Икономически изследвания
Economic Studies
Volume 29 (5), 2020

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OVEREDUCATION AND ECONOMIC GROWTH: THEORETICAL BACKGROUND AND EMPIRICAL FINDINGS FOR THE REGION OF CENTRAL AND EASTERN EUROPE[3]

One of the issues which has gained considerable attention in the recent labour market literature is the increase of both average educational attainment of the population and qualification mismatch. With regard to that, this paper aims at examining the impact of overeducation on long-run economic growth. It discusses the main transmission channels and mechanisms of that impact. Moreover, by incorporating qualification (mis)match in the neoclassical model of growth with human capital the study presents an empirical estimation of the link between mismatch of tertiary education graduates and real GDP per capita growth across the EU members from Central and Eastern Europe. The results show that though investments in human capital accelerate the rate of growth, the higher percentage of mismatched graduates displays a negative effect. This outcome is robust to the changes of the approach used to measure overeducation and the method of estimation as well.
JEL: I25, E24, E27, E13

Introduction

The rising average educational attainment of the population, accompanied by an increasing extent of qualification mismatch in the labour market, has been widely acknowledged in the recent economic studies. The qualification mismatch is defined as a difference between one's educational degree completed and the qualification required by his or her job.[4] It is classified as either horizontal or vertical. Eurostat (2009, p. 131) defines horizontal

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[3] This paper is written under a scientific project titled IRISI, financed by the Bulgarian National Science Fund under a contract № KP/06/OPR 01/4/ 21.12.2018.
[4]It must be noted that the qualification or education mismatch refers to the educational attainment of a worker. A broader category called "skill mismatch" has also been defined in the relevant studies, though the two terms – qualification mismatch and skill mismatch – have often been used interchangeably. Skill mismatch assumes a differences between the overall skills which an individual acquires by various means including formal education and the skills required by his or her job. It is measured most often on the basis of subjective worker's self-assessment. On the other hand, qualification mismatch is related mostly to person's education. It is a difference between one's educational attainment and educational degree required by one's occupation. With regard to that, the terms "qualification mismatch" and "education mismatch" are used as synonyms in the relevant literature as it is here. They are used interchangeably throughout the paper.

mismatch as an employment position, which is not in the same field as the educational qualification of the employee. An example would be a person with a bachelor the degree in Finance who performs a job requiring a bachelor degree in Information Technology. On the other hand, vertical qualification mismatch is employment below or above the theoretical skill level acquired (Eurostat 2009, p. 131). A worker is said to be over/under-qualified if he or she has a higher/lower educational level than needed for the job performed.

Here, the focus is on vertical qualification mismatch. According to the estimates, about one-third of workers in the developed world experience qualification mismatch (OECD, 2013) as the vertical mismatch prevails. It appears to be rather a persistent than temporary phenomenon (Mavromaras et al., 2013). The primary reasons for that is the continuously increasing participation in education. As a result, the supply of education by degrees outpaced its demand. Another reason is the accelerating exit rates of older workers who usually possess lower education than younger people entering the active population.

The relevant papers examine mostly the size of the qualification mismatch or the factors which determine it as in Goos, Manning, & Salomons (2009), Beaudry, Green, & Sand (2013), Kupets (2016), Erdsiek (2016), and Verhaest, Sellami, & Van der Velden (2017). Another popular issue is the impact of mismatch on wages or wage inequality (Budria & Moro-Egido 2008; Autor & Dorn 2013) as well as unemployment (Birk 2001). Verhaest & Omey (2006) and McGowan & Andrews (2015**)** consider the impact of mismatch on labor productivity.

With regard to the abovementioned, the purpose of this study is twofold. On the one hand, it aims at summarizing the transmission channels and mechanisms through which vertical qualification mismatch specifically overeducation affects per capita income growth. To the best of authors' knowledge, there is no study presenting a theoretical explanation of that relation. The papers which are discussed in the next section examine the impact of over- or undereducation on determinants of the growth rate such as productivity, wages, investments, etc. With regard to that, these studies create a basis for an explanation on how mismatch might affect GDP per capita changes. On the other hand, the paper tries to quantify the impact of overeducation of tertiary education graduates on the real GDP growth rate by examining the 11 new EU member states from Central and Eastern Europe, henceforth NMS.

The paper is organized as follows. Section 1 describes the theoretical background by summarizing the studies on qualification mismatch. Section 2 discusses the approaches used to measure the vertical qualification mismatch and outlines the trends across the NMS. Section 3 describes the methodology of the study and presents an analysis of the empirical outcome. Section 4 tests the robustness of regression output by adopting a dynamic approach to education mismatch. The last part of the paper presents some concluding remarks.

The primary contributions of the study to the existing literature might be summarized as follows. First, it develops a theoretical framework of the impact of qualification (mis)match on economic growth. Second, it modifies the augmented neoclassical model of growth with human capital by differentiating between well-matched and mismatched labour. Last but not least, the study goes beyond the static measurement of overeducation by developing a dynamic view to the vertical qualification mismatch of tertiary education graduates.

1. Vertical qualification and economic growth: transmission channels and mechanisms

Qualification mismatch could influence the rate of economic growth in a number of ways. By referring to the relevant theoretical and empirical studies, the next lines propose a theoretical explanation of that relationship. The most straightforward supply-side relation is through the impact of (mis)match on labour productivity. According to the theory of human capital, rising educational attainment is a factor for better productivity since it is believed to develop or upgrade the individual's skills and knowledge. In the case of perfectly competitive markets, the real wage should equal the worker's marginal product. All other things being equal, over/under-qualified employees earn higher/lower wages than their well-matched peers, thus signalling differences in their productivity (Quintini, 2011). Since, on its side, productivity is positively linked to income per capita growth, a rise of overqualification among employees is expected to enhance the long-run growth prospects.

It must be noted that the abovementioned explanation suffers from two major drawbacks. First, it implies that the human capital stock possessed by an individual is the primary factor determining his or her productivity. Second, it assumes that the wage equals the marginal worker productivity. Thus, a higher/lower wage is considered an indicator of higher/lower productivity. But, in case of market failures such as imperfectly competitive markets, collective bargaining, employers' discriminating practices or rent-seeking behaviour, the higher wage of an over-educated worker does not necessarily mean that he/she is more productive. Moreover, in terms of Spence's theory (1973), the higher educational degree is a signal for higher qualification motivating employers to pay more to the university graduates without taking into account their productivity (see, also Garcia-Mainar & Montuenga 2019). All that might lead to wrong conclusions regarding the impact of qualification mismatch on productivity and, hence, economic growth.

Among the empirical studies which find a positive relation between overeducation and productivity are those of Van der Meer (2006) and McGuiness and Sloan (2011). Opposite to them, Rumberger (1987) points out that the years over the required schooling do not increase productivity significantly since the workers cannot fully utilize the additional skills and capabilities being acquired at school. On the other side, using data for Belgian firms Mahy et al. (2015) conclude that the direct impact of overeducation on productivity is conditional upon a number of factors such as a higher share of high-skilled jobs, knowledge-intensive industries as well as the degree of uncertainty of the economic environment.

An alternative explanation of the link between vertical qualification mismatch and productivity arises from the theories in the field of organizational behaviour by relating mismatch to job satisfaction. Workers with higher than the required level of skills or education would not be fully satisfied by their current occupations which might be harmful for their productivity. Additionally, decreasing satisfaction at work would lead to a higher job turnover, especially for educated individuals, which, in turn, would affect firm's performance negatively. In contrast with the previous explanation, this one implies a negative relation between qualification mismatch, productivity and the real growth rate. In this line, support for such an adverse effect of mismatch on job satisfaction could be found in Tsang et al. (1991), Battu et al. (1999), Verhaest and Omey (2009). But, in this line of thinking, another strand of literature indicates that more than required educated workers possess characteristics such as consciousness (Barrick, Mount, 1991) or better work attitude (Weiss, 1995) positively correlating with their productivity.

Besides, the abovementioned within-firm effects economic growth might be influenced by reallocation effects of qualification mismatch on aggregate productivity. McGowan and Andrews (2015) claim that in an economy where companies with different productivity levels co-exist, the less effective ones might hire the over-skilled labour thus not allowing for that labour to be efficiently utilized by more productive companies. This results in resource misallocation and lower productivity at a national level which consequently harms long-run growth potential.

A number of papers focuses on the direct effect of qualification mismatch on wages and returns of schooling (Bauer, 2002; Dorn, Sousa-Poza, 2005). Verdugo and Verdugo (1989) find a negative effect on the wages of persons, who possess education higher than the mean education of those in the same occupational group. Hartog (2000, p. 135) points out that, in overall, the returns of overeducation though positive, are lower than the returns for just matched education. According to the ORU (over-, required- and under-qualification) specification one additional year of overeducation leads to a lower wage premium compared to one additional year of schooling required for one's occupation. The former varies from half to two-thirds of the latter which means that individuals with an excess qualification face wage penalty compared to those who possess the right level of education for the job they hold. The returns of under-schooling appear to be negative. All these estimates imply that the higher extend of mismatch in an economy, especially the overqualification, would lead to a downward bias of the overall returns of education which consequently might suppress the growth rate.

Technology adoption or investments is the next channel of influence of mismatch on growth which is worth mentioning. Studies show that skill shortages reduce investments and R&D spending (Forth, Mason, 2006). In light of this, it is reasonable to assume that under-qualification or poor quality of education even in the case of many over-educated would affect growth negatively as long as skills are related to qualification. On the other hand, the rising educational attainment and overeducation in a certain economy might attract investors' attention, thus stimulating capital formation and growth.

The next channel concerns vacancies and the rate of unemployment. The differences between the qualification being supplied by the graduates and the qualification, skill and competences being demanded by the employers could prevent the latter from hiring over- or under-educated workers which are expected to increase the structural long-term unemployment (Mardsen et al., 2002; Birk, 2001) which adversely affects aggregate supply and GDP growth.

To the authors' knowledge, the only two studies which focus on the link between education mismatch and growth are those of Jaoul-Grammare and Guironnet (2009) and Ramos et al. (2009) producing contradictory results. But, they do not discuss explicitly the theoretical aspects of that relationship. The first paper estimates the causality between overeducation, wages and growth in France. The study finds that the higher share of over-educated workers with a university degree exerts an unfavourable pressure on GDP at least in the short run by decelerating its rate of growth.

The paper of Ramos et al. (2009) utilizes two measures of vertical mismatch. A person is considered over-educated if his or her years of schooling are above the mode for the particular occupation in a given region and country. The second measure is based on the match between educational levels according to ISCED levels and occupations, according to ISCO. The sample comprises 26 NUTS-I regions, 72 NUTS-II regions and 164 NUTS-III regions across 6 European countries – Austria, France, Greece, Ireland, Portugal and Spain. Contrary to the previous study, the output indicates the existence of a positive statistically significant correlation between overeducation and the rate of real GDP increments at a regional level. The result for the under-educated workers is negative. That outcome might be explained by the opportunity for the educated workforce to take advantage of qualified jobs.

2. Overeducation: measurement and trends across the new EU member states

This section summarizes the approaches used to measure qualification mismatch and presents some statistical data on overeducation among university graduates. The measurement methods could be classified into two major groups: statistical data assessment and workers' self-assessments. One popular approach of the first type is based on systematic job analysis. It involves a comparison between the educational degrees according to the International Standard Classification of Education (ISCED) and the required degree according to the International Standard Classification of Occupations (ISCO) of Organization of Economic Cooperation and Development. This study is based on this measure of vertical qualification mismatch due to its objectivity and availability of comparable data for a large panel of European countries.

The main drawback of this approach is its implicit assumption that attainment of a certain educational degree guarantees the accomplishment of a set of presumed knowledge, skills and competences. But, the latter is dependent on the quality of education in the country as well as the personal characteristics in case of over- and under-achievers at school (Chevalier, 2003). Therefore, some persons might be wrongly identified as over-educated whilst, in fact, their real qualification just matches the job they hold since they have not acquired the skills that can be the basis of competence development after hiring. It is worth mentioning another important disadvantage of the method. It assumes fixed mapping over a longer period of time between the educational levels and job categories. But, in case of rapid changes in technologies, organizations and the way of doing business such a time-invariant map would not adequately represent the educational requirements for some occupations. As a result, an individual with a given educational degree who takes a lower-level job would continue to be classified as over-educated few years later while, actually, he or she might possess the right education for that job if the nature or the scope of the occupation has changed over the years without that being considered by the static mapping framework. On its side, that might bias the statistics regarding the extent of the qualification mismatch. One way to correct that is to subtract such workers from the mismatched whereas counting them as properly educated. Such an approach is adopted in section 5 below.

The second method for approximating the extend of qualification mismatch assumes a comparison between one's education and the average educational level of workers in the job the person holds (Groot, van den Brink, 2000; Mendes de Oliveira, Santos, Kiker, 2000; Ramos et al., 2009). People whose level of education exceeds the mean, median or mode by, for example, one standard deviation are considered to be over-educated. This method results in an objective assessment since the proper education-occupation mapping is defined by the market. But, its important disadvantage is related to the quality of the country's educational system. If the school does not provide relevant skills and knowledge, there would be a downward bias in the evaluation of overeducation. The reason is that some people with higher educational degrees might take jobs located down the occupational ladder instead of jobs corresponding to their degree due to lack of presumed theoretical knowledge or skills. That might bias upward the mean educational level for some occupations. As a result, some of over-educated would misleadingly be counted as properly educated. An example is a woman with a bachelor degree who works as an office assistant. If a prevailing number of employees having completed tertiary education take such jobs, that woman would not be counted as over-educated while, in fact, her job does not require a university degree.

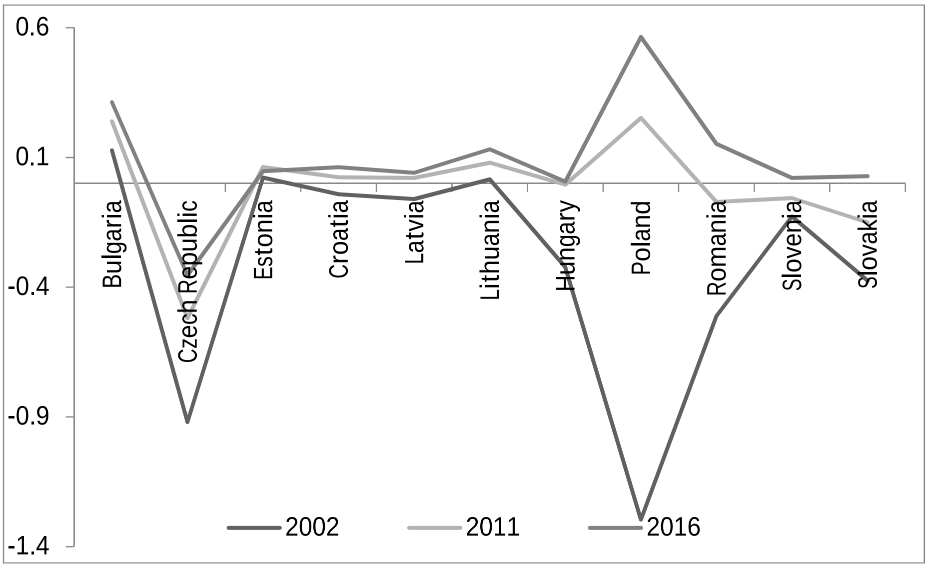
As it was mentioned above, the second group of methods is based on subjective self-assessments. A mismatch is recorded in case of a difference between the educational degree (or skills) required for the specific job taken by an employee and his or her actual educational level (or skills) (Frei, Sousa-Poza, 2005). Alternatively, one might report his or her opinion regarding the minimum level of education necessary to perform his or her job.

The study utilizes the first approach for measuring the degree of vertical qualification mismatch. Taking into account the mapping matrix being proposed by the International Standard Classification of Occupations (ISCO-08), the over-educated comprise the university graduates taking any job position different from Managers, Professionals, Technicians and Associate professionals. Utilizing that definition, figure 1 shows the rate of overeducation among the active population having completed university education across the eleven new EU member states. It compares the incidence of mismatch in 2000, 2011, and 2016.

Figure 1

Supply and demand of tertiary education across the new member countries*

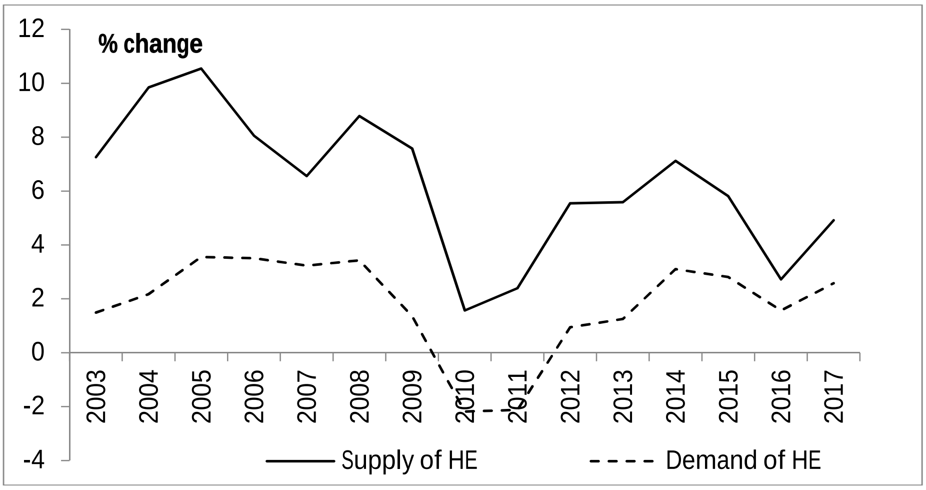
(a) Supply minus demand of higher education



* Difference between the number of tertiary education graduates representing the supply of higher education and the number of properly matched tertiary education graduates representing the demand of higher education. The values are expressed in thousands.

Source: Eurostat, author's calculations.

*(b) Percentage change in the demand and supply of higher education**



*Average values for the new member states are presented.

Source: Eurostat, author's calculations

The first graph illustrates the difference between the supply of university graduates in the active population (in thousands) and the demand calculated as the number of employees taking jobs requiring at least a bachelor degree (in thousands). It indicates the existence of a surplus of workers with higher education. That is clearly expressed since the year 2011 onwards. In 2016, all countries but the Czech Republic report a larger supply of university graduates in comparison with the demand. However, the second picture showing the rate of change of the respective supply and demand implies that recently (2016-2017) the supply of tertiary education approaches its demand thus shrinking the recorded surplus. In view of these figures, the next section draws attention on the impact of overeducation on GDP per capita growth rate.

3. Impact of vertical mismatch on the rate of economic growth: methodology of the study and empirical results

The model of economic growth with human capital developed by Mankiw, Romer and Weil (1992), henceforth MRW model, is a widely used instrument for exploring economic growth and its underlining determinants. An overview of its modifications could be found in Neycheva (2019). This study also utilizes the MRW model but, in order to examine the effect of overeducation of tertiary education graduates on long-run growth rate the model has been extended by differentiating between the stock of human capital and the vertically (mis)matched employees (see, eq. 6 below).

In this section, the rate of vertical qualification mismatch is measured by applying a static approach. It assumes a fixed mapping between one's educational degree completed according to ISCED (International Standard Classification of Education) framework and occupations based on the International Standard Classification of Occupations (ISCO). Following the descriptive analysis of mismatch of higher education graduates given above, the next section introduces a revised dynamic approached of estimating the rate of (mis)match. The annual data are supplied by the Labor Force Survey of the European Statistical Office (EUROSTAT). The survey presents the distribution of the graduates by a range of occupations following ISCO-08. The investigated time period is 2000-2016. The sample comprises Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia, Slovakia, and Croatia. The next lines present a mathematical description of the MRW model, the regression equations and the variables as well as the econometric output.

In the MRW model the Cobb-Douglas aggregate production takes the following form:

$$Y(t) = A(t) * K(t)^{\alpha} * H(t)^{\beta} * L(t)^{1-\alpha-\beta} \tag{1}$$

In equation (1) *Y* is output, *K* denotes the stock of physical capital, *H* is the stock of human capital, while *VQM* denotes vertically matched employees. *K*, *H* and *VQM* depreciate at an exogenous rate δ. The supply of labour (*L*) is growing at rate *n*, while the level of technology (*A*) changes at rate *g*. The constants α and β measure the elasticity of physical and human capital, respectively. As a result, the dynamic path of the capital inputs expressed in effective units of labour can be described as:

$$\dot{k_t} = s_k * y_t - (n + g + \delta) * k_t \quad (2a)$$

$$\dot{h_t} = s_h * y_t - (n + g + \delta) * h_t \quad (2b)$$

The small letters – $k = K/AL$, $h = H/AL$, and $y = Y/AL$ are for the quantities per an effective labour unit. s_k and s_h are the rates of accumulation of physical and human capital, respectively. The assumption of diminishing returns to capital implies that $\alpha + \beta < 1$. Under these initial conditions, the capital follows a convergence path to the steady-state (k^*, h^*) given by the system of equations (3):

$$k^* = \left(\frac{s_k^{1-\beta} * s_h^{\beta}}{n+g+\delta}\right)^{\frac{1}{1-\alpha-\beta}} \quad (3a)$$

$$h^* = \left(\frac{s_k^{\alpha} * s_h^{1-\alpha}}{n+g+\delta}\right)^{\frac{1}{1-\alpha-\beta}} \quad (3b)$$

In the above system of equations k^* and h^* denote the steady-state level of physical or human capital, respectively. Substituting (3) into the production function (1) and taking logs, one could come to two alternative ways of expressing the equilibrium level of income per capita (y^*): either as a function of human capital investments s_h (4a) or as a function of the human capital level *HKSTOCK* (4b).

$$\log y^* = lnA(0) + gt - \frac{\alpha+\beta}{1-\alpha-\beta}\log(n + g + \delta) + \frac{\alpha}{1-\alpha-\beta}\log(s_k) + \frac{\beta}{1-\alpha-\beta}\log(s_h) \quad (4a)$$

$$\log y^* = lnA(0) + gt - \frac{\alpha}{1-\alpha}\log(n + g + \delta) + \frac{\alpha}{1-\alpha}\log(s_k) + \frac{\beta}{1-\alpha}\log(\text{HKSTOCK}) \quad (4b)$$

The empirical model built upon (4) should be data-dependent (Mankiw et al., 1992, p. 418). If the time series represents the stock of human capital, as in this case, the regression should be based on the second equation (4b). Equation (5) displays the growth dynamics toward equilibrium in terms of the steady-state human capital level (*HKSTOCK*).

$$\begin{aligned} \text{dlog}(y_t) \equiv \log(y_t) - \log(y_0) \\ &= \left(1 - e^{-\lambda t}\right)\log A_0 - \left(1 - e^{-\lambda t}\right)\log(y_0) + gt \\ &+ \left(1 - e^{-\lambda t}\right)\frac{\alpha}{1-\alpha}(\log(s_k) - \log(n + g + \delta)) \\ &+ \left(1 - e^{-\lambda t}\right)\frac{\beta}{1-\alpha}\log(HKSTOCK) \qquad (5) \end{aligned}$$

The parameter λ measures the rate of convergence to the equilibrium level of income per head. The baseline regression model (6) utilizes the last equation. However, in addition to the total human capital (*HKSTOCK*) it includes the rate of vertical qualification match (*VQM*) in equation (6a) or the rate of vertical qualification mismatch (*VQMIS*) in equation (6b) below.

$$\text{d}\log y_t = a_0 + a_1\log(y_0) + a_2(\log(s_k) - \log(n + g + \delta)) + a_3\log(\text{HKSTOCK}) + a_4\log(VQM) + \varepsilon \quad (6a)$$

$$\mathrm{d}\log y_t = a_0 + a_1 \log(y_0) + a_2(\log(s_k) - \log(n + g + \delta)) + a_3 \log(\mathrm{HKSTOCK}) + a_4 \log(VQMIS) + \varepsilon \quad \text{(6b).}$$

The dependent variable (*dlog* y_t) is the first difference of real Gross Domestic Product (GDP) per unit of active population calculated in logs. The output per unit at the beginning of each time period is presented by *log* y_0. The rate of investments in physical capital (s_k) is approximated by the fixed capital formation in both public and private institutions expressed as a share of GDP.

The rate of qualification mismatch (*log VQMIS*) in (6b) comprises the active population with tertiary education (ISCED 5-8) holding jobs different from Managers, Professionals, Technicians and Associate professionals expressed as a percentage of all tertiary education graduates in the labour force. It is also calculated in logs. Alternatively, the share of matched higher education graduates expressed in logs is denoted by *log VQM* in (6a). The overall stock of human capital (*HKSTOCK*) comprises the active population (15-74 years of age) having completed at least upper secondary education (ISCED 3-8). The construction of the variables in this way solves the problem of potential correlation between *HKSTOCK* on the one side and the variables *VQMIS* or *VQM* on the other side, which would adversely affect the econometric outcome. Thus, the correlation coefficient turns to be small (0.15) and insignificant.

The parameter n equals the percentage change of the active population between 15 and 74 years of age. In the relevant studies, the rate of capital depreciation (δ) is usually set at 3% annually, while g is supposed to equal 2% per year. Therefore, for the sum (g+δ), the annual value of 5% is used most often. In order to get estimates as close as possible to the real-life data, here g is approximated by annual productivity growth across the countries under investigation. The average value over the examined period for the sample as a whole is 3% per year. Therefore, with an annual depreciation rate of 3%, the value of (g+δ) is fixed to 6% since it is seems more realistic.

In the regression models based on equation (6) the variables *dlog* y_t *log* y_0, s_k, *VQM, VQMIS* and n+g+δ are introduced as five-year averages over the examined period i.e. 2000-2004, 2001-2006, and so on. That helps for the cyclical fluctuations in the economic activity to be flattened and the tendencies in the growth path to be examined. Appendix 1 presents a summary of descriptive statistics – mean and standard deviation – of the regression variables for the overall sample and by country as well. It reflects the structural differences across the new member states. The standard deviation expressed as a percentage of the panel mean is highest for the variable *log VQMIS* (14.8%). This is supported by Figure 1 above illustrating the dynamics of the differences between the supply and demand of higher education across the economies being considered here. The parameter *log* (n+g+s) also varies substantially – the standard deviation is about 10% of the sample average. This is due mainly to the differences in the growth rate of active population n as well as the rate of technical progress g.

With regard to that, it should be pointed out that as it is usual for panel data the econometric output sheds light on the link between education (mis)match and real GDP per capita growth for the sample as a whole. It does not give a rationale for conclusions and implications on a country basis. In order to tackle the potential problem of heteroscedasticity or general correlation of observations within a cross-section, we use the Panel Estimated General Least Squares (EGLS) method with SUR (Seemingly Unrelated Regressions) weights (Beck, Katz 1995).

As it is reasonable, the variable log y_0 has a negative slope, thus proving the cohesion across the new EU members. The countries with a lower initial income per capita are expected to grow faster. The results also imply that the higher percentage of graduates whose education just matches the educational standards for their occupations accelerates the GDP per capita rate of change (Table 1, model 1). This is evident by the positive and statistically significant slope of the variable *VQM*.

Table 1

Estimation of the restricted MRW model[a] extended by the rate of vertical qualification (mis)match

	Model 1[b]	Model 2
Dependent variable: first difference of log GDP per a unit of active population (dlog yt)		
const	-0.015 (0.242)	1.153*** (0.315)
log y_0	-0.167*** (0.006)	-0.164** (0.012)
log s_k -log $(n+g+\delta)$	0.095*** (0.009)	0.084*** (0.014)
log HKSTOCK	0.170*** (0.039)	0.123* (0.074)
log VQM[c]	0.200*** (0.031)	
log VQMIS[c]		-0.034*** (0.007)
N of obs.	99	99
adj. R sqr.	0.913	0.734
Normality of residual (p-value)	0.205	0.233
Pesaran CD test (p-value)[e]	0.744	0.495

[a] The abbreviation MRW refers to the neoclassical growth model with human capital developed by Mankiw, Romer and Weil (1992)

[b] Panel EGLS estimates using period SUR weights are presented. Standard errors are in parentheses.

[c] Percentage of active population with higher education working as Managers, Professionals, Technicians and Associate professionals.

[d] Percentage of active population with higher education with any occupation different from Managers, Professionals, Technicians and Associate professionals.

[e] Pesaran's cross-section dependence test. Null hypothesis: No cross-section dependence in residuals.

On the contrary, qualification mismatch does not positively contribute to the rate of GDP growth (Table 1, model 2). Though small (-0.034), the regression coefficient for *log*

VQMIS is negative and statistically significant at the 5% level (see Table 1, model 2). Taking into account that this is a “log-log” relation, the result shows that if the share of the vertically mismatched holding at least a bachelor degree increases by one percentage point, the growth rate of aggregate output might decrease by 0.03%. The larger absolute value of the slope coefficient for the properly educated (0.2) implies that the impact of the qualification match on growth is stronger.

It must also be pointed out that in all cases, the variable measuring the country’s overall human capital stock (*log HKSTOCK*) is also positively related to the growth rate in the long run. But, its impact is lower than that for properly educated employees (*log VQM*) due to the counter-effect of overeducation on the real GDP increments. Thus, the empirical outcome suggests that not only the overall quantity of human capital matters for the growth dynamics but also its distribution among just-, over-, and undereducated population.

4. Robustness of the regression output

The previous section relies on the static approach assuming fixed mapping over a long period of time between educational attainment and jobs (Sparreboom, Tarvid 2016, p. 23). As it was mentioned earlier, a major drawback of such an approach is that it does not take into account the impact of technological changes on workers’ qualification, knowledge and skills. It is likely that employers respond to these new challenges to the labor market by increasing the qualification requirements for some jobs down the ladder, which having been traditionally occupied by people with lower educational background. In this vein, the abovementioned negative result about the link between overeducation and growth might be affected by this disadvantage of the static approach. In response to that in the current section, a revised “dynamic” view to vertical qualification mismatch is adopted.

Since 2011 onwards, the number of vertically mismatched employees are reduced by clerical support workers with higher education. The occupations include secretaries, office clerks and administrative assistants, receptionists, human resources specialists, labour relations specialists, bookkeeper assistant, etc. The reason is that individuals in these jobs intensively employ digital technologies to a greater or lesser extent. In the new member countries, their share changed almost three times since 2002 onwards – from 11.5% to 30.4% as a larger jump has been recorded after the year 2011.

A summary of descriptive statistics for the newly constructed variables *log VQMnew* and *log VQMISnew* is presented in Appendix 2. In all cases the vertical mismatch diminishes after subtraction of clerical support workers. However, the biggest percentage decrease has been recorded for the Czech Republic (10.5%), Romania, Croatia, and Slovakia (5.6%). These numbers indicate that in these economies a significant part of higher education graduates has been employed at positions of support workers requiring upper secondary education.

Table 2

Panel estimates[5] of the restricted MRW with a dynamic view of vertical (mis)match

	Model 1 [a]	Model 2
Dependent variable: first difference of log GDP per a unit of active population (dlog yt)		
const	0.283 (0.418)	1.195** (0.594)
log y_0	-0.115*** (0.016)	-0.124*** (0.014)
log s_k -log $(n+g+\delta)$	0.083*** (0.015)	0.079*** (0.014)
log HKSTOCK	0.169* (0.098)	0.184* (0.099)
log VQMnew[b]		-0.168** (0.077)
log VQMnew*dummy		-0.024*** (0.002)
log VQMISnew[c]	0.060*** (0.017)	
log VQMISnew*dummy	-0.041*** (0.004)	
N of obs.	99	99
adj. R sqr.	0.817	0.821
Normality of residual (p-value)	0.554	0.503
Pesaran CD test (p-value)[e]	0.245	0.244

[a] Panel EGLS estimates using period SUR weights are presented. Standard errors are in parentheses.
[b] Percentage of active population with higher education who work as Managers, Professionals, Technicians and Associate professionals up to 2010, clerical support workers have been added since 2011 onwards.
[c] Percentage of active population with higher education with any occupation different from Managers, Professionals, Technicians and Associate professionals up to 2010; since 2011 clerical support workers have been excluded.
[d] Dummy equals 0 over the period 2000-2010 and 1 over the period 2011-2016.
[e] Pesaran's cross-section dependence test. Null hypothesis: No cross section dependence in residuals.

The regression model is estimated using that newly calculated indicator of qualification (mis)match. The variable denoted *VQMISnew* (Table 2, model 1) presents the percentage of the active population with higher education with any occupation different from Managers, Professionals, Technicians and Associate professionals up to 2010. Since 2011 clerical support workers have also been excluded from the group of mismatched. The dummy

[5] In order to test the robustness of the outcome the dynamic GMM has been also applied with one lag regression variables as internal instruments. It produces similar results in terms of both signs and values of the regression coefficients. In general, the dynamic GMM developed by Arellano and Bond (1991, 278) is designed for panels with a large number of cross section units (N) over few time periods (N > T). Here, the panel dimensions are almost equal (N = 11, T = 9) therefore the GMM output is not displayed. The results are available upon request.

variable equals 0 up to 2010, and 1 afterwards (Table 2). The model also contains an interaction term *log VQMISnew*dummy* which equals 0 up to 2010 and has the same value as *log VQMIS* from then onwards. That would allow for a better evaluation of the impact of the newly adopted dynamic framework on the regression results. In the second modification (Table 2, model 2) the properly matched individuals according to the new measurement method (*log VQMnew*) have been introduced. In addition, an interaction term with the dummy variable is also defined (*log VQMnew*dummy*). The estimation method is the same as that in the previous section. That allows for the comparison of the results and ascertains the robustness of the regression output as well.

The results once again confirm that an increase of the overall stock of human capital (*log HKSTOCK*) is positively related to the real GDP per head increments. If the former grows by 1%, the latter would rise by 0.17-0.18%. Yet, the negative impact of vertical qualification mismatch remains despite the newly adopted method for measuring it. This is evident by the regression coefficient for the interaction term (*log VQMISnew*dummy*), which measures the impact of oversupply of higher education after the year 2011. The output presented in Table 2 also proves the robustness of the results discussed in the previous section.

At first glance, the addition of clerical support workers to the vertically matched graduates leads to a counter-intuitive outcome since the regression coefficient of the variable *log VQMnew* (Table 2, model 2) is below zero and statistically significant. But, the interaction with the dummy regressor gives evidence that the result might be explained by the structural change in the data. Probably, the negative slope of *log VQMnew*dummy* is affected by the growing share of employees with tertiary education holding clerical jobs after the year 2011. The results also show that a rise of the jobs down the ladder occupied by college or university graduates does not contribute to the growth successfully. Thus, the second econometric output once again provides support for the hypothesis that the rising rate of vertical qualification mismatch is always negatively associated to the income per capita changes.

In view of the theoretical hypotheses being raised in Section 1 the following explanations might be given for the negative link between qualification mismatch and economic growth. First, over-educated workers receive lower wages than their just-educated peers which exhibits a downward pressure on per capita income growth. Second, higher education graduates might possess theoretical knowledge but at the same time might lack necessary practical skills and competencies for the positions down the occupational ladder which they occupy. Yet, they are employed due to the lack of adequate labour supply. Third, overeducation might lead to lower job satisfaction which affects productivity and hence growth adversely.

From a policy perspective, the study implies that investments in human capital and the broader access to education benefit the long-run economic development. But, the attention should be drawn not only to graduation rate per se but also on the distribution of the country's human capital by educational degrees or fields of study. Higher educational attainment of the population does not go hand in hand with adequate skills which affect negatively technology adoption and firm performance at a micro-level and resource misallocation at a macro level. Improved quality of education, life-long learning and career guidance are among the measures for mismatch reduction. In light of the study outcome, a better match between educational attainment of the labour force and the specific economic structure might solve the problem of rising qualification mismatch across the European countries and enhance their long-run prospects for growth.

5. Conclusion

This paper draws attention on the link between vertical qualification mismatch and the rate of growth in the long run. It utilizes the extended neoclassical model of growth in order to find empirical evidence on that relation. The regression outputs confirm the positive growth impact of the overall human capital stock and the contribution of the properly matched university graduates taking positions such as Managers, Professionals, Technicians and Associate professionals. On the other hand, the increasing percentage of people whose education is above the requirements for the job positions they hold, affect growth negatively. The inclusion of clerical support workers to the properly educated graduates leads to a negative results regarding the link between university education and growth.

Though the empirical evidence on the influence of mismatch on growth is very limited as it was pointed out in section 1, the results obtained here could find support in a number of studies focusing on the region of Central and Eastern Europe. In light of the statistical data on the extend of vertical mismatched in the Bulgarian economy in section 2, the econometric output provides support for the conclusion of Vassileva (2019) that employment has not been significantly affecting Bulgaria's economic growth since the recent global crisis. As well, Rangelova and Bilyanski (2018) consider low productivity in Bulgaria as one of the main obstacles to economic development and cohesion with the EU countries. Gerunov (2014) derives a negative and statistically insignificant relation between educational attainment and the rate of change of real GDP for a panel of countries, including those considered here. Neycheva (2010) also cannot find evidence that higher public investments in education in the new member states increase labour productivity and growth. As the current study is one of the first ones exploring the direct relationship between (mis)match and economic growth, further evidence is needed in this regard.

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Appendix 1

Descriptive Statistics of the regression variables included in the model

Country	Statistics	log y_t^a	log y_0	log HKSTOCK	log s_k	log $(n+g+\delta)$	log VQMIS	log VQM
Bulgaria	mean	9.00	8.84	4.41	3.12	1.75	3.03	4.30
	st dev	0.12	0.20	0.04	0.10	0.12	0.11	0.02
Czech Republic	mean	10.06	9.94	4.53	3.33	1.83	2.21	4.48
	st dev	0.08	0.13	0.02	0.02	0.04	0.30	0.04
Estonia	mean	9.81	9.63	4.49	3.41	1.81	3.23	4.23
	st dev	0.08	0.16	0.01	0.06	0.08	0.02	0.01
Latvia	mean	9.58	9.35	4.46	3.28	1.61	2.92	4.32
	st dev	0.12	0.21	0.03	0.06	0.21	0.02	0.01
Lithuania	mean	9.69	9.41	4.52	3.09	1.58	3.01	4.31
	st dev	0.15	0.24	0.03	0.08	0.13	0.17	0.05
Hungary	mean	9.99	9.92	4.45	3.12	1.92	2.51	4.44
	st dev	0.03	0.07	0.02	0.05	0.08	0.10	0.03
Poland	mean	9.77	9.62	4.50	3.02	1.79	2.70	4.37
	st dev	0.16	0.19	0.03	0.08	0.06	0.25	0.04
Romania	mean	9.19	8.96	4.30	3.24	1.50	2.56	4.41
	st dev	0.16	0.26	0.04	0.13	0.23	0.25	0.05
Slovenia	mean	10.35	10.26	4.44	3.17	1.85	2.23	4.45
	st dev	0.06	0.08	0.04	0.16	0.15	0.20	0.05
Slovakia	mean	9.79	9.62	4.53	3.21	1.86	2.43	4.41
	st dev	0.15	0.20	0.01	0.08	0.03	0.29	0.06
Croatia	mean	9.92	9.92	4.41	3.17	1.82	2.41	4.38
	st dev	0.04	0.04	0.05	0.07	0.16	0.40	0.02
NMS-11	*mean*	*9.74*	*9.59*	*4.46*	*3.20*	*1.76*	*2.66*	*4.37*
	st dev	*0.38*	*0.44*	*0.07*	*0.14*	*0.18*	*0.39*	*0.08*
	stdev (% mean)	*3.91*	*4.64*	*1.62*	*4.26*	*10.22*	*14.76*	*1.84*

[a] The dependent variable $dlog\ y_t$ is calculated as a first difference of $logy_t$ which represents real Gross domestic product per unit of active population (15-74 years of age). The variables $dlog\ y_t$ $log\ y_0$, s_k, *VQM, VQMIS and* $n+g+\delta$ are introduced as five-year averages over the examined period 2000-2016 i.e. 2000-2004, 2001-2006, and so on.

Appendix 2

Descriptive statistics of the variables representing vertical qualification (mis)match according to the dynamic approach

Country	Statistics	log VQMISnew	Static vs. Dynamic approach (%)[a]	log VQMnew
Bulgaria	mean	2.90	-4.25	4.34
	st dev	0.08		0.02
Czech Republic	mean	1.98	-10.49	4.51
	st dev	0.03		0.01
Estonia	mean	3.13	-3.21	4.27
	st dev	0.12		0.03
Latvia	mean	2.77	-5.13	4.35
	st dev	0.15		0.03
Lithuania	mean	2.93	-2.55	4.32
	st dev	0.25		0.07
Hungary	mean	2.33	-7.02	4.46
	st dev	0.12		0.01
Poland	mean	2.55	-5.52	4.40
	st dev	0.12		0.01
Romania	mean	2.41	-5.60	4.44
	st dev	0.08		0.02
Slovenia	mean	2.15	-3.50	4.47
	st dev	0.07		0.02
Slovakia	mean	2.30	-5.56	4.44
	st dev	0.13		0.03
Croatia	mean	2.28	-5.60	4.40
	st dev	0.20		0.01
NMS-11	*mean*	*2.52*	*-5.16*	*4.40*
	st dev	*0.37*		*0.08*
	stdev (% mean)	*14.81*		*1.71*

[a] Percentage difference between the rate of vertical mismatch according to the dynamic approach (log VQMISnew) introduced in section 4 and that rate according to the static approach (log VQMIS) applied in section 3.