as i) estimate that the association amongst profession fulfillment and performance only rises to 30 percent; (ii) researchers regarding the effect of ORU on profession fulfilment has produced conflicting outcomes; (iii) insufficient skilling expected affects productivity via channels other than work gratification. According to distribution or human capital theory (Becker, 1964; Sattinger, 1993), for example, a reduction in work satisfaction can be remunerated by new trainings obtained in school. Consequently, the uncontaminated and net effect of overeducation may be beneficial to company productivity (as our results show). Many studies have been conducted on the mismatch between education and job in countries around the world. Consider Indonesia, India, Pakistan, Turkey, Germany, Thailand, Cambodia, Iran, Belgium, etc. Such study regarding the relevant issue this is the first time that this study was conducted in Afghanistan. As a policy tool, governments should consider high levels of education especially over-education of young and older workers to increase productivity in both short and long-run. We only take into account of the NACE classification like A, B, C, D, F, H, J, and L. Finally, we acknowledge the limitations of our analysis, such as the limited time frame and budget. We hope to expand this work in the future to cover the remaining sectors based on the NACE classification.

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