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The Impact of R&D on Skill-specific Employment Rates in the UK and France

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We apply nonlinear Autoregressive-Distributed Lag (ARDL)-based methodologies to examine the nature of the effects of changes in R&D (intensity) on the employment rates of 'high-skill', 'medium-skill' and 'low-skill' labour and also whether or not these effects are symmetric. The empirical results based on the annual data for the period of 1991–2017 have suggested that while increased R&D has favourable effects on the employment rate of 'high-skill' labour in France, it has a negative impact on this type of labour in the UK. On the other hand, while the given increase in R&D has been found to be negatively affecting the employment rates of both 'low-skill' and 'medium-skill' labour in France, it has no impact on the employment rates of these two types of labour in the UK. These results may suggest that the dominant form of technological change in France is possibly a combination of 'low-skill automation' and 'task-based' whereby new technologies are simultaneously leading to replacement of 'low-skill' and 'medium-skill' labour by machines and the creation of new tasks (jobs) in which 'high-skill' labour has a comparative advantage. In the UK, the dominant form of new technologies resulting from additional R&D efforts seems to be in the form of 'high-skill automation' whereby 'Robotics and Artificial Intelligence' kind of new technologies might be causing replacement of 'high-skill' labour with machines. These results suggest that new technologies might be exerting adverse effects on income distribution in different ways in the UK and France.

1. Introduction

One of the most critical insights of the recent theoretical work investigating the nature of the relationship between technological change and employment has been not only the likelihood of its highly complex nature but also the possibility of the endogeneity of this relationship. The complexity seems to arise particularly in relation to the possibility of the varying nature of the effects of different types of technological change on different types of labour (in terms of skill levels) and the possible endogenous nature of the R&D efforts in response to changing relative price of machines (capital) against each type of skill-specific labour (i.e. high-skill, medium-skill and low-skill). Furthermore, the dynamic adjustment of the economy (in terms of output growth, income distribution, wages of each type of labour, etc.) in response to a given technological change could involve alternative scenarios depending on different assumptions about certain critical parameters, such as the nature of the initial technological change and the respective elasticities of substitution between machines and each type of labour. In this context, the nature of technological change could be such that it can be a 'task-based' type or 'automation' type; while the first type of technological change usually involves creation of new tasks (or jobs) for labour, and is rightfully named as task-based technological change, the second type is classified as an automation type of technological change, which is usually associated with displacement (or replacement) of labour by machines (Acemoglu and Restrepo 2016, 2017, 2018a, 2018b).

Technological developments in the area of 'robotics and artificial intelligence' are considered to be automation type and naturally their potential long-term consequences on the employment rates (of not only unskilled but also skilled labour), relative wages, income distribution, savings rates, capital accumulation, and economic growth have been the focus of recent theoretical and empirical research (Sachs and Kotlikoff 2012; Michaels *et al.* 2014).

Even though the automation type of technologies are normally expected to cause displacement of labour in tasks previously performed by labour causing a decrease in the employment and wages of labour, the productivity improvements resulting from automation have the potential to increase the demand for labour in non-automated tasks. In other words, the dynamic adjustment of the economies to new technologies generated by new R&D efforts is likely to involve a relatively more complex mechanism and therefore render their long-run effects theoretically highly ambiguous in terms of not only aggregate employment but also skill-specific employment rates, income distribution, and economic growth. This insight, in turn, suggests that the nature of the long-run effects of R&D efforts on employment rates of high-skill, medium-skill and low-skill labour in each country are ultimately an empirical matter. And this argument forms the main motivation of the current study, which primarily focuses on investigating the effects of changes in R&D intensities (proxied by the percentage of R&D spending in GDP) on the respective employment rates of high-skill, medium-skill and low-skill labour in two of the advanced European economies, namely the UK and France.

To the best of our knowledge, this issue has not been empirically investigated yet for advanced European countries such as the UK and France. Our findings are likely to provide valuable insights about the possible differential employment effects of R&D efforts in different European countries and therefore can potentially help both individual policymakers and EU authorities in designing better incentives and tax break policies for the private sector involved in R&D.

Naturally, R&D is the single most important determinant of the rate of technological progress in advanced economies in contrast to less developed countries where (R&D efforts are very limited and) trade and FDI can potentially be very important in improving technological level. France and the UK are two of the most advanced European economies, along with Germany, which have been at the forefront of artificial intelligence and industrial innovation for decades. However, these two countries have different labour markets because (1) since 2004, the UK has not been applying any transitional restrictions on the labours from newly joined EU members; (2) on 30 April 2011 the 'Accession State Worker Registration Scheme' was closed in the UK; (3) for many years the citizens of almost all EU countries have been able to be self-employed and manage businesses, set up their own companies, or accept offers of work in the UK. All of these factors have made UK's labour market much more flexible than France's labour market. Therefore, we expect different reactions of the respective employment rates of each type of labour to technological change in these two countries not only because of the difference in labour markets, but also due to the possible differences in the dominant form of the technological change that has been taking place in each country, and this makes it worthwhile comparing them in this study.

To this end, we apply alternative Nonlinear Autoregressive-Distributed Lag (NARDL) based methodologies (such as asymmetric ARDL bounds testing, and dynamic multiplier analysis) to empirically examine not only the qualitative and quantitative nature of the effects of R&D on each type of (skill-specific) labour, but also the presence of any kind of asymmetry in these effects (for each country) with respect to positive and negative shocks to R&D. However, it is worth underlining that employment rates of high and low-skill labour are likely to be affected by a number of different economic and institutional factors in addition to the rate and type of technological progress (Bassanini and Duval 2009).

The rest of this paper is organized as follows: in the second section, we briefly review the basic insights of selected recent theoretical literature. The third and fourth sections are the data and methodology sections. The fifth section is devoted to the presentation and discussion of empirical results. The final section concludes with a brief summary of the basic findings and insights of the paper.

2. Literature Review

In this section, we attempt to report the key insights of some of the recent theoretical literature that have focused on understanding the possible effects of different types of technological changes (resulting from R&D efforts) not only on the overall employment rates but also on the employment rates of different types of (skill-specific) labour. The main insight that has emerged from this new body of theoretical literature (which is still ongoing) is the idea that the nature of the overall equilibrium effects of new technologies – not only on employment rates but also on growth, capital accumulation, relative wages, and income distribution – is likely to be determined by far more complex dynamics than the standard neoclassical or even new growth theory-based models would suggest. Furthermore depending on the type of technological change, the qualitative (and quantitative) nature of these effects has been shown to be (at least theoretically) very different.

In the standard growth models, technological progress is assumed to raise the general productivity of all factors of production (such as labour and capital) leading to an improvement in what is called 'total factor productivity'. This increase, in turn, is intuitively expected to increase the demand for both labour and capital, which can (at least partly) explain the observed correlation between growth and employment rates in advanced economies (such as the US and Japan) in the twentieth-century (Blanchard 2009). However, the developments in the labour markets and the distribution of income and wealth, especially in the last decade of the twenty-first century have started causing a great deal of concern (among economists and policymakers alike) regarding whether or not at least some part of these adverse developments could be resulting from the nature of the new technologies.

The new line of theoretical research that has attempted to shed some light on the issues briefly highlighted above has particularly revealed that some of the key elements that are likely to play a critical role in determining the nature of the effects of new technologies are the presence of heterogeneity in the skill levels of labour and the nature of the technological change itself – whether or not technological change is 'automation type' or 'task creation type', and if it is automation type whether it is 'low-skill automation ' or 'high-skill automation'. Similarly, even when the new technologies are 'task creation' type, so that they entail the creation of new tasks and jobs for labour, the critical question would be whether these newly created tasks would require high-skill labour or medium-skill labour or low-skill labour. This relatively new perspective in modelling the nature of the technological progress in understanding the nature of the dynamic interactive mechanisms between technology and macroeconomy can be considered as a response to the growing concern about the possible sources of rising income inequality, especially in the last decade or two, even in developed countries. As Gordon (2009) and Atkinson *et al.* (2011) have underlined, while one of the distinguishing features of this rise in inequality is the falling share of labour income relative to capital, another is the increase in discrepancy between the respective GDP shares of wage incomes of skilled and unskilled labour. Sachs and Kotlikoff (2012) have used an overlapping generation based model to show that under certain conditions these two features of growing income inequality could be due to the rapid expansion of brainpower in the last decade or so. In their model, both young and old generations work in the production process; while young generations (who are the unskilled labour) work with machines to produce intermediate products, the skilled labour (the older generations) work with intermediate products to produce the final goods. One of the main predictions of this framework is that when the respective degrees of substitutability 'between machines and unskilled labour' and 'between intermediate goods and skilled labour' are sufficiently high, a given technological progress can not only worsen the income distribution between skilled and unskilled labour but also lower the long-run growth rate of the economy through a reduction in the rate of accumulation of physical capital by lowering the national saving rate.

Some of the recent empirical work that has examined the wage and employment effects of new kinds of technologies that are in the form of 'automation' especially in advanced economies (such as the US) includes Brynjolfsson and McAfee (2012), Micheals *et al*. (2014), Ford (2015) and Acemoglu and Restrepo (2017). One of the common insights that has emerged from all of these studies is the fact that the process of automation (which entails substitution of machines for labour) has already started impacting the real wages and employment of unskilled and medium-skilled labour negatively. However, it is worth noting that the authors of one of these studies (Acemoglu and Restrepo 2017) have raised the possibility that it is too early to be pessimistic about the ultimate effects of the new technologies on employment and income distribution. Using a model where the nature of technological change is 'task-based' according to which robots compete against labour in the production of a variety of tasks, they show that, in the long run, it may be possible for the (economy-wide) expansionary effects of increased productivity generated by new robotics (automation) technologies to more than offset their negative effects on employment operating through their direct displacement effects on labour.

As Acemoglu and Restrepo (2018a) have underlined, most of the existing approaches to the nature of the production functions (used in macroeconomics) are such that technology is assumed to be in the form of factor-augmenting. In particular, automation can (intuitively) be modelled as a 'capital-augmenting' form of technological change, which normally should lead to an increase in the demand for labour and wages (Acemoglu and Restrepo (2016)). Some authors have pointed out that the automation kind of new technologies are not just associated with the development of more productive vintages of existing machines, but rather the development of new kinds of machinery that can be used to perform tasks that were previously carried out by human labour (Acemoglu and Restrepo 2018b). One of the main differences between the standard approach based on factor-augmenting technological change and the 'task-based' approach is the possibility of technological progress leading to lower wages and employment in the latter approach. Even when the nature of the technological change is automation type, this may not necessarily lead to an increase in unemployment. This is due to the fact that the economy-wide expansionary (employment) effects of higher productivity brought about by the 'new automation' kind of technologies can more than offset the negative (displacement) effects on labour. However, it is worth noting that some authors have been pointing out that the real risk for labour can come not from highly productive but from relatively not-so-productive automation technologies, which are just productive enough to be adopted and displace labour but not sufficiently productive enough to generate strong expansionary effects on employment (Acemoglu and Restrepo 2018b; Brynjolfsson and McAfee 2012; Ford 2015). In case the overall net effect of the 'automation kind of new technologies' on employment happens to be negative, one of the critical questions that needs to be answered is whether or not these negative effects are particularly operational for the employment rates of high-skilled, medium-skilled or low-skilled labour. Even if the net overall employment effects of the new technologies (regardless of their type) are positive, there exists a distinct possibility for (both qualitatively and quantitatively) the presence of differential effects on the respective employment rates of each type of (skill-specific) labour. Naturally, the investigation of these critical issues is ultimately an empirical matter. As briefly mentioned before, one of the critical determinants of the qualitative nature of the possible differential effects of new technologies on different types of labour is likely to be whether it is the high-skilled or medium-skilled or low-skilled labour that has a comparative advantage relative to capital in the newly created tasks. In other words, even if automation types of new technologies create new tasks and jobs for labour, this may entail positive expansionary employment effects for specific types of labour while having negative adverse displacement effects for other types of labour. For example, certain applications of AI (Artificial Intelligence) kinds of new technologies in education, health care, and design may generate new employment opportunities for relatively high skilled labour (Acemoglu and Restrepo 2018b). Some of the empirical studies that have investigated these issues (particularly for the US) have produced evidence for the contribution of automation of a range of low-skill and medium-skill occupations to wage inequality and employment polarization (Autor *et al*. 2003; Goos and Manning 2007; Michaels *et al*. 2014). Furthermore, the empirical work of Frey and Osborne (2017) who have classified 702 occupations based on their susceptibility to automation has suggested that over the next two decades 47% of US workers are at risk of automation. But Acemoglu and Restrepo (2017) argue that these pessimistic predictions based on the observational analysis of the present and recent data cannot reflect the 'equilibrium impact' of these new technologies on employment and wages, particularly because there is no guarantee that firms would choose to automate, which would depend on the substitution of machines for labour. In addition, the nature of the technological change is likely to be endogenous; this particularly means that if the cost of a specific kind of labour falls relative to machines and other kinds of labour, then firms may direct their R&D efforts to generate new (skill-based) technologies that exclusively require the use of that specific kind of labour. In this context, Acemoglu and Restrepo (2016) suggest that the 'automation kind' of new technologies can be of two types 'low-skill automation' and 'high-skill automation', whereby capital can have a comparative advantage not only in routine and manual tasks (with low complexity) but also in complex tasks which would be carried out by high-skill labour otherwise.

One of the main insights emerging from the brief discussion of the relevant aspects of the selected literature is the fact that the qualitative and quantitative nature of the effects of new technologies resulting from increased R&D intensity on the employment rates of each type of (skill-specific) labour could be very different. Furthermore, what is largely missing in the past literature is the investigation of the possibility of these effects (for each type of labour) being asymmetric in nature for the cases of increases and decreases in R&D intensity. In addition, the past literature has largely ignored the empirical analysis of the determination of the dominant form of technological change in a country by examining the causal effects between the changes in R&D intensity and the employment rates of high-skill, medium-skill, and low-skill labour. These issues form some of the main motivations of the present study, which aims at empirically examining the issues for the UK and France, so as to carry out a comparative analysis for these two countries regarding the possible differences in the dominant form of technological change in each country. However, before we present the 'data and methodology' section, we believe that it is important to underline the fact that there are many other economic and institutional factors (such as output gap and union density) that are likely to affect the change in the rates of employment for each possible (skill-specific) type of labour (Bassanini and Duval 2009).

3. Data and Variables

The annual data used in this study include: 'R&D intensity', which is intramural R&D expenditure as a percentage of GDP (RD), inflation rate (INF), real interest rate (INT) and employment rates by educational attainment level (%), which is calculated by dividing the number of persons employed and aged 20–64 by the total population in the same age and skill group. This variable is defined in three sub-variables indicating the employment of people with (1) less than primary, primary and lower secondary education (emp1); (2) upper secondary and post-secondary non-tertiary education (emp2) (3) Tertiary education (emp3).

The inflation rate and GDP 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. Real interest rate and employment series are also obtained from Eurostat. The data cover the time period between 1991 and 2017 for France and the UK. It is worth mentioning that some people didn't declare their level of education in the survey provided by Eurostat, so we discard them from our sample. Another control variable adopted in this study is the output gap, which is the difference between actual GDP and potential GDP divided by the potential GDP.

According to the theory of Philips curve, unemployment and inflation have an inverse relationship because an increase in aggregate demand due to a fiscal stimulus increases the demand for labour and nominal wages and decreases the unemployment rate. However, higher wage costs lead to higher prices. In addition, considering the fact that INF is not correlated with RD in our data set, inflation can be a suitable control variable in our study.

4. Methodology

The non-linearity of many processes and variables has long been noted. The joint issues of non-linearity and non-stationarity considered in a substantial body of literature reveal that the assumption of linear adjustment is restrictive and linear models

1. https://data.worldbank.org/
2. https://ec.europa.eu/eurostat/data/database

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are not able to provide reliable forecasts or sufficiently rich information about phenomena.

Sometimes the usual cointegration tests do not detect any long-run relationship between the series, but a hidden cointegration can be detected between negative and positive components of those series (Granger and Yoon, 2002). Although the symmetric linear combination of non-stationary variables is used to present the long-run relationships in most of the studies, it has also been tried to model the asymmetry of the relationship between different variables in some research papers (e.g. Shiller, 1993, 2005). Most of these papers used the two step Engle-Granger method, but this is not inherently efficient. In this paper, we employ Dynamic Multipliers and Asymmetric Cointegration test in a non-linear ARDL framework developed by Shin *et al*. (2014). This technique is able to model asymmetries both in the patterns of dynamic adjustment and in the long-run coefficients. Actually, when the system moves toward a new equilibrium following a shock to a variable, negative and positive shocks are reflected in asymmetric adjustment patterns which are traced out by asymmetric cumulative dynamic multipliers. A non-parametric bootstrap technique is also used to compute the confidence intervals for dynamic multipliers, and *p*-values for cointegration tests.

The NARDL method of estimation is valid irrespective of the integration order of the variables (I(0), I(1) or mutually cointegrated). The Zivot-Andrews unit root test is employed in this study to ensure that maximum order of integration is one.

4.1. The Non-linear ARDL Model

Equation (1) shows the NARDL (p,q,r) model considered in this study.

$$emp_t = \sum\nolimits_{j=1}^{p} \varphi_j \, emp_{t-j} + \sum\nolimits_{j=0}^{q} (\theta_j^+ \, RD_{t-j}^+ + \theta_j^- \, RD_{t-j}^-) + \sum\nolimits_{j=0}^{r} n_j \, INF_{t-j} + \varepsilon_t \tag{1}$$

where θ_j^+ and $\theta_j^-$are the asymmetric distributed lag parameters, φ_j is the autoregressive parameter, and ε_t is the error term. RD is decomposed into RD^- and RD^+ representing the partial sum processes of negative and positive changes in RD. Equation (1) shows how the employment rate is a function of its own lags, the lags of R&D components, and the lags of inflation rate. In this equation, p, q and r represent the maximum number of lags considered for the employment rate, R&D components and inflation rate respectively.

4.2. Bounds-testing the Asymmetric Long-run Relationship

Equation (2) is used to test whether there is asymmetric cointegration between variables.

$$\begin{aligned} \Delta emp_t = {} & \rho \xi_{t-1} + \sum\nolimits_{j=1}^{p-1} \gamma_j \, \Delta emp_{t-j} + \sum\nolimits_{j=0}^{q-1} (\pi_j^+ \, \Delta RD_{t-j}^+ + \pi_j^- \, \Delta RD_{t-j}^-) \\ & + \sum\nolimits_{j=0}^{r} \alpha_j \, \Delta INF_{t-j} + e_t \end{aligned} \tag{2}$$

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where Δ indicates the first difference, and $\xi_{t-1} = emp_t - \beta^+ RD_t^+ - \beta^- RD_t^- - \delta INF_t$ is the non-linear error-correction term. In addition, $\beta^+ = -\frac{\theta^+}{\rho}$ and $\beta^- = -\frac{\theta^-}{\rho}$ are asymmetric long-run coefficients. If $\rho = 0$, equation (2) reduces to an equation containing only first differences, which means no cointegration exists between the levels of emp_t, RD_t^+, RD_t^-, and INF_t. F_{PSS} is defined based on the F-test of the joint null, $\rho = \theta^+ = \theta^- = \eta = 0$.

For each significance level, two sets of critical values are presented by Pesaran *et al.* (2001). One set is derived on the assumption that all variables in the model are I(1), while the other set assumes that variables are I(0). If the calculated F_{PSS} exceeds both critical bound values, the null hypothesis is rejected and the variables are cointegrated, if it is less than both critical values, the null hypothesis is not rejected, and if it is between them the result is inconclusive.

4.3. Asymmetric Long-run Coefficients and Dynamic Multipliers

In this article, we study two general forms of asymmetry: (1) adjustment asymmetry presented by the patterns of adjustment from initial to final equilibrium after the shock; (2) reaction or long-run asymmetry identified by $\beta^+ \neq \beta^-$.

The asymmetric dynamic multipliers of one unit change in RD_t^+ or RD_t^- on *emp* can be derived by using 'ARDL in levels' presented by equation (3)

$$\varphi(L)\, emp_t = \theta^+(L) RD_t^+ + \theta^-(L) RD_t^- + \eta INF_t + e_t \tag{3}$$

The cumulative dynamic multiplier impacts of RD_t^+ and RD_t^- on emp_t is defined as follows:

$$m_h^+ = \sum\nolimits_{j=0}^{h} \frac{\partial\, emp_{t+j}}{\partial RD_t^+},\; m_h^- = \sum\nolimits_{j=0}^{h} \frac{\partial emp_{t+j}}{\partial RD_t^-}, h = 0, 1, 2, \ldots \tag{4}$$

where m_h^+ indicates the summation of changes in emp_t due to the positive changes in *RD*. On the other hand, m_h^- indicates the summation of changes in emp_t due to the negative changes in *RD*. Usually, dynamic adjustment patterns associated with m_h^+ and m_h^- are not symmetric and illustrate the duration of disequilibrium, which is an important feature of a non-linear ARDL model.

The Wald statistic (following an asymptotic χ^2 distribution) is also used to test the null hypothesis of symmetric long-run coefficients. Normally, we expect the result of the Wald test to be consistent with the patterns of dynamic multipliers.

5. Results

Tables 1 and 2 show the descriptive statistics and unit root test results for all variables.

According to Table 1, the range of variation of RD for both France and the UK is around 0.3%; on the other hand, the range of variation of different kinds of employment is around 7%. These two figures give us a sense of the expected coefficient of R&D in the employment rate equation.

Table 1. Descriptive statistics.

		emp_1	emp_2	emp_3	*INF*	*RD*
UK	Mean	62.256	77.756	85.780	2.117	1.652
	Median	63.800	77.400	85.600	2.110	1.637
	Maximum	66.700	80.600	87.800	4.463	1.864
	Minimum	55.500	75.000	82.700	0.050	1.546
	Std. Dev.	3.643	1.880	1.505	0.154	0.084
	Skewness	–0.743	0.157	–0.292	0.392	1.240
	Kurtosis	2.025	1.604	1.969	2.959	4.129
France	Mean	54.880	70.972	79.692	1.454	2.171
	Median	54.900	70.800	79.300	1.665	2.180
	Maximum	58.600	73.000	83.000	2.813	2.320
	Minimum	50.500	68.900	76.700	0.038	2.020
	Std. Dev.	2.144	1.265	1.744	0.749	0.085
	Skewness	–0.076	0.126	–0.010	–0.484	–0.136
	Kurtosis	2.389	1.593	2.142	2.289	1.840

Table 2. Unit-root test results.

		emp_1	emp_2	emp_3	*INF*	*RD*	*INT*	*OG*
France	Level	0.9438	0.86	0.0098***	0.0485**	0.8454	0.1121	0.8604
	1st difference	0.0112**	0.0030***			0.0040***	0.0007***	0.0866*
UK	Level	0.8797	0.8288	0.6152	0.1655	0.4475	0.0915*	0.8383
	1st difference	0.0683*	0.0286**	0.0483**	0.0071***	0.0205**		0.0898*

The figures in the table are P-values.
*, **, *** indicate significance at 10, 5 and 1% level.

According to Table 2, the maximum order of integration for all of the series employed in this study is one. Therefore, the NARDL model can be applied to investigate the relationship between the variables. However, before going directly to the non-linear specification, we estimate some linear regressions correlating R&D intensity and employment rates, conditional on relevant control variables identified in the literature to highlight what we gain from using a non-linear specification. We employ the ARDL method because our series, including real interest rate (INT) and output gap (OG), have different orders of integration. The correlation matrix of independent variables and the results of these linear estimations are presented in Tables 3 and 4 respectively.

According to Table 3, there is no multicollinearity problem between RD and other control variables. Table 4 shows the results of ARDL bound testing (column 4) and the long-run relationship between skill-specific employment, R&D intensity, and different control variables (column 5). In the case of France, there is a long-run relationship between (a) emp_1, RD and INF; (b) emp_2, RD and INF; (c) emp_2, RD and OG; and (d) emp_2, RD and INT. In the case of the UK, there is a long-run

Table 3. Correlation matrix of independent variables.

Country		RD	INF	OG	INT
France	RD	1.00	–0.27	–0.47	–0.04
	INF	–0.27	1.00	0.11	0.51
	OG	–0.47	0.11	1.00	0.22
	INT	–0.04	0.51	0.22	1.00
UK	RD	1.00	0.29	–0.22	0.28
	INF	0.29	1.00	0.38	0.21
	OG	–0.22	0.38	1.00	0.21
	INT	0.28	0.21	0.21	1.00

Table 4. Linear estimations.

Country	Dependent variable	Independent variable	Cointegration	Equation *RD*	*INF*	*OG*	*INT*	*C*
France	emp_1	RD, INF	Yes	–21.433***	2.1614**			49.798***
	emp_2		Yes	–29.676**	–4.747*			54.220***
	emp_3		No					
	emp_1	RD, OG	No					
	emp_2		Yes	–10.514**		1.5343*		39.354***
	emp_3		No					
	emp_1	RD, INT	No					
	emp_2		Yes	–13.146***			–0.176	30.035***
	emp_3		No					
UK	emp_1	RD, INF	No					
	emp_2		No					
	emp_3		No					
	emp_1	RD, OG	No					
	emp_2		No					
	emp_3		Yes	–9.279		1.808***		20.073***
	emp_1	RD, INT	No					
	emp_2		No					
	emp_3		Yes	–25.348***			–0.0149	42.762***

*, **, *** indicate significance at 10, 5 and 1% level.

relationship between (a) emp_3, RD and OG; and (b) emp_3, RD and INT. In each of these cases, the long-run coefficients are estimated.

The results of asymmetric bounds testing are presented in Table 5. The null hypothesis of this test is 'no long-run relationship between variables'. According to this table, F_{PSS} exceeds the upper bound in four cases and rejects the null hypothesis. Therefore, there is cointegration between RD_t^+, RD_t^-, INF_t and all three proxies of employment in the case of France, and between RD_t^+, RD_t^-, INF_t and emp_3 in the case of the UK.

This is an important finding that might be taken as strong statistical evidence of the possible effects of changing the R&D intensity on the employment of labour with different skill-levels in the long run in France. One possible interpretation of this result is that the expansionary effects operating through productivity improvements

Table 5. Asymmetric bounds testing results.

Country	Dependent variable	Significance	I(0) Bound	I(1) Bound	F-statistic	Asymmetric Cointegration
France	emp_1	10%	2.676	3.586	4.055*	Yes
		5%	3.272	4.306		
		1%	4.614	5.966		
	emp_2	10%	2.915	3.695	4.869**	Yes
		5%	3.538	4.428		
		1%	5.155	6.265		
	emp_3	10%	2.676	3.586	4.739**	Yes
		5%	3.272	4.306		
		1%	4.614	5.966		
UK	emp_1	10%	2.915	3.695	1.874	No
		5%	3.538	4.428		
		1%	5.155	6.265		
	emp_2	10%	2.915	3.695	2.096	No
		5%	3.538	4.428		
		1%	5.155	6.265		
	emp_3	10%	2.676	3.586	21.816***	Yes
		5%	3.272	4.306		
		1%	4.614	5.966		

*, **, *** indicate significance at 10, 5 and 1% level.

(resulting from additional R&D efforts) could be playing a role in this relationship in this country in the long term. The peculiar result for the UK points to the fact that the relationship between the nature of technological changes resulting from R&D and employment is likely to be more complicated, particularly for advanced economies as suggested by some of the recent theoretical literature discussed earlier in Section 2.

Table 6 presents the long-run coefficients derived from level equations of the NARDL model. We let INF be dynamic or fixed in the equations and report the best model in each case. The significance of long-run coefficients obtained in this step is consistent with asymmetric cointegrations detected by asymmetric bounds testing in the previous step.

5.1. Asymmetric Long-run Coefficients and Dynamic Multipliers in the Case of France

According to Table 6, in the case of France, the coefficients of RD^+ and RD^- are significant in all three equations of emp_1, emp_2 and emp_3, except for the coefficient of RD^- in the equation of emp_3. The significant long-run coefficients obtained in this step show an inverse relationship between RD and emp_1 and emp_2.[3] An increase in RD increases emp_3, but decreases in RD do not have any significant impact on it.

3. Please note that a negative coefficient means dependent and independent variables move in opposite directions.

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Table 6. Levels equations and long-run coefficients.

Country	Model	Dependent variable	Independent variable	Coefficient	Prob.
France	1	emp_1	RD+	–19.7906***	0.0031
			RD–	–18.2049***	0.0088
			INF	1.9197**	0.0123
			C	50.2912***	0.0000
	2	emp_2	RD+	–12.4670***	0.0022
			RD–	–14.0715***	0.0052
			C	68.5572***	0.0000
	3	emp_3	RD+	11.7398***	0.0002
			RD–	0.2219	0.9037
			INF	0.6438*	0.0697
			C	76.6324***	0.0000
UK	4	emp_1	RD+	–13.1050	0.4922
			RD–	12.7318	0.6038
			C	72.2611***	0.0000
	5	emp_2	RD+	–7.4080	0.7225
			RD–	2.6063	0.9238
			C	85.0248***	0.0000
	6	emp_3	RD+	–18.9521***	0.0048
			RD–	–9.2632**	0.0182
			INF	–0.9933***	0.0091
			C	87.5972***	0.0000

*, **, *** indicate significance at 10, 5 and 1% level.

Both coefficients of RD^+ and RD^- are significant and almost similar in models 1 and 2, indicating a symmetric long-run impact of R&D on the employment rate of low-skill and medium-skill labour. On the other hand, the significant coefficient of RD^+ and insignificant coefficient of RD^- in model 3 suggest an asymmetric relationship between R&D and employment rate of high-skill people. These findings are confirmed by Wald test results in Table 7.

The Wald test is applied to check whether R&D has a symmetric long-run impact on different types of employment in models 1, 2, 3 and 6; and the results are illustrated in Table 7. The null hypothesis of 'long-run symmetry' is not rejected by Wald tests in the case of emp_1 and emp_2 equations, indicating the symmetric effect of R&D expenditure on the employment rate of low-skill and medium-skill labour. This null hypothesis is rejected in model 3, suggesting the asymmetric effect of R&D expenditure on the employment rate of high-skill people.

The above-mentioned symmetric and asymmetric effects are reflected in the related patterns of dynamic multipliers in Table 8. As we can see in this table, in the case of France, both short-run and long-run symmetries in the impact of an increase or decrease in R&D expenditure on the employment rate of low-skill and medium-skill labour are noticeable. In contrast, the impact of R&D expenditure

Table 7. Wald test results of long-run symmetry.

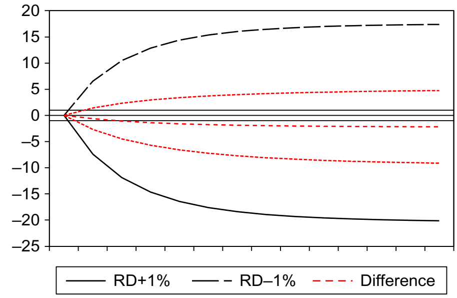
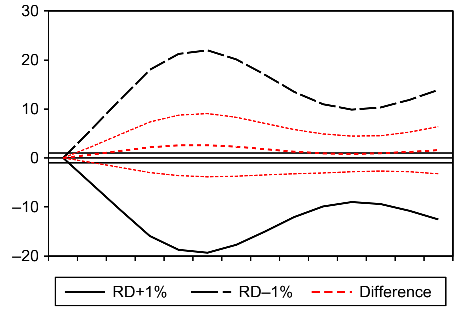
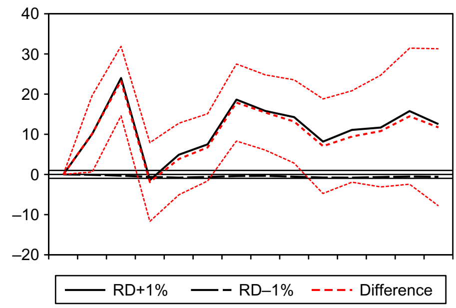
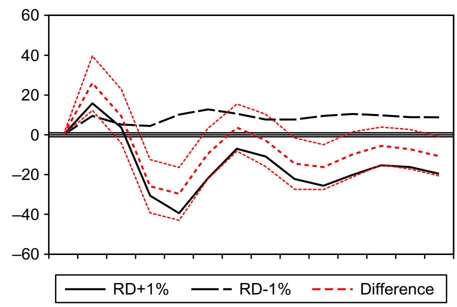
Country	Model	Dependent variable	t-Statistic	Prob.
France	1	emp_1	0.2914	0.7736
	2	emp_2	–1.3597	0.1877
	3	emp_3	10.4381	0.0000
UK	6	emp_3	–4.4674	0.0002

on the employment rate of high-skill people is asymmetric, suggesting the flexibility of a high-skill labour market to hiring, and its restrictions on firing. An increase in R&D expenditure creates new tasks for high-skill people and makes employers hire a given number of such people, and apparently employed high-skill people don't lose their jobs after a decrease in R&D expenditure. In other words, the labour market does not have any tendency to return to its initial state even after a decrease in R&D intensity. On the other hand, the automation generated by R&D investments can replace low-skill and medium-skill labour. In addition, a given increase in R&D expenditures is associated with a corresponding reduction in (ordinary) investment expenditures in tangible capital. In other words, firms might be more likely to finance additional R&D by cutting down their investment expenditures on tangible capital which was previously used to create jobs for low-skill and medium skill labour.

5.2. Asymmetric Long-run Coefficients and Dynamic Multipliers in the Case of the UK

According to Table 6, in the case of the UK, the coefficients of $RD^+$and RD^- are only significant in the equation of emp_3. The significant long-run coefficients obtained in this step show an inverse relationship between RD and emp_3. Furthermore, the null hypothesis of 'long-run symmetry' is rejected by the Wald test in Table 7 (model 6), indicating an asymmetric effect of R&D expenditure on the employment rate of high-skill people. This result is in line with different magnitudes of the coefficients of $RD^+$and RD^- in model 6 in Table 6. This asymmetric effect is also reflected in the related patterns of dynamic multipliers in Table 8. As we can see in this table, in the case of the UK, a decrease in R&D expenditure always has a positive impact on the employment of high-skill people, but an increase in R&D expenditure has a positive impact in the short-run and a negative impact in the long-run; and the negative impact is greater than the positive impact. An increase in R&D investment leads to employment of researchers in the short-run, but the technology created by them can put hordes of engineers out of work in the long-run. Apparently, it doesn't mean that a decrease in R&D investment leads to hiring the same number of high-skill people in the long-run; and that's the likely reason behind the detected asymmetry.

Table 8. Patterns of dynamic multipliers.

Country	Detected long-run relationship	
France	RD↑, emp_1↓ RD↓, emp_1↑	
	RD↑, emp_2↓ RD↓, emp_2↑	
	RD↑, emp_3↑	
UK	RD↑, emp_3↓ RD↓, emp_3↑	

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The reason behind the positive effect of a decrease in R&D investment on the employment rate of low-skill and medium-skill labour in France and high-skill people in the UK can be summarized in transferring financial resources, and investment in the other sectors that can create new jobs and increase the employment rate. Growth and job creation arise both through the expansion of existing firms and through new firm creation, although new firms generate more net employment in response to local investment opportunities (Glaeser *et al.* 2015; Adelino *et al.* 2017). And these investment opportunities can be provided by transferring resources from the R&D sector to the other sectors.

5.3. Robustness Check

The main independent variable in our study is *RD*, and *INF* is a control variable. In the next step, we modify the regression specifications by replacing *INF* with *OG* to examine how core regression coefficient estimates behave. The results are presented in Table 9. We let *OG* be dynamic or fixed in the equations and report the best model in each case.

As we can see, the results in Table 9 are consistent with our results in Table 6. *RD* components have a long-run and negative relationship with emp_1 and emp_2 in France and of emp_3 in the UK. On the other hand, there is no significant relationship between *RD* components and emp_1 and emp_2 in the UK.

6. Conclusions

This study contributes to the existing literature on the R&D–employment nexus for two advanced economies, namely the UK and France, in a number of ways. Employing non-linear ARDL methods it has attempted to examine (a) the existence of a long-run (cointegrating) relationship between R&D (intensity), inflation and employment (rate) of high-skill, medium-skill and low-skill labour; (b) the qualitative and quantitative nature of the long-run effects of the changes in R&D on the employment rate of each type of labour and whether or not these estimated effects are asymmetric or not; (c) the qualitative and quantitative nature of the dynamic response of the employment rate of each type of labour over time to shocks in R&D and again the presence of asymmetries in these dynamic responses over time.

In what follows, we first underline the basic findings of the empirical work in relation to the above-listed main motivations of the article and then briefly discuss the main insights that can be derived from these findings, particularly in terms of the possible dominant form of technological change and its implications for relative wages and income distribution in each country. (i) There exists a long-run relationship between R&D, inflation and each type of (skill-specific) employment rate in France. But in the UK such a long-run relationship between the three variables has been detected only for the employment rate of high-skill labour. (ii) The estimated long-run coefficients suggest that while a given increase in R&D in France

Table 9. Robustness check.

Country	Dependent variable	Independent variable	Coefficient	Prob.
France	emp_1	RD+	–30.508 ***	0.0002
		RD–	–29.816 ***	0.0009
		C	51.398 ***	0.0000
	emp_2	RD+	–14.098 ***	0.0014
		RD–	–15.659 ***	0.0058
		C	68.757 ***	0.0000
	emp_3	RD+	7.456 ***	0.0002
		RD–	–2.603	0.1464
		C	77.445 ***	0.0000
	emp_3	RD+	7.852 ***	0.0000
		RD–	–2.826 *	0.0598
		OG	–0.039	0.7828
		C	77.190 ***	0.0000
UK	emp_1	RD+	–19.655	0.1102
		RD–	–10.422	0.2267
		C	63.388 ***	0.0022
	emp_2	RD+	9.120	0.3083
		RD–	9.552	0.3039
		C	9.804 ***	0.0002
	emp_2	RD+	19.214	0.2294
		RD–	18.908	0.2073
		OG	10.993	0.1718
		C	11.457 ***	0.0064
	emp_3	RD+	–26.019 **	0.0357
		RD–	–25.747 **	0.0457
		OG	0.406	0.5053
		C	79.718 ***	0.0000

has an adverse (negative) effect on the employment rates of low skill and medium-skill labour, a given decrease has the opposite (positive) effects on the employment of both types of labour. Conversely, a given increase in R&D has been found to have a positive impact on the employment rate of high-skill labour. But the reductions in R&D seem to have no significant impact on the employment rate of high-skill labour in France. In the UK, the estimation results have produced evidence of a long-run effect of R&D only on the employment rate of high-skill labour. However, the qualitative nature of this effect is in contrast to that of France; while a given increase in R&D in UK exerts a negative effect on the employment of high-skill labour, a given decrease has been found to increase the employment of this type of labour in the long run. (iii) The results obtained from dynamic multiplier analysis are almost perfectly consistent with the estimation results based on long-run levels equations reported above. In particular, this type of analysis has produced almost perfectly symmetric responses of the respective employment rates of low-skill and medium-skill labour to given positive and negative shocks in R&D in the case of France. But there is an

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asymmetric response of high-skill employment to positive and negative shocks in R&D; while a positive shock generates positive response, a negative shock has no impact on high-skill employment in France. And for the UK, dynamic multiplier analysis has produced evidence of an asymmetric and inverse response of the employment rate of high-skill labour to R&D expenditures over time.

The main empirical findings of this article, highlighted above, are likely to offer (what we believe to be) critical insights regarding the possible 'dominant form of the technological change' in the UK and France based on the differential effects of R&D on the employment of alternative types of (skill-specific) labour and its potential effects on the relative wages of different types of labour and income distribution in each country. The finding that while an increase in R&D (intensity) in France is likely to lower both low-skill and medium-skill employment, and it has a positive impact on high-skill employment, suggests that the dominant form of technological change in France could be characterized as 'low-skill automation' which simultaneously creates 'new tasks' that can be performed by high-skill labour. This kind of technological innovation process would be associated with the introduction of new machines that would replace the low-skill and medium-skill labour and at the same time lead to the creation of new tasks in which high-skill labour has a comparative advantage (Acemoglu and Restrepo, 2016). In other words, technological change in France seems to be predominantly 'skill-biased' so that it is favouring the employment of 'high-skill labour' at the expense of 'low-skill' and 'medium-skill' labour. On the other hand, the dominant form of technological change in UK seems to be in the form of 'high-skill automation' (typical examples being robotics and AI), which are particularly replacing high-skill labour with machines and having no (statistically significant) effects on the employment of low-skill and medium-skill labour.

As pointed out earlier, the dynamic effects of different forms of technological change are likely to affect relative wages and income distribution in different ways. In this context, the fact that technological change (resulting from increased R&D efforts) seems to be 'skill-biased', meaning that it is favouring high-skill labour at the expense of other types, could have been generating forces in the labour market of France that can lead to a decrease in the wages of low-skill and medium-skill labour relative to that of high-skill labour. In addition, the replacement of low-skill and medium-skill labour by new machines (capital) might be accompanied by the decrease in the income share of labour in general, particularly if the increase in the employment and wages of high-skill labour are not sufficiently high. In other words, technological change in France might be generating forces in the labour markets so as to worsen the income distribution in favour of high-skill labour and capital owners.

The possible increase in the socio-economic inequality between high-skill labour and others (low- and medium-skill labour) that can be caused by the positive impact of technological change (which seems to be skilled-biased) on the employment of high-skill labour in France, can (at least partly) be corrected by encouraging the type of R&D investment that creates tasks for low-skill and medium-skill labour in the longer run. Therefore, policymakers are advised to stop and reverse the growth of the gap between low-skill and high-skill labour by considering incentives on these sort of R&D investments (Mincer and Danninger 2000).

On the other hand, in the UK, where the dominant form of technological change seems to be 'robotics and AI', the dynamic effects of new technologies might be exerting forces in the labour market so as to reduce the wage discrepancy between high-skill labour and other types of labour. In other words, the wages of high-skill labour relative to those of low-skill and medium-skill labour might be negatively affected by the new technologies. And what is more important is the likelihood of new technologies (resulting from increased R&D) leading to a deterioration in the overall income distribution in favour of capital owners and against labour in general. This seems to be a likely scenario considering the fact that increased R&D has been found to have adverse effects on the employment of high-skill labour without any offsetting positive effects on the employment of other types of labour, suggesting that the net impact of new technologies on overall employment and relative income of labour could very well be negative.

In light of the basic insights of the current study, we believe that future research that focuses on directly examining the impact of R&D efforts on the relative incomes of different types of labour and capital and overall income distribution in different countries can provide a better perspective on the possible adverse effects that new technologies have been exerting on unemployment problems and income and wealth distribution in particularly developed countries. The results of such studies can be used in evaluating whether or not any kind of systematic intervention policies (to be adopted by the policymakers) regarding the nature of the R&D efforts by the private sector and higher-education institutions could help to improve the socio-economic welfare of the country in question.

7. Limitations and Further Research Directions

As pointed out above, new research almost always raises new questions. In this context, this study has suggested a number of potential new research questions.

One target for additional research can be analysing the likely asymmetric impact of technological progress on unemployment rate controlling for the power of labour unions or employment regulations for different skill levels. When data over a longer time are available, the changes in labour market regulations can be considered in the estimation by using dummy variables. A regime switching technique can also be employed to model accurately the effect of technological progress on the unemployment rate between the dates of changes in market regulations. Another target for future research can be studying the impact of adoption of technology on income distribution, wage inequality and the welfare level of society by employing above-mentioned methodologies.

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