Can Increasing the R&D Intensity Lower Unemployment Rate? Case of Five Selected European Countries

*Serhan ÇIFTÇIOĞLU – Amin SOKHANVAR**

Abstract

This paper empirically examines the short-term and long-term effects of changes in R&D intensity on particularly the rate of unemployment in addition to economic growth for a sample of five European countries. Utilizing annual data for the sample period of 1991 – 2017, two alternative methodologies, namely the 'ARDL bounds testing' and 'PMG estimation' are employed. The empirical results have shown that there exists a long-run relationship between R&D, unemployment rate, and economic growth in four of the five countries investigated. Furthermore, the results of panel data analysis have suggested that even though in the long-run a given increase in R&D is likely to lower the rate of unemployment (in the average country of the sample), in the short-run, it can have adverse effects on unemployment. The paper argues that these empirical results can be taken as an evidence for the idea that even though the dominant form of technological change is in the form of 'new task creation' instead of 'automation', in the short-run new technologies may lead to an increase in the rate of unemployment due to the possible mismatch between the skills required by the newly created tasks (jobs) and the skills of the existing pool of workers.

Keywords: *R&D; unemployment rate, economic growth, technological progress*

JEL Classification: E24, J23, O00, O15, O38

Introduction

Since the seminal work of Solow (1957) which has suggested that in the long--run, the main engine of sustained improvements in per capita income is the growth in productivity that results from technological progress, the economists have been trying to better understand the possible determinants of the rate of this

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progress. The original Solow model (also known as neo-classical growth model) assumes that the rate of technological progress is exogenously given. However, the subsequent works by a new generation of economists have shown how this rate can be endogenously determined through alternative channels such as production process itself, and accumulation of respective stocks of physical capital (through investment) and human capital (Romer, 1987; Romer, 1990; Lucas, 1988). Some variants of this new line of work (which has been referred to as New Growth Theory) have been based on the assumption that the 'process of production of new knowledge' (new technologies) is similar to that of production of ordinary goods and services; in both cases, the inputs to the production process are capital and labor. Therefore, technological progress requires allocating relatively larger amounts of labor and capital to the sector specializing in the production of new knowledge which, in practice, meant the R&D (Research and Development) sector. In the neo-classical growth theory, it is implicitly assumed that technological progress improves the respective productivities of all types of factors of production in a proportional manner. And that's why in neo-classical growth model the general increase in the productivities of all inputs resulting from a given improvement in technology is referred to as an improvement in total factor productivity (TFP). This aspect of neo-classical growth models naturally embodied the implicit assumption that technological improvements are neutral in terms of their productivity effects on different types of inputs (such as capital and labor). And this, in turn, suggested that under certain conditions (such as competitive markets and constant returns to scale), technological progress is expected to increase the demand for both labor and capital in similar proportions. This property of standard growth models seems to have provided the foundation of a somewhat optimistic outlook regarding the long-term sustainability of the improvements in living standards and the attainability of relatively low rates of unemployment.

The optimistic view of technological progress (briefly summarized above) naturally explains (to a great extent) the main motivation for ever growing focus of public policymaking on R&D in the last few decades. In particular, economists and policymakers have been attempting to design and implement both micro and macro-based policies to stimulate R&D efforts of not only private and public sectors but also institutes of higher education. And this is well justified in light of the fact that there is a body of empirical literature that has produced evidence of R&D having positive effects on productivity and output growth both at micro (firm and industry) and macro (aggregate economy) levels. We briefly present the findings of some of this literature in the next section. However recently some authors such as Sachs and Kotlikoff (2012), Acemoglu and Restrepo

(2017; 2018a; 2018b; 2018c and 2018d) have started questioning the positive and optimistic outlook that both neoclassical and new growth theory-based models have portrayed in terms of the impact of technological improvements on key macro-parameters. Their works have suggested that new technologies might have adverse effects not only on unemployment and income distribution but also on economic growth. The main motivation of this new line of theoretical research seems to be the rising unemployment of particularly unskilled labor and the corresponding increase in the degree of income inequality not only between the owners of capital and labor but also between the skilled and unskilled labor. The main argument of this new line of research is the idea that one of the main factors responsible for the rising unemployment and income inequality could be the nature of the technological progress itself. We present and discuss the key aspects of this new line of theoretical research particularly in terms of their assumptions and predictions in some detail in the next section. However, it is worth to note that the nature of technological progress is not the only possible source of rising income inequality. Globalization in the form of increased trade, capital flows, and offshoring possibilities could have been playing an important role in this process (Grossman and Rossi-Hansberg, 2008; Autor, Dorn and Hanson, 2015).

The possibility of technological changes (resulting from R&D) having negative impact on unemployment and even economic growth (through lowering national saving rates) forms the main motivation of the present study. Blanchard (2009) has argued that such concerns are not justified in light of the positive correlation between productivity growth and employment in the twentieth century in advanced economies such as US and Japan. However as pointed out earlier above, the recent socio-economic developments in terms of persistence of high unemployment of particularly unskilled labor as well as growing income and wealth inequality in the era of increased intensity of R&D has prompted a new line of research that has been particularly aiming at identifying the conditions under which technological changes can generate such unfavorable outcomes. The likelihood of negative outcomes seems to be higher if the nature of technological change is in the form of automation instead of task creation which is discussed in some detail in the next section.

In light of the points raised above, the present study is an attempt to empirically investigate the relationship between R&D intensity (proxied by the total R&D expenditures as a percentage of GDP) and unemployment rate and economic growth (both in the short-run and long-run) for a sample of five European countries. However, we note that the main focus of our paper is on R&D and Unemployment nexus which is largely missing in most of the past empirical literature. The methodologies employed in our empirical analysis are as follows:

First, we apply the ARDL bounds testing approach to examine the presence of a long-run relationship between R&D, unemployment and economic growth in each country individually. Secondly, we use ARDL (Autoregressive Distributed Lag) approach to examine the nature of the dynamic relationship between unemployment rate and R&D for the panel of five countries making our sample over the period of 1991 – 2017.

The rest of the paper is organized as follows: The next section is particularly devoted to the discussion of the main insights and arguments of the recent theoretical literature in addition to the brief presentation of the key findings of the selected past empirical literature. The second and third sections are the Data and Methodology sections. The empirical results are presented and interpreted in the fourth section. The last section concludes with a brief summary of the key findings of the paper and their policy implications.

1. Literature Review

In this section, first, we present the key insights of the selected (particularly recent) theoretical literature that primarily focused on the dynamic effects of technological changes on unemployment, economic growth, and income distribution. Then we briefly report the key findings of the relevant empirical literature which have exclusively focused on investigating the productivity and income effects of increased R&D intensity without examining unemployment – R&D nexus.

One of the theoretical models that suggests that the nature of the employment effect of a given improvement in technology is likely to be ambiguous is that of Blanchard (2009). Blanchard specifies a production function whereby the output is produced using labor and the level of technology determines the productivity level of a unit of labor. This feature of the model means that technological progress automatically leads to (labor) productivity growth. In this simple model, the employment effects of productivity growth are ambiguous; it depends on whether or not the output growth (resulting from higher productivity) is proportionately bigger or smaller than productivity growth itself. If it is bigger, then employment increases. Otherwise, it decreases. Blanchard argues that the answer in the short-run will critically depend on the source of productivity growth. If the source of productivity growth is the general implementation of a new invention, this is likely to increase not only the aggregate supply at each price level but also the aggregate demand for consumer and investment goods by making consumers and firms more optimistic about future income. In this case, output and employment increase in the short-run. However, if the source of productivity growth is the improvement in the efficiency of firms (in using existing technologies) there is no guarantee that aggregate demand will increase. On the contrary, firms may lay off some workers as they attempt to improve efficiency. And this may lead to workers' pessimism about future income prospects leading to lower consumption and higher savings. In Blanchard model, in the medium term, the natural rate of unemployment is not affected by productivity growth and therefore by technological progress as long as workers have perfect foresight in forming their expectations of productivity growth. If the workers cannot adjust their expectations quickly to a given decrease in productivity growth, the natural rate of unemployment may increase. In contrast, when actual productivity growth happens to be higher than the expected productivity growth, this will lower the natural rate of unemployment through the changes in the real wage in the medium term.

The rising income inequality in the last few decades has been the focus of research by a number of authors such as Atkinson, Picketty and Saez (2011) and Gordon (2009). It has been shown that the recent worsening of income inequality has particularly two features; the falling share of labor income relative to that of capital and the growing discrepancy between the share of wage income of highly skilled labor and that of unskilled labor. As Sachs and Kotlikoff (2012) suggest these two aspects of growing income inequality may be associated with the accelerated growth in brain machine power. In addition, it may point out to the possibility of the recent technological progress being 'skill-biased'; it is favoring skilled labor.

In addition to the possibility of technological changes worsening income distribution, some authors have even started to raise the possibility of technological progress exerting adverse effects on the process of economic growth. For example, Zuleta (2004; 2008 and 2012) have shown how technological progress can negatively affect capital accumulation and output growth in the long-run. Another study that used an overlapping generations based model to show the possibility of 'immiserizing technological progress' is that of Sachs and Kotlikoff (2012). In their model, they assume that all the young generations are 'unskilled labor' who work with machines to produce 'intermediate products' which, in turn, are used together with 'skilled labor' (who are old generations) to produce the final output. The authors show that under certain conditions, an improvement in the efficiency of machines can lower output growth in the long-run by negatively affecting saving rate and rates of accumulation of both physical and human capital. The conditions that will increase the likelihood of such a negative outcome of technological progress are given as 'high substitutability of machines and unskilled labor', 'low substitutability of intermediate goods and skilled labor' and 'high share of skilled labor in the final output'.

There are a number of authors who have been pointing out that the process of 'substitution of machines in place of labor' has already started exerting adverse effects on employment and wages in particularly advanced economies such as US. For example, Brynjolfsson and McAfee (2012), Michaels, Natraj and Van Reenen (2014), Ford (2015) and Acemoglu and Restrepo (2017) have empirically produced some evidence of how automation, robotics, and artificial intelligence might have been affecting real wages and employment of unskilled and medium-skilled labor negatively. However, Acemoglu and Restrepo (2017) suggest that these observed (negative) effects do not reflect the 'equilibrium impact effects' of new technologies, and the dynamic adjustment of wages and employment levels will continue into the future resulting in (probably) with less pessimistic equilibrium outcomes in terms of employment and income distribution. This less pessimistic view of authors is supported by the predictions of the 'task-based' nature of the technology aspect of the model they developed and used as a basis of their empirical analysis. In this model, robots compete against labor in the production of a variety of tasks. The introduction of robots to the production process may affect employment and wages negatively or positively depending on the relative sizes of these opposing effects. The negative effect of robots on employment is due to the 'direct displacement of labor' by robots. And the positive effect operates through the economy-wide expansionary effects of higher productivity (resulting from the use of robots) on aggregate demand that stimulate the demand for labor. Authors' estimates for US economy suggested that so far, the negative impact of introduction of robots on employment has been limited corresponding to a 0.18 – 0.34 percentage decline in the employment to population ratio. But they argue that if the use of robots in US industry spreads as expected, the future negative effects could be much bigger.

In a subsequent paper, Acemoglu and Restrepo (2018b) developed a conceptual framework which assumes that R&D may lead to two different kinds of technological progress. The first one is the 'automation of existing tasks' which inevitably leads to substitution of machines in place of labor and raises unemployment and consequently lowers the share of labor in income. The second one leads to introduction of new tasks in which labor has a comparative advantage and therefore leads to a decrease in unemployment. Depending on certain conditions, it is possible for the R&D process to generate two types of innovations simultaneously in such a way that the economy stays on a stable balanced growth and inequality remains stable in the long-run. Stability in this model results from an important feature of the model: The automation technology which raises unemployment leads to a reduction in the cost of production using labor which, in turn, endogenously encourages R&D efforts to create new tasks (that require labor). Whether or not the long-run equilibrium will involve full automation critically depends on how low long-run rental rate of capital is relative to wages. When there is heterogeneity in skills and skilled labor has a comparative advantage in new tasks, this model predicts that there will be growing income inequality between unskilled and skilled labor in response to automation at least in the short and medium terms. In a follow-up paper (Acemoglu and Restrepo, 2018a), the same authors build on their earlier work by developing a task-based model whereby the nature of automation itself can be of two types; low-skill automation vs. high-skill automation. In the case of low-skill automation, technological innovation is such that it leads to replacement of low-skilled labor by capital. On the other hand, the second type of automation leads to replacement of high-skilled labor. While the low-skill automation increases wage inequality, the high-skill automation decreases it in the long-run. The empirical results obtained by Graetz and Michaels (2018) seem to lend support to the predictions associated with low-skill automation. They have empirically shown that investments in industrial robots were associated with not only faster productivity growth and higher wages for high-skill labor, but also adverse employment effects for low--skill and middle-skill labor.

In a relatively more recent paper, which is an extension of Acemoglu and Restrepo (2016), Zeira (1998) and Acemoglu and Autor (2011), Acemoglu and Restrepo (2018c) develop a framework whereby the automation and thus artificial intelligence and robotics replace workers in tasks that they previously performed. Automation exerts a strong downward pressure on employment and wages through this ‘displacement effect’. However, the authors point out that there are countervailing forces in the adjustment process that may increase the demand for labor. One of these forces is the ‘productivity effect’ generated by the falling costs of producing in automated tasks. This is likely to be expansionary for the economy and increase the demand for labor in non-automated tasks. In addition, capital accumulation caused by automation will also increase the demand for labor. Authors argue that a more countervailing force that is likely to increase the labor demand is the ‘creation of new tasks’ in which labor has comparative advantages. In relation to this latter point, the authors suggest that one of the challenges that economies can face as technology progresses is the ‘potential mismatch between the skill requirements of new technologies and tasks, and the skills of workforce’. Such a mismatch is likely to slow down the adjustment of labor demand to technological improvements that are particularly in the form of automation, artificial intelligence, and creation of new tasks. And this could result in a situation that can be characterized as ‘excessive automation’ which may be responsible for the recent slowdown in productivity growth in US despite the increased R&D efforts.

It is highly critical to recognize that in contrast to standard approaches (which assume that technological progress is 'factor-augmenting' that leads to an increased demand for labor), this new 'task-based approach' allows for the possibility of technological progress exerting adverse effects on employment (Acemoglu and Restrepo, 2018c). And again, interestingly the past empirical literature has almost exclusively reported positive effects of increased R&D intensity on productivity (in terms of labor productivity or TFP (total factor productivity)) and output growth. It is also worth to note that the long-term aggregate employment effects of R&D intensity have not been the focus of most of the past empirical literature. Usually, the differences in the results of the past literature on R&D and productivity (or output) nexus have been in relation to the relative size of the estimated effects. These differences seem to reflect the differences in the methodologies, samples and the sample periods of the data used.

Some of the studies that have utilized cross-sectional firm and industry data and found positive output elasticity of R&D intensity include Mc Morrow and Röger (2009), Hall, Mairesse and Mohnen (2010), and Tsai and Wang (2005). On the other hand, examples of studies that utilized time-series data (at firm and industry level) which reported similar positive output effects include Verspagen (1995) and Griliches and Mairesse (1984). And Coe and Helpman (1995) and Lichtenberg (1992) are only two of the studies that have utilized aggregate data and reported positive effects of R&D on TFP and per capita output.

The earlier theoretical work by Griliches (1973) and Terleckyj (1974) had assumed that R&D activities play a critical role in improving productivity growth. The implicit assumption of these early studies seems to be the assumption of a linear relationship between the two variables.

However, some of the recent empirical studies have suggested that this relationship might be non-linear. For example, Kancs and Siliverstovs (2017), utilizing two firm-level data sets for OECD countries have found out that the impact of R&D investment on firm productivity is different at different levels of R&D intensity: the productivity elasticity being higher (lower) at higher (lower) levels of R&D intensity. The findings of Coccia (2018) who has investigated the optimal R&D investment (and corporate tax) rates that can maximize the labor productivity suggested that beyond certain optimal threshold levels of R&D intensity the labor productivity begins to decline. Again, this finding suggests that the relationship between R&D intensity and productivity, output and employment is possibly involving a relatively more complex dynamics than standard models of growth would predict.

Another study that has produced interesting insights regarding the non-linearity (and therefore complexity) of the relationship between productivity growth and R&D intensity is that of Wakelin (2001). Using the data for 170 UK firms the estimation of a Cobb-Douglas type of production function has shown not only that productivity growth is positively affected by R&D intensity but also the rate of return on R&D is higher for 'innovative- firms' than 'non-innovative firms'. In other words, the levels of (historically accumulated) stocks of knowledge capital have been positively affecting the magnitude of the productivity improvements that might result from a given increase in R&D effort. This firm-level finding yields important insights regarding how similar increases in R&D intensity could have differential effects on productivity, output, and employment depending on the available stock of knowledge capital in each country.

One of the critical issues relating to the R&D efforts of individual firms or industries is the idea that their efforts may indirectly have beneficial effects for others which are primarily expressed as 'spill-over effects' on the growth of productivity and value-added of other firms and industries (or even countries). As pointed out by a number of authors this kind of spill-over effects of R&D efforts are likely to play a critical role in the process of economic growth (Griliches, 1991; 1998; Griffith, Redding and Van Rennen, 2004 and Badinger and Egger, 2016). This insight can (at least to a certain extent) be taken as a reminder of the importance of working with aggregate macro data (in addition to microdata) to capture the overall effects of R&D activities on the macroeconomic performance of an economy in terms of not only productivity and output growth but also unemployment. And in conjunction with this latter point, the growing focus of the recent theoretical work on the effects of R&D on unemployment (in addition to output and productivity) forms the fundamental motivation of the main empirical focus of the present study.

2. Data

The annual data used in this study include: 1. Percentage growth of GDP per capita (GDPG); 2. Unemployment as a percentage of total labor force (UE); 3. Inflation rate (INF); 4. Intramural R&D expenditure as a percentage of GDP (RD). This measure of R&D is also referred to as 'R&D intensity'.

The first three series are obtained from the World Bank database.[1] The Intramural R&D expenditure is obtained from Eurostat[2] in Million units of national currency and divided by GDP (current local currency unit) to calculate RD series for each country.

[1] <https://data.worldbank.org/>.

[2] <https://ec.europa.eu/eurostat/data/database>.

These four variables are available for 11 European countries covering the period 1991 – 2017. Because the long-run analysis in this study is based on ARDL model, the maximum order of integration of the series for each country has to be one. In other words, GDPG, UE, and RD should be either I(0) or I(1). Phillips-Perron unit-root test has been employed in this step to check the stationarity of different variables for different countries; and the integration orders obtained are illustrated in Table 1. Only in five out of 11 countries, this condition is satisfied. Hence, our sample of countries is restricted to Austria, Italy, Netherlands, Romania, and UK. It is worth to mention that different countries might have different rates of return on R&D investment.

T a b l e 1

The Order of Integration and Optimal Number of Lags for Different Countries

Country	RD	GDPG	UE	INF
Austria	I(0)	I(0)	I(1)	I(1)
Italy	I(1)	I(0)	I(1)	I(0)
Netherlands	I(1)	I(1)	I(1)	I(1)
Romania	I(1)	I(0)	I(1)	I(0)
United Kingdom	I(1)	I(0)	I(1)	I(1)

Source: Authors.

3. Methodology

In order to examine Economic growth- Unemployment- R&D expenditure nexus in different countries of our sample, the ARDL Bounds Test is used in this study to check the long-relationship between the series respectively. In addition, Panel ARDL and Pooled Mean Group (PMG) estimation are used to study the dynamics of the interactions between these variables in an average country of our sample.

3.1. ARDL Model

ARDL as a method of studying cointegrating and long-run relationships among variables is a standard least-squares regression containing the lags of both independent and dependent variables as regressors (Pesaran and Shin, 1998). Traditional methods of studying cointegrating relationships, such as Johansen's (1995), Engle and Granger (1987), Dynamic OLS, or Fully Modified OLS require all variables to be I(1), but ARDL method can be applied regardless of whether the variables are I(1) or I(0). This method has also some other advantages over other methods: 1. symmetry in the number of lag terms is not required in the ARDL method; each variable can have its own lag length. 2. this method is applicable even if the sample size is small. 3. it avoids endogeneity and serial correlation problems.

3.1.1. ARDL Bounds Testing

Pesaran, Shin and Smith (2001) suggest an approach to test whether there is a long-run (level) relationship between the variables. This test is based on the joint F-statistic for cointegration analysis, and the result is determined based on equation 1.

$$\Delta UE_t = D_0 + \sum_{i=1}^{p} D_{1i} \Delta UE_{t-i} + \sum_{i=0}^{q} D_{2i} \Delta RD_{t-i} + \sum_{i=0}^{r} D_{3i} \Delta GDPG_{t-i} + D_4 UE_{t-1} + + D_5 RD_{t-1} + D_6 GDPG_{t-1} + \varepsilon_t \tag{1}$$

The null hypothesis of no long-run relationship between the variables in equation (1) is specified by $H_0 : D_4 = D_5 = D_6 = 0$.

For each significance level, two sets of critical values are presented by Pesaran, Shin and Smith (2001). The 1st set is derived on the assumption that all variables in the model are I(1), while the 2nd set assumes that variables are I(0). If the calculated F-statistic exceeds the value of the critical bounds, the null hypothesis H_0 is rejected and the variables are cointegrated. If the calculated F-statistic is less than lower bound, the null hypothesis H_0 is not rejected and the variables are not cointegrated. A critical value between upper and lower bound indicates an inconclusive result.

3.1.2. Panel ARDL and PMG Estimation

The PMG estimator of Pesaran, Shin and Smith (1999) for ARDL models is popular in panel settings especially for the panels with a large number of time-series observations and a small number of cross-sectional units, because alternative GMM estimators are not appropriate in those settings. In this method, the cointegration form of the simple ARDL model is taken and adopted for a panel setting by allowing the cointegrating terms, short-run coefficients, and intercepts to differ across cross-sections.

Equation 2 shows the ARDL model considered in this study for a panel of five countries of our sample:

$$UE_{it} = \mu_i + \sum_{i=0}^{q} \delta_{1i} RD_{i,t-i} + \sum_{i=0}^{r} \delta_{2i} INF_{i,t-i} + \sum_{i=1}^{p} \lambda_i UE_{i,t-i} + \varepsilon_{it} \tag{2}$$

Equation 3 shows the error-correction equation:

$$\Delta UE_{it} = \phi_i \left(UE_{i,t-i} - \theta_{0i} - \theta_{1i} RD_{it} - \theta_{2i} INF_{it} \right) - \sum_{i=0}^{q} \delta_{1i} \Delta RD_{i,t-i} - - \sum_{i=0}^{r} \delta_{2i} \Delta INF_{i,t-i} + \varepsilon_{it} \tag{3}$$

where

$$\theta_{0i} = \frac{\mu_i}{1-\lambda_i}, \ \phi_i = -(1-\lambda_i)$$

δ_{1i} and δ_{2i} are ARDL short-run coefficients, θ_{1i} and θ_{2i} are long-run coefficients, ε_{it} is white noise error term, Δ indicates the 1st difference, ϕ_i is the speed of adjustment and should be significant and negative. Actually, ϕ_i indicates how quickly the system returns to its long-run equilibrium. Finding the coefficients in equations 2 and 3 reveals the nature of relationships between the variables in an average country of our sample.

Before estimating the above-mentioned regression, the stationarity of the variables is checked by the panel unit-root test introduced by Im, Pesaran and Shin (2003). Akaike information criterion is employed to determine the optimal number of lags of dependent and independent variables in the ARDL model. A maximum number of five lags is selected for all variables.

4. Empirical Results

In this section, we first present the empirical results obtained from the application of ARDL based methodologies to investigate the long-run relationship between RD, UE and GDPG for each country individually and between RD and UE (collectively) for the panel of the five countries making up our sample. And then we attempt to underline, interpret and discuss the economic meaning of the critical aspects of these results in the last part of this section.

4.1. ARDL Bounds Testing Results

The results of PP unit root test for different countries of our sample are presented in Table 1. According to this table, the maximum order of integration of variables in our sample is one, which indicates the appropriateness of application of ARDL model for our sample of countries.

The results of the ARDL Bounds test for different countries are presented in Table 2.

F-statistic is greater the upper bound in the case of four countries, and the Null Hypothesis of ‘No long-run relationships exist’ is rejected at 1% significance level in the case of Austria, Netherlands, and Romania. This Null Hypothesis is rejected at 10% significance level in the case of Italy. These results indicate that there is a long-run relationship between UE, GDPG, and RD in all countries of our sample except UK.

T a b l e 2

ARDL Bounds Tests Results

Country	Significance	I0 Bound	I1 Bound	F-statistic	Cointegration
Austria	0.10 0.05 0.01	4.19 4.87 6.34	5.06 5.85 7.52	10.78***	Yes
Italy	0.10 0.05 0.01	2.17 2.72 3.88	3.19 3.83 5.30	3.59*	Yes
Netherlands	0.10 0.05 0.01	2.17 2.72 3.88	3.19 3.83 5.30	11.31***	Yes
Romania	0.10 0.05 0.01	4.19 4.87 6.34	5.06 5.85 7.52	15.67***	Yes
UK	0.10 0.05 0.01	2.17 2.72 3.88	3.19 3.83 5.30	1.36	No

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels respectively.

Source: Authors.

4.2. PMG Estimation Results

PMG Estimation is used in this step to examine the relationship between UE and RD for a panel of five countries of our sample. INF is selected as a control variable in this regression. The panel unit-root test shows that all three variables are I(1). We analyze UE as a function of RD and investigate the long-run and short-run dynamic estimated coefficients presented in Table 3.

T a b l e 3

Long-run and Short-run Elasticity Estimates

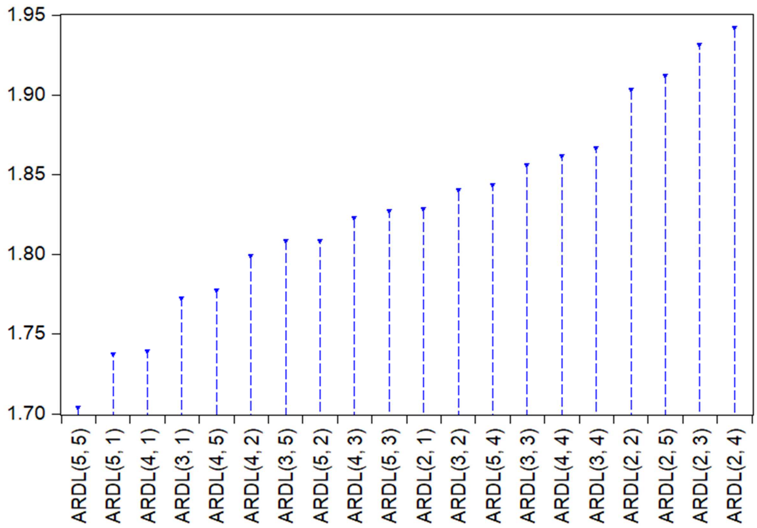
Dependent Variable: Δ(UE)			
Variable	*Coefficient*	*t-Statistic*	*P-value*
Long-run Equation			
RD	–4.1756***	–2.8992	0.0050
Short-run Equation			
ECT(-1)	–0.8033***	–2.7824	0.0070
Δ(UE(-1))	0.4759***	3.4499	0.0010
Δ(UE(-2))	0.1642	0.6975	0.4878
Δ(UE(-3))	0.3257***	5.0261	0.0000
Δ(UE(-4))	0.2216	1.4436	0.1534
Δ(RD)	3.7300**	2.3113	0.0238
Δ(RD(-1))	2.5258**	2.4543	0.0166
Δ(RD(-2))	2.3364	1.1858	0.2398
Δ(RD(-3))	3.2752**	2.5656	0.0125
Δ(RD(-4))	1.5500	0.7366	0.4639
INF	0.0033	0.0212	0.9831
C	8.1927***	3.2604	0.0017
@TREND	0.1038	0.8207	0.4146

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels respectively.

Source: Authors.

Using the Akaike information criterion (AIC), ARDL(5,5) is selected as the best model. Figure 1 illustrates AIC calculated for different models with different numbers of lags. The less AIC estimator, the higher the quality of the model.

Figure 1
Akaike Information Criteria (top 20 models)



Source: Authors.

It is worth to mention that in our PMG estimation, RD and INF have been considered as dynamic and fixed regressors respectively. Therefore, INF, intercept (C), and @TREND are not a part of the long-run relationship.

The coefficient of ECT(-1) is –0.8033 which is significant at 1% level. This coefficient indicates an 80% speed of adjustment. It means any deviation in the system from long-run equilibrium level is corrected by 80% after one year.

The Jarque-Bera test is employed for residual diagnostics. The null hypothesis is “residuals are normally distributed”. The obtained Jarque-Bera statistics equal to 0.62 and the p-value equal to 0.73 indicate that there is no normality problem in the ARDL model presented in Table 3.

Actually, in the above-mentioned analysis, we have investigated both long--run and short-run relationships between UE and RD for an average country in our sample by applying PMG approach to the estimation of an augmented version of the Phillips-curve equation for the panel of our sample of five countries. We assume that in the long-run, the UE is determined by the rate of technological progress which is proxied by the level of RD in our model. In the short-run, in addition to (current) inflation (INF), lagged values of UE and RD are allowed to affect the current level of UE. The insights of the recent theoretical literature (that we briefly summarized in the first two sections) suggest that the short-run and even long-run effects of technological progress on unemployment can be favorable or unfavorable depending on certain factors. Particularly, if the nature of technological progress is largely in the form of 'task-creation' rather than 'automation' (or artificial intelligence and robotics) an increase in R&D can lower the (natural) rate of unemployment. Otherwise, it can raise the rate of unemployment. But, even if the nature of the technological change is dominated by 'task-creation' in the short-run, unemployment can still increase if the skills required by the newly created tasks do not match the skills of the available workforce. On the other hand, the basic hypothesis of Phillips-curve equation is the idea that inflation rate and unemployment rate are inversely related especially in the short-run; higher inflation is expected to be associated with lower unemployment in the presence of some kind of rigidities in the adjustment of nominal wages. But, in the long-run, it is assumed that inflation rate has no impact on the rate of unemployment.

The results of the panel estimation of the model explained above have been reported in Tabe 3. We underline the most important aspects of these estimation results below but leave their economic interpretation and discussion to the last part of this section:

a) In the long-run, a higher RD is highly likely to be associated with lower UE.

b) The fact that the estimated coefficients of two of the lagged values of RD are positive and significant suggests that in the short-run (and possibly even in the medium term) a given increase in RD can raise UE.

c) The estimated coefficient of (the contemporaneous) INF is statistically insignificant suggesting that inflation is not correlated with UE.

d) In the short-run, the estimated coefficients of past (lagged) values of UE are positively associated with current UE. This shows the persistence of unemployment over time.

4.3. Interpretation and Discussion

The main findings of the statistical results presented in the first part of this section are stated and briefly discussed below:

a) In the long-run, there exists a long-run equilibrium relationship between the three variables, namely RD, UE and GDPG for all countries with the exception of UK. This is an important finding that might be taken as strong statistical evidence of possible favorable effects of increasing the R&D intensity on the process of economic growth and unemployment in the long-run in four of the countries investigated. One possible interpretation of this result is that not only the expansionary effects operating through productivity improvements but also 'new tasks (jobs) creation' nature of the technological progress (resulting from additional R&D efforts) could be playing a role in this relationship in these four countries (Austria, Italy, Netherlands, and Romania) in the long term. The peculiar result for UK points out to the fact that the relationship between the nature of technological changes resulting from R&D, economic growth, and unemployment is likely to be more complicated particularly for advanced economies as suggested by some of the recent theoretical literature discussed earlier in the 'literature review' section.

b) The application of PMG estimation methodology to the panel of five countries (for a framework that is an augmented version of Phillips curve relationship between unemployment and inflation rate) has produced evidence of a negative relationship between R&D and unemployment rate in the long-run. However, the fact that some of the estimated delayed (lagged) effects of R&D on UE turned out to be significantly positive, suggest that in the short-run, a given increase in R&D (in the average country of our sample) could possibly be exerting adverse effects on unemployment. Some of the plausible factors that might (at least partly) be contributing to these opposite long-run and short-run effects of R&D on unemployment are as follows: i) The dominant aspect of technological change resulting from R&D efforts is possibly in the form of (new) 'task-creation' rather than automation and artificial intelligence which usually entails replacement of labor by machines. This could be an important contributing factor to the unemployment lowering effect of R&D in the long-run. ii) This favorable effect of R&D on unemployment in the long-run could also be due to the possibility of expansionary effects of a given increase in R&D (operating through the productivity improvements resulted from new technologies) and could be more than offsetting their adverse (displacement) effects on labor. iii) In the short-run (and possibly even in the medium run) technological improvements (generated by increased R&D efforts) seem to be leading to a temporary increase in the rate of unemployment. This could be due to the 'mismatch' between the skills required by 'newly created tasks (jobs)' by new technologies and the skills of the available workforce which is a phenomenon that has been pointed out by the recent literature as presented in the 'literature review' section.

Conclusions

This study contributes to the existing literature about the macroeconomic effects of R&D intensity particularly by focusing on its relationship with unemployment in addition to economic growth in a sample of five European countries. And this has been largely motivated by the insights of the recent theoretical literature on 'technological progress- unemployment-growth' nexus. This new line of research itself seems to be motivated by the rising unemployment of particularly unskilled labor, worsening of income and wealth distribution, and even falling productivity growth in certain advanced economies despite the increases in R&D intensities in the last decade. One of the main insights of this emerging new research is the possibility of technological progress leading to higher rates of unemployment, worsening of income distribution, and even lower rates of economic growth through lower rates of national savings under certain conditions (Sachs and Kotlikoff, 2012). Such a pessimistic scenario has been shown to be more likely particularly if the nature of technological change resulting from R&D activities is largely in the form of 'automation and artificial intelligence'. Even if the nature of technological improvements is largely in the form of 'task-creation' which generates new jobs (tasks) for labor, the dynamic adjustment to a new long-run equilibrium can be painful particularly when the skills required by the newly created tasks do not match the skills of the existing workforce. In this case in the short-run (or even medium run) even task-based technological changes could raise the rate of unemployment (Acemoglu and Restrepo, 2018d).

The empirical results of the present study (based on ARDL bounds testing) have suggested that there exists a long-run relationship between R&D, unemployment rate, and economic growth (GDP growth) for four of the countries (namely Austria, Netherlands, Italy, and Romania) investigated. For UK no such long-run relationship has been found.

Two of the most critical findings of the empirical work carried out in this study are obtained from the ARDL based panel regression of unemployment based on a modified version of Phillips curve kind of equation which hypothesized that while in the short-run inflation can affect unemployment, in the long-run, the only determinant of unemployment is R&D. The estimation results have shown that in the long-run an increase in R&D is likely to be associated with lower rates of unemployment. However, in the short-run, some of the lagged effects of R&D have been found to be correlated with higher rates of unemployment for the average country in our sample. These two results (together) seem to suggest that the nature of technological change resulting from R&D activities has been probably largely in the form of 'task-creation' instead of 'automation and artificial intelligence'. But possibly due to the 'mismatch between the skills required by the newly created tasks (jobs) and the skills of available workforce in these countries, technological progress might be causing some temporary increase in the rate of unemployment.

In light of the main findings of the present study and other relevant recent research summarized in the first two sections, the main policy insights of this empirical study can be listed as follows: a) Public policymakers should be more aware of the adverse effects of certain forms of technological changes such as automation and artificial intelligence on employment and income distribution. And in this regard they can find welfare improving to design incentive programs and policies that may aim at fine-tuning the balance between the R&D efforts that focus on introducing 'automation, artificial intelligence and smart machines' type of innovations as opposed to those that primarily focus on innovations that will largely create ' new tasks and jobs'. b) Even if the nature of technological change happens to be in the form of 'task-creation' it is obvious that there is a need for improving the skill levels (stock of human capital) of the existing workforce regularly so as to match the skills that will be required by the new technologies. However, this requires a much broader and deeper coordination of public sector, private sector, institutes of higher education (and other research centers), and labor markets (trade unions). This latter point is particularly motivated by the critiques of Gummeson (2014) who has argued that the ongoing innovation activities by the private firms or otherwise may not be necessarily generating additional socio-economic value to the society. Future research attempting to understand the conditions under which firms find profit-maximizing to direct their R&D efforts to generate automation vs. task creation kind of technologies can offer valuable insights to the policymakers. Policymakers can attempt to design incentive programs (such as low-cost investment credits and tax breaks) to firms and other institutions involved in R&D so as to encourage them to generate new technologies that are relatively more in the form of 'task-creation'. Joint initiatives of local and central governments with private firms and labor unions in terms of 'labor training programs' focusing on the provision of new skills (required by upcoming new technologies) to the workforce can potentially lower the unemployment rate even in the short-run.

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