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Do Technological Innovations Affect Unemployment? Some Empirical Evidence from European Countries

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Abstract: This paper analyses theoretical and empirical scientific literature about the impact of technological innovations on unemployment, considering the former as a key driver of long-term productivity and economic growth. Using panel data from 25 European countries for the period of 2000–2012, we aim to examine whether technological innovations affect unemployment. We used triadic patent families per million inhabitants as our main proxy for technological innovations, as well as other unemployment controls, in our model, which were estimated using System Generalized Method of Moments (SGMM). Finding no significant relationship between technological innovations and unemployment in our base estimation, we re-estimated it testing the impact with a time lag as well as using alternative proxies for technological innovations. Overall, the research estimations do not suggest that technological innovations have an effect on unemployment.

Keywords: technological innovations; unemployment; triadic patent families

JEL Classification: O33; E24; O52

1. Introduction

For more than two centuries, since the very beginning of the Industrial Revolution, the global economy has been moving rapidly forward due to new technologies. Each new technological wave has a positive effect on economic growth, productivity and opportunities for new business types. The researchers in many ways define the impact of innovation on labor market parameters: employment, unemployment, labor demand, wages and etc. One approach (Say 2009; Schumpeter 2017) suggests that technological progress leads to process and product innovation, which, in turn, leads to job creation. According to others (Wood 2004; Feldmann 2013), technological change can increase unemployment. Liso and Leoncini (2011) state that technological advancement provides opportunities for higher wages for skilled workers due to increased demand, while others (Piva et al. 2006) note that technological change negatively influences skilled and unskilled workers. As Alonso-Borrego and Collado (2002) noticed, technological innovation is one of the main sources for the creation and destruction of jobs.

Technological innovation is understood as a systematic, on-going, non-reflexive and managed process (Garud et al. 1997) is one of the key driving forces influencing long-term productivity and economic growth. As a result, the innovation process and the impact of the actions necessary to identify technological change are of interest to companies, governments and academics. It should be noted that innovation is sometimes viewed as a phenomenon that can also have negative effects associated with unemployment.

During the past three decades, much attention was paid to skill-biased technological change that firstly was empirically explored by Berman et al. (1994) who proved the existence of strong correlations between industry skill upgrading and increased investment in both computer technology and R&D in the U.S. manufacturing sector. Caselli and Coleman (2006) argue that developed countries use skilled labor more efficiently than developing countries that is caused by technology adoption because developed countries are skilled-labor-abundant and they choose technologies suitable for skilled labor while developing countries are low skilled-labor-abundant and they use technologies appropriate to unskilled labor. Acemoglu and Autor (2011) state that skill-based technological change reduces the demand for routine jobs that can be computerized.

Taking into account various effects revealed in scientific literature that innovations have on labor market as well as little empirical research at macro level on how innovations affect unemployment, in this paper we aim to examine nexus between technological innovation and unemployment in European countries. Technological innovation and its impact on labor market is a topic of great interest because it reveals the tendencies and the problems labor market encounters due to technological change. This paper, analyzing this topic, has four main novelties vis-à-vis previous literature in the area. First, this paper uses a unique dataset, which merges 25 European countries. Second, this paper investigates macro level research what is rare in the scientific literature of this topic. Third, triadic patent families to population as a measure of technological innovation is very new. Fourth, this paper investigates the impact of both triadic patent families to population (as a measure for innovation outputs) and R&D expenditures (as a measure for innovation inputs) on unemployment (two different measures—two different comparable results).

The rest of the paper is organized as follows: related literature concerning the nexus between technological innovation and unemployment is reviewed in Section 2. Section 3 presents model and data with descriptive statistics as well as estimation technique. The empirical findings are presented in Sections 4 and 5 concludes the paper.

2. Literature Review

2.1. The Nexus between Technological Innovation and Unemployment

Schumpeter introduced the concept of innovation in the 20th century, describing it as an industrial mutation describing it as an industrial mutation which is constantly changing the economic structure from within, destroying the old one while creating a new one. This is called as the process of creative destruction (Schumpeter 2008). According to J. A. Schumpeter, technological breakthrough will not be regarded as innovation if it does not generate economic or net profit growth. Hence, innovation can be understood as the basis of competition and the key driver of economic development.

According to Barnhizer (2016), it is not people but the convergence of technological innovations that more and more influences the nature of work, economy, social inequality and the existence of a middle class. The fact that developed economies, such as Western European countries and the United States, face the technological convergence is in line with Schumpeter's idea of creative destruction but with a warning about the destructive destruction of economic and institutional forms. Power and technology are pushing the society in this direction.

The importance of innovation is increasing and it is relevant to understand a different role of various types of innovation. All innovations, throughout history, have been categorized in many ways. The variety of approaches for categorizing innovations considers many different aspects and it helps to measure and allow comparing innovations. Four types of innovations—product, process, marketing and organizational—are defined in The Oslo Manual[1] (OECD 2005). This paper concerns the impact of technological innovation on unemployment, hence, only product and process innovations are the

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[1] The Oslo Manual is the foremost international source of guidelines for the collection and use of data on innovation activities in industry (OECD 2005).

interest of this paper, because, as Ramanauskienė (2010) and Hoover (2012) mentioned, there are two types of technological innovation:

- *Product*. It is linked to the revolution of new breakthroughs: the use of new materials and components, the acquisition of new products, such as telegraph, railways, cars, radio, etc. This leads to a qualitative improvement of life and opens up new opportunities in various areas. Technological progress makes it possible to produce more with lower costs.
- *Process.* It means new production organization methods (new technologies). An example of process innovations is H. Ford's idea of producing replaceable parts, assembling production lines, what allowed to produce cheap cars.

As Flichy (2007) states, the separation of process and product innovation is often artificial. However, it should be noted that the latter classification is mostly used in scientific research assessing the impact of technological innovations on labor market parameters.

There is a contradiction between researchers about the impact of product and process innovation on employment. According to Vivarelli (2014), Harrison et al. (2008), researchers distinguish two key aspects—product innovation provides new products on the market, which stimulates a new demand—this leads to a positive relationship between technological change and employment (Van Reenen 1997; Bogliacino and Vivarelli 2012; Vivarelli 2014; Marcolin et al. 2016) and process innovation leads to a negative effect on the labor force due to the replacement of labor with new machines, equipment and an increase in productivity and efficiency of firms (Van Reenen 1997; Peters 2004; Pianta 2004; Vivarelli 2014). In general, since the technological changes make it possible to produce in lower costs, a direct effect of innovation is technological unemployment. This idea contradicts Schumpeter's statement that technological progress leads to process and product innovation, which naturally leads to job creation (Ziemnowicz 2013). According to Marxist philosophy, it is inconceivable that newly-engineered labor-saving machines could create a sufficient number of jobs (Wood 2004).

An overview of research by Feldmann (2013) notes that most of them prove that technological change can increase unemployment in certain circumstances and in some cases even in the long run and this confirms the 19th century Malthus' statement that a rising demand for a product due to reduced prices is unlikely to be sufficient as demand for redundant workers is decreasing. Profit growth cannot be sufficient unless the companies firstly invest in capital-intensive technologies. Finally, lower wages may be a reason that companies will not be encouraged to hire more employees due to a reduced demand for products. As a result of all these factors, innovation leads to technological unemployment (Malthus 2008; Vivarelli 2014), which leads to the fact that some workers lose their jobs, as a direct consequence of labor-saving innovation. Autor (2015) states that there is no long-run increase in unemployment caused by technological progress but changes in technology affect the types of jobs available. Some people (according to their occupation's probability of computerization) are at a high, medium or low risk (Frey and Osborne 2017). Brynjolfsson and McAfee (2011) also acknowledge ideas about the deep changes that computerization is bringing but, as the authors note, these changes can become more valuable because people who had the wrong skills now can find more valuable skills and be more desirable for employers.

Despite this concern, the economic theory points out the existence of indirect effects that can counterbalance the reduction in employment (Bogliacino and Vivarelli 2012; Vivarelli 2015). The proponents of classical economic theory have raised the theory, the one that K. Marx later referred to as the theory of compensation: technological changes can lead to various market compensation mechanisms: new machines, lower prices, new investments and lower wages (Vivarelli 2014). These compensation mechanisms can offset the initial influence of labor-saving innovation in process innovation (Meschi et al. 2016).

Taking into account all provisions, the results from theoretical studies do not provide clear-cut answer about the impact of technological innovation on unemployment. There is a confrontation between two views: one states that labor-saving innovations create technological unemployment, the other view argues about questionable compensation mechanisms, resulting from prices and new demand, that absorb unemployment (Piva and Vivarelli 2005). Therefore, empirical analyses, that reveal and prove the results received in different ways with different methods, different measurement instruments, are needed that can take into account the overall impact of technological innovation on unemployment.

2.2. Empirical Research on the Quantitative Assessment of Technological Innovations' Impact on Labor Market Parameters

In most research, R&D expenditures are a measure of innovation inputs and patents are a measure of outputs (Fai and von Tunzelmann 2001; Bonanno 2016; Vivarelli 2014, 2015). Although Kromann et al. (2011) argue that the best variable reflecting technological changes in the economy is R&D expenditures, the patents, as Kortum (1997) suggests, is the main technological variable reflecting the important aspects of the technological process and, presumably, "correlating with the immeasurable dimensions of technological change." However, according to Feldmann (2013), Dernis and Khan (2004), the following limitations on the calculation of patents under their registration at the national patent office can be pointed out: first, the registration of patents in one office varies greatly according to their technical and economic significance; secondly, it is difficult to compare them internationally, since they are affected by local preferences and geographic location. For these reasons, the number of triadic patent families per one million inhabitants (independent/exogenous variable) which avoids these limitations is used in the research as the main output indicator of technological innovation. Triadic patents are patents registered in three patent systems: the European Patent Organization, the US Patent and Trademark Office and the Japanese Patent Office. This indicator is recommended to be used in all macro-level studies aimed to assess technological progress. In addition, this indicator falls into the European Union (EU) aggregate innovation index as one of the indicators of the intellectual property factor group—another argument justifying the significance of this indicator.

It should be noted that this variable also has disadvantages: (i) triadic patents do not differ between product and process innovation; (ii) SMEs rely less on patenting than large companies and that produces bias, since the average size of firms varies from country to country; (iii) some industries rely more on patents than others, which reflects a further bias, as the structure of industries varies between countries; (iv) the significance of triadic patent families varies among families; (v) application for the patent and its registration abroad costs money, so patents of a lower value are usually only completed in the country of the inventor, despite the fact that the European Patent Organization, the US Patent and Trademark Office and the Japanese Patent Office propose to take into account the potentially higher value of patents when they are registered with all three organizations (Feldmann 2013).

There are relatively very few research on the impact of technological innovations on labor market parameters at macro level. According to Vivarelli (2014), the macroeconomic studies of innovation impact on employment are limited to the period 1980–1990 and microeconomic studies began later and now are more frequent. As this research considers macro level effect, only previous empirical research at macro level are presented in Table 1 and research on technological innovation impact on labor market parameters at sectoral and micro level are presented in Appendix A.

Macro level research explore the impact of technological innovations on the economy as a whole. However, analyzed research (see Table 1) provides an unambiguous answer about the impact of technological innovation on labor market parameters. Feldmann (2013) in his research showed that technological progress increases unemployment in the short term but, for example, Marcolin et al. (2016) proved that technological innovation has a positive effect on employment.

Table 1. Research on technological innovation impact on labor market outcomes.

Level of Analysis	Author(s), Year	Measurement of Technological Innovation(s)	Labor Market Outcome(s)	Impact		
				Positive	Negative	Non-Significant/ Unclear
Macro level	Pini (1995)	R&D expenditure, patents	Employment	X		
	Vivarelli (1995)	R&D linked to product and process innovations	Employment			X
	Simonetti et al. (2000)	R&D linked to product and process innovations	Employment			X
	Tancioni and Simonetti (2002)	R&D linked to product and process innovations	Employment			X
	Feldmann (2013)	Triadic patent families to population	Unemployment	X		
	Evangelista et al. (2014)	ICT	Employment	X		
	Marcolin et al. (2016)	ICT-intensity, patents	Employment	X		

As noticed in the theoretical analysis, the empirical analysis usually also distinguishes the impact of product and process innovations on labor market parameters. Authors (e.g., Blanchflower and Burgess 1998; Greenan and Guellec 2000; Greenhalgh et al. 2001; Hall et al. 2008; Harrison et al. 2008; etc.) find a positive relationship between product innovation and employment. The employment effects of process innovations are less clear in empirical research. The results of studies are not significant (e.g., Hall et al. 2008; Harrison et al. 2008; etc.), the impact of process innovation on employment is negative (e.g., Dachs and Peters 2014; Falk 2015; Kwon et al. 2015; etc.) or positive (e.g., Casavola et al. 1996; Smolny 1998; Greenhalgh et al. 2001; Lachenmaier and Rottmann 2011; etc.).

The limitation of micro level studies is that these studies do not take into account impact on competing firms of the same industry and the impact on other industries (Feldmann 2013). Sectoral level studies estimate the net employment effect in particular industries but they do not take into account the cross-sectoral indirect (compensative) effects of technological change (Bogliacino and Vivarelli 2012). The majority of the sectoral level studies explore the innovation impact on employment and these studies are more popular in relation to skills than micro level studies. The main findings of the sectoral level studies are that process innovation is labor saving and product innovation is employment friendly (e.g., Mehta and Mohanty 1993; Huo and Feng 2010; etc.) and that technological innovation increases the relative demand for skilled workers (e.g., Machin and Van Reenen 1998; Morrison Paul and Siegel 2001).

Hence, with no clear both theoretical and empirical predictions, the impact of technological innovation on unemployment is a question of this research. The interest can be explained by few arguments: *first*, there are only few macro level research of technological innovation impact on labor market parameters; *second*, there are only few research about the impact on unemployment; *third*, there is no clear answer about technological innovation impact on unemployment.

Reviewing research concerning particularly the issues of unemployment, we distinguished variables that influence unemployment and that we have to control in our model while examining technological innovation impact on unemployment (see below):

- *Foreign direct investment*. According to Blomström et al. (1997) and Lipsey et al. (2010), net incoming investment is likely to reduce unemployment, while net outflow may have different effects. In addition, as Feldmann (2013) suggests that foreign direct investment is likely to be a source of international technological prevalence.
- *Tax wedge on labor cost*. It is a variable expressed as the sum of taxes on salary, income or consumption. The tax wedge is an additional burden (cost) for companies. From a theoretical point of view, work-related taxes reduce employment, as they increase the employer's wage costs and reduce employee wages, after deducting taxes (Boeri and Van Ours 2008). According

to Nickell (1997), the impact of this variable on unemployment depends on who carries the tax burden. If taxes are paid by employees lowering wages after tax, then the demand for labor should not be affected—the real impact of all this should then depend on what is going on with the labor supply. If employees increase demand at the current wage level, compensating lower wages after taxes, the correlation may even be negative, i.e., higher taxes relate to lower unemployment. If taxes cannot be diverted to salaries due to the bargaining power of the union, the lowest wage level or the compressed wage structure, then demand for labor is likely to be negatively influenced and unemployment will increase (Baccaro and Rei 2007).

- *GDP (gross domestic product) per capita*. Empirical studies (e.g., Meidani and Zabihi 2011; Malley and Molana 2007) reveal the relationship between unemployment and GDP—the unemployment rate is most often negatively related (i.e., GDP is increasing, unemployment is decreasing) with GDP per capita, however, in some research a positive correlation exists between these variables.
- *Public unemployment spending*. Research by Bertola et al. (2007) and Nickell et al. (2005) showed that unemployment benefits increase unemployment. This is also confirmed by the theory of labor economics, according to which, unemployment benefits reduce the intensity of job search and willingness to accept job offers.
- *Consumer price index (CPI)* is the main indicator of inflation. Traditional explanation of inflation impact on unemployment is usually based on Phillips curve: an approach developed by Phillips (1958) and Samuelson and Solow (1960). Recent research (Henzel and Wollmershäuser 2008; Kim and Ahn 2008; Zhang and Clovis 2010; Basarac et al. 2011; Malikane and Mokoka 2014) confirmed the validity of Phillips curve approach that increasing inflation decreases unemployment.
- *Trade union density.* This is the percentage of employees belonging to trade unions. According to Baccaro and Rei (2007), this indicator can affect unemployment in two ways: *first*, higher average wages; *second*, through the compressed salary structure. In the first case, if the union affects labor costs over their market-clearing price, employees who want to work for prevailing wages do not find job. In the second case, the salaries of workers with lower productivity are likely to be determined by the prevailing trends in the labor market. Moreover, according to Soskice (1990), when collective bargaining is coordinated, the unions intend to internalize the spill-over effects associated with their wage policies. Therefore, it can be noted that the relation between the density of unions and coordination of negotiations should be negative. Research by Blanchard and Wolfers (2000) and Baccaro and Rei (2007) showed that higher union density is associated with higher unemployment.
- *Wage bargaining coordination*. This variable is related to lower unemployment, as coordinated bargaining tends to internalize the spillover effects of wage bargaining and leads to lower real wage establishment than in uncoordinated bargaining (Tarantelli 1986; Soskice 1990; Flanagan 1999). According to Saint-Paul (2004), a positive relationship between bargaining coordination and unemployment may also be if one party decides that coordination may potentially increase the monopoly power of the unions. According to Calmfors and Driffill (1988), countries can be divided into two groups: the first, where salaries are centrally established, such as Belgium and the Nordic countries; the second, where salary establishment system is highly decentralized, for example the UK. It has been shown that in countries where the salary establishment system is highly centralized or highly decentralized there is lower inflation and higher employment, in the case of decentralized or centralized systems, there is low inflation and high employment. Nickell et al. (2005) and Feldmann (2011) showed that the high degree of *coordination of wage-setting* is associated with relatively low unemployment.
- *Collective bargaining coverage.* Collective agreements are negotiating processes between the employee and the employer, defining employment relationships that are particularly relevant to salaries, working hours and work standards. However, in some cases this may also mean labor market regulation (Cazes et al. 2012). Collective bargaining coverage is an indicator reflecting the

impact of collective bargaining on employment (OECD 2005); this is "the proportion of employees covered by collective bargaining" (Estep 2016). According to Feldmann (2013), the power of trade unions would be stronger if employers voluntarily or for some legal or administrative reasons apply agreed terms of contracts and for those employees who are not the members of trade union. Therefore, a high rate of collective bargaining coverage is likely to influence the increase of unemployment.

As this overview of theoretical and empirical research indicates, the results can differ according to country's economic, technological and labor market development. Therefore, this indicates the need of empirical research on the impact of technological innovation on unemployment.

3. Model, Data and Estimation Method of the Research

This research encompasses 25 European countries: Austria, Belgium, Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey and the United Kingdom. Lack of data for all necessary variables for the research reduced the number of European countries included in the analysis. Data covers the period of 2000–2012 on yearly basis, thus this enables us to capture just short-term effect of technological innovation on unemployment.

Empirical research is based on dynamic panel data regression model and two-step generalized method of moments (GMM) to estimate it. The most generalized dynamic panel data model takes the form:

$$Y_{\mathrm{i,t}} = \delta Y_{i,t-1} + \alpha + \beta_i X_{i,t} + \mathrm{c}_i \mathrm{C}_{i,t} + \mu_i + \varphi_t + \mathrm{e}_{it}, \quad (1)$$

where: Y—dependent (endogenous) variable; $Y(-1)$—lagged dependent variable; i and t stand for cross-sectional unite (country) and time (year), respectively; α—constant; X—core independent variable of the research (theoretically assumed as exogenous but this assumption is hard to hold); C—vector of control variables; μ—time-fixed unobserved cross-sectional heterogeneity; φ—time effects that are constant for all cross-sectional observations; δ, β, c—parameters that show impact of right-hand side variables on dependent variable and need to be estimated; e—error that is normally distributed with constant variation and zero serial correlation.

GMM is used for estimating the model because it enables us to deal with potential endogeneity problem of right-hand side variables. Following the GMM methodology, first—we will differentiate the equation, second—for estimation as instruments will use lagged observations of the first difference of the independent variables. GMM method is presented and discussed in detail by Arellano and Bond (1991). Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998), regarding weak instrumental variables and suggestions by Arellano and Bover (1995), suggest overcoming that problem by using additional moment conditions for an equation expressed in levels are also employed in the analysis. Combination of equation in differences with equation in levels is called system GMM (SGMM). As Bond et al. (2001) and Hauk and Wacziarg (2009) stressed, for estimating more consistent and efficient parameters the SGMM should be used for panel data regressions.

Properties of GMM estimators for panel data, which have become very popular in the empirical literature, are not well known when the number of cross-sectionals is small. Soto (2009) as well as Hayakawa (2007) analyzed the properties of various GMM and other estimators applying Monte Carlo simulations. They found that SGMM estimator is less biased than the first differencing or the level estimators. To take into account the concern of Blundell and Bond (1998) about the downward-biased tendency of standard errors estimated by the SGMM approach for small finite samples we used finite-sample corrections to the asymptotic covariance matrix of the parameters suggested by Windmeijer (2005), which are nowadays almost universally used.

To investigate the overall validity of the SGMM estimation, based on Arellano and Bond (1991) and Blundell and Bond (1998), two tests must be carried out: (1) the Sargan test, which tests the validity of the instruments; and (2) the AR(2) test, which tests the presence of second-order serial correlation. The SGMM estimation results are valid only after passing the above two tests.

Table 2 presents variables used in the empirical research as well as their measurement and the expected impact on dependent variable.

Table 2. Research variables, their measurement and expected effect on dependent variable.

Variables (Acronym)		**Measurement**	**Expected Correlation with Dependent Variable**
Dependent variable	Unemployment (*unem*)	Total (% of total labor force)	-
Core independent variables	Triadic patent families (*tfp*)	Per million inhabitants	+ive
	Expenditure on R&D (*exp_RD*)	% of GDP	+ive
Control variables	Inward foreign direct investment (*fdi_inv*)	Inward FDI stocks (% of GDP)	−ive
	Outward foreign direct investment (*fdi_out*)	Outward FDI stocks (% of GDP)	−ive/+ive
	Tax wedge on labor cost (*tax*)	% of total labor costs	−ive/+ive
	Gross domestic product (*gdp*)	GDP per capita	−ive
	Public unemployment spending (*bnf*)	% of GDP	+ive
	Consumer price index, CPI (*cpi*)	2010 = 100	−ive/+ive
	Trade union density (*tud*)	Decimal fraction of wage and salary earners that are trade union members	+ive
	Coordination of wage-setting/wage bargaining coordination (*wbc*)	Coordination of wage-setting: 1—Fragmented wage bargaining, confined largely to individual firms or plants 2—Mixed industry and firm-level bargaining, weak government coordination through MW setting or wage indexation 3—Negotiation guidelines based on centralized bargaining 4—Wage norms based on centralized bargaining by peak associations with or without government involvement 5—Maximum or minimum wage rates/increases based on centralized bargaining	−ive
	Collective bargaining coverage (*cbc*)	Decimal fraction of all wage and salary earners in employment with the right to bargaining	+ive

Trade union density, coordination of wage-setting and collective bargaining coverage variables are some of the most commonly used proxies for wage bargaining systems (wbs) and they will be used as alternatives while estimating the model for robustness check:

$$unem_{i,t} = \delta \cdot unem_{i,t-1} + \alpha + \beta \cdot tpf_{i,t} + c_1 \cdot fdi\_inw_{i,t} + c_2 \cdot fdi\_out_{i,t} + c_3 \cdot tax_{i,t} + c_4 \cdot gdp_{i,t} + c_5 \cdot bnf_{i,t} + c_6 \cdot cpi_{i,t} + c_7 \cdot wbs_{i,t} + \mu_i + \varphi_t + e_{i,t}, \quad (2)$$

where: *unem*—unemployment level; *unem*(−1)—lagged unemployment level variable; *tpf*—triadic patent families per million inhabitants; *fdi_inw*—inward FDI stocks (% of GDP); *fdi_out*—outward FDI stocks (% of GDP); *tax*—tax wedge on labor cost; *gdp*—GDP per capita; *bnf*—public unemployment spending; *cpi*—consumer price index; *wbs* will be alternatively proxied by using: *tud*—trade union density, *wbc*—coordination of wage-setting, *cbc*—collective bargaining coverage.

The descriptive statistics of the variables are shown in Table 3.

Table 3. Descriptive statistics.

Variable	Observations	Mean	St. Dev.	Min	Max
unem	544	9.04	6.03	1.10	37.30
tpf	413	22.74	43.23	0.01	302.20
exp_RD	511	1.47	0.93	0.17	7.00
fdi_inw	452	57.27	93.93	7.40	1822.60
fdi_out	444	42.26	54.51	0.20	476.80
tax	512	36.57	8.59	11.90	51.40
gdp	543	32,321.00	27,543.00	1609.30	178,710.00
bnf	362	0.94	0.78	0.00	3.55
cpi	528	92.96	14.28	19.28	146.07
tud	475	33.09	21.32	5.65	92.46
wbc	462	2.71	1.25	1.00	5.00
cbc	398	61.47	27.62	5.39	100.00

The descriptive statistics of the variables expressed in percentage changes are shown in Table 4.

Table 4. Summary statistics of variables expressed in percentage changes.

Variable	Observations	Mean	St. Dev.	Min	Max
unem	510	2.66	20.38	−37.50	148.28
tpf	371	17.95	148.81	−92.30	2000.00
exp_RD	471	2.87	10.15	−30.02	109.41
fdi_inw	416	8.15	48.39	−49.66	922.21
fdi_out	409	17.52	142.92	−65.82	2843.20
tax	477	−0.38	3.87	−36.02	19.04
gdp	509	6.13	11.86	−27.55	45.26
bnf	323	7.96	44.22	−48.87	408.36
cpi	495	3.01	4.37	−4.47	54.40
tud	410	−2.68	5.78	−60.40	32.85
wbc	431	0.82	18.47	−80.00	200.00
cbc	323	−1.33	7.38	−58.68	33.33

4. Estimation Results

Estimations (I)–(III) in Table 5 present three main estimations of Equation (2). They differ in terms of which variable is used to proxy wage bargaining system. All three estimations passed AR(2) and Sargan tests and thus instruments are valid and results are not affected by second-order serial correlation.

Table 5. Estimation results of general model.

Regressors	(I)	(II)	(III)	(IV)	(V)	(VI)
unem(−1)	−0.0095 (−0.0406)	0.0847 (0.3298)	−0.0704 (−0.3480)	−0.1545 (−0.6435)	0.1734 (0.7458)	0.3548 (1.3380)
const	24.4595 *** (4.8719)	26.8262 *** (2.7712)	14.7437 *** (3.2841)	0.1742 (1.5100)	0.1773 * (1.8990)	0.0269 (0.2130)
tfp	0.0391 (1.0875)	0.0078 (0.1604)	−0.1195 ** (−2.4237)	0.0361 (0.6613)	−0.0357 ** (−2.311)	−0.0231 (−0.6074)
tpf(−1)				0.0030 (0.0856)	−0.0764 *** (−3.5290)	−0.0357 (−0.5888)
tpf(−2)				−0.0286 (−0.7250)	−0.0374 (−1.3770)	0.0067 (0.1288)
tpf(−3)				0.0428 (1.3240)	0.0051 (0.1833)	0.0018 (0.0539)

Table 5. *Cont.*

Regressors	(I)	(II)	(III)	(IV)	(V)	(VI)
fdi_inw	−0.2942 *** (−3.2246)	−0.2990 *** (−3.0501)	−0.2038 *** (−3.5170)	−0.1003 (−0.1620)	0.1698 (1.5590)	0.0345 (0.0403)
fdi_out	0.1504 *** (3.3707)	0.0687 ** (1.9869)	0.0999 *** (2.5975)	−0.1083 (−0.9702)	0.1410 (0.9312)	0.2181 (0.7136)
tax	−0.6345 *** (−3.3390)	−0.4974 * (−1.8868)	0.0706 (0.3527)	6.5548 (1.0690)	−1.8506 (−0.9022)	−0.6114 (0.1007)
gdp	−1.0080 *** (−4.2362)	−0.4820 ** (−2.0937)	−0.3110 * (−1.7043)	−3.2039 (−0.9656)	−1.3872 * (−1.9100)	0.2880 (0.0916)
bnf	0.4349 *** (6.6521)	0.4445*** (3.6069)	0.4406*** (5.5457)	−0.6074 (−0.5691)	0.2254 *** (2.9010)	0.4117 *** (3.6490)
cpi	−2.2878 *** (−4.9252)	−4.0226 *** (−2.7645)	−1.9268 *** (−2.7832)	13.2747 (0.7829)	2.0432 (1.3840)	−2.4810 *** (−2.8130)
tud	0.0174 (0.6512)			3.0757 (1.4880)		
wbc		−0.1581 *** (−3.1691)			−0.1717 * (−1.9460)	
cbc			−0.1975 *** (−2.7413)			0.0729 (0.2288)
Error AR(2) test	1.3784 (0.1681) [a]	1.6085 (0.0991)	0.6466 (0.5179)	0.6827 (0.4948)	1.4879 (0.1368)	−0.0314 (0.9750)
Sargan over-identification test	1.4246 (0.8039) [a]	1.1994 (0.7732)	4.3351 (0.5781)	4.3030 (0.5530)	3.6705 (0.4967)	5.0628 (0.3703)
Number of countries	25	24 [b]	25	25	24	25
Number of observations	285	275	242	207	200	175

Note: all variables are logged. All estimations are 2-step SGMM including equations in levels. z-scores are presented in parentheses of estimates. *, **, *** indicates significance at the 10, 5 and 1 percent level, respectively. All estimates include time dummies. [a] *p*-value presented in parentheses of AR(2) and Sargan tests. [b] Estimation does not include Iceland because of lack of the data on *wbc* variable.

All estimations, except one, do not suggest that technological innovations (approximated by Triadic patent families (*tfp*) have an effect on unemployment. The third estimation shows negative correlation, i.e., higher innovation activity is associated with lower unemployment rate, what is not in line with our general hypothesis. Almost all control variables included in the model are statistically significant: inward FDI negatively and outward FDI positively associated with unemployment rate, economic growth as well as higher price index, as a subsequence of economic growth, negatively correlate with unemployment rate, more generous public spending on unemployment seems to have negative outcome—it increases unemployment due to lowering alternative costs of work. Higher tax wedge on labor cost decreases unemployment but this is suggested just by estimation [I]. Trade union density unlike with wage bargaining coordination or collective bargaining coverage seems to have no effect on unemployment. In most of the cases, except for GDP and CPI, estimated magnitude of control variables' impact on unemployment rate does not differ much from estimation to estimation.

Having no clear empirical evidence of relationship between technological innovation and unemployment, following Feldmann (2013), who is arguing that this relationship could occur with a time lag, we augmented our general Equation (2) to examine this potential delay of effect in time that was not captured by our previous estimations (see Estimations (IV)–(VI) in Table 5).

Nonetheless, we were testing impact consistently with a delay up to three years, just in one case this impact was captured (see Estimation (V)) and did not change after adding more lags. Like in previous case, this impact is negative and does not have verification in other estimations.

Next step of our research is related to changing a core independent variable that was used to proxy technological innovations. Doing so we are performing robustness check of findings regarding our core independent variable. As it was mentioned in the literature review, two alternative approaches are usually employed while searching for variables to proxy technological innovations—the first one to measure output was already adopted, the second one concentrates on input. For a measuring input for technological innovations, we used variable R&D intensity (expenditures on R&D to GDP ratio). According to Vivarelli (2015), R&D intensity is associated with product innovations and creation of new jobs and thus negatively correlates with unemployment but many research listed in Table 1 and Appendix A find strong empirical link between R&D intensity, innovations and productivity growth, revealing that R&D being a foundation of technological progress at macro, sectoral or micro level could make impact on unemployment.

Estimation results of Equation (2) with R&D intensity variable instead of Triadic patent families are presented in Table 6. All other variables in Equation (2) remain the same.

Table 6. Estimation results with alternative core independent variable.

Regressors	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
unem(−1)	−0.2123 (−0.6412)	0.7606 * (1.7780)	0.6411 *** (3.0880)	−0.1757 (−0.5246)	0.5311 (0.7977)	0.5247 *** (2.6680)
const	0.2896 ** (2.0240)	0.0666 (0.7427)	0.0854 (1.126)	0.1653 (1.2710)	−0.0616 (−0.1569)	0.0149 (0.1555)
exp_RD	0.3133 * (1.9600)	−1.1571 (−1.3370)	−0.3196 (−0.6251)	0.1885 (1.0220)	−0.6198 * (−1.8760)	0.3389 (0.6967)
exp_RD(−1)				0.4551 (1.1250)	−1.0037 * (−1.8040)	0.0558 (0.0708)
exp_RD(−2)				0.5023 *** (3.0900)	−0.6924 (−1.4860)	−0.1335 (−0.2484)
exp_RD(−3)				0.0548 (0.1388)	1.5332 (1.5790)	0.2581 (0.3593)
fdi_inw	0.5442 (1.4250)	−0.5225 * (−1.9150)	0.0546 (0.4407)	−0.2386 *** (−3.0160)	−0.4066 ** (−2.0640)	−0.1588 (−0.7381)
fdi_out	−0.2486 * (−1.6930)	0.1941 (−1.9150)	0.1008 (0.9132)	0.2273 *** (2.5770)	0.2220 (0.7156)	0.24852 (1.4210)
tax	−1.3716 (−0.5100)	4.2048 (1.0700)	−3.0450 (−1.4180)	2.0796 (0.9722)	0.8196 (0.1513)	−1.8100 (−0.9853)
gdp	0.9767 (1.2110)	−0.4772 (−0.3803)	0.2848 (0.4436)	−1.5139 (−1.3900)	−1.0445 (−0.6012)	−0.0673 (−0.0881)
bnf	0.6823 *** (2.6180)	0.1350 (0.6900)	0.3427 *** (4.0830)	−0.0213 (−0.1123)	−0.0765 (−0.6264)	0.3441 *** (3.4580)
cpi	−11.2546 (−1.3940)	4.0532 (0.9258)	−0.1826 (−0.1082)	6.3396 (1.3950)	4.9574 ** (2.0150)	−0.9789 (−0.5745)
tud	3.4459 *** (2.9180)			3.9298 *** (2.7010)		
wbc		−0.0373 (−0.4092)			−0.4244 *** (−3.1180)	
cbc			0.1894 (0.3055)			0.5252 * (1.9060)
Error AR(2) test	1.3018 (0.1930)	0.1461 (0.8838)	0.1745 (0.8615)	0.3290 (0.7348)	0.6101 (0.5418)	−1.4187 (0.1560)
Sargan over-identification test	4.3321 (1.0000)	9.7972 (1.0000)	6.0488 (1.0000)	2.5043 (1.0000)	1.4737 (1.0000)	8.0036 (1.0000)
Number of countries	25	24	25	25	24	25
Observations	281	270	235	227	218	191

Note: see notes below Table 5.

All new estimations (VII)–(XII) in Table 6 passed AR(2) and Sargan tests and thus instruments are valid and results are not affected by second-order serial correlation. We do not find strong empirical evidence of an R&D intensity effect on unemployment because in the case of just one estimation (*X*) relationship is significant and positive (with a two year lag).

5. Conclusions

Is the technological innovation a major driver of the increasing unemployment in European countries? This issue is argued frequently in the debates but the important issue has not been so well-analyzed empirically at macro level. As theoretical analysis shows there are relatively few research on the impact at macroeconomic level and it provides proof that technological innovation influences changes of unemployment.

Our regression results indicate that technological innovations have no effect on unemployment what shows that the macro-analysis is inconclusive. This can be explained by the measurement limitations that total unemployment rate might be a rather broad variable to capture effects of technological innovations. Possible future studies should distinguish unemployment by types for more detailed analysis of the effect on structural or long-term unemployment also including other control variables such as employment protection legislation index, unemployment benefit ratio, workers' average hourly salary, public debt, minimum wage adjusted for inflation and etc.

The other explanation is that country specific macroeconomic conditions and regulations are important for the situation in labor market what affects the investment decisions of firms. On the labor supply side, preferences for leisure, institutional restrictions including working time and household composition are significant thus this was not the object of the current research. Therefore, it is difficult to estimate the impact of technological innovation at the time the innovation is introduced when the lagging compensation effects are unknown. Future research can include investigating the long-run effects of innovations in order to analyze major shifts in economy.

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Appendix A

Table A1. Research on technological innovation impact on labor market outcomes.

Level of Analysis	Author(s), Year	Measurement Instrument(s) for Technological Innovation(s) as Exogenous Variable(s)	Labor Market Outcome(s) as Endogenous Variable(s)	Positive	Negative	Non-Significant/Unclear
Sectoral level	Mehta and Mohanty (1993)	Technology elasticity (adoption)	Labor demand		X	
	Berman et al. (1994)	Investment in computers, expenditures on R&D	Skilled labor force demand	X		
	Bogliacino and Vivarelli (2011); Bogliacino and Vivarelli (2012)	R&D expenditure	Labor demand	X		
	Goux and Maurin (2000)	New technologies usage	Labor demand			X
	Gera et al. (2001)	The stock of R&D, the stock of patents	Skilled labor force demand	X		
	Morrison Paul and Siegel (2001)	Investment in technology, R&D investment	Labor demand		X	
	Evangelista and Savona (2002)	Innovation intensity	Employment		X	
	Piva et al. (2006)	ICT technologies	Skilled and unskilled labor force demand		X	
	Pieroni and Pompei (2008)	Patent per capita	Gross job turnover rate	X		
	Bogliacino and Pianta (2010)	R&D expenditure, expenditure for innovation-related machinery	Employment	X		
	Huo and Feng (2010)	The index of process and product innovation intensity	Employment	X		
Micro level	Casavola et al. (1996)	R&D expenditure, patents, software licenses	Employment	X		
	Doms et al. (1997)	Automation technologies	Wages, occupational mix, workforce education	X		
	Dunne et al. (1997)	R&D stock, technology adoption	Employment, labor share change	X		
	Van Reenen (1997)	Patents	Employment	X		
	Blanchflower and Burgess (1998)	Introduction of new technology	Employment	X		
	Klette and Førre (1998)[2]	R&D investments	Job creation			X
	Smolny (1998)	Product and process innovations[3]	Employment	X		
	Boone (2000)	Product and process innovations	Unemployment		X	
	Gatti (2000)	Product-oriented and knowledge-based R&D	Unemployment	X		
	Greenan and Guellec (2000)[4]	Product and process innovation	Employment	X		
	Aguirregabiria and Alonso-Borrego (2001)	Investment on R&D, purchases of technological capital	Employment by occupations	X		
	Falk and Seim (2001)	Investment in IT	High-skilled employment	X		
	Greenan et al. (2001)	R&D expenditure, IT adoption and intensity of usage	Wages, skill composition, employment	X		

Table A1. *Cont.*

Level of Analysis	Author(s), Year	Measurement Instrument(s) for Technological Innovation(s) as Exogenous Variable(s)	Labor Market Outcome(s) as Endogenous Variable(s)	Positive	Negative	Non-Significant/Unclear
Micro level	Luque (2005)	Technological intensity	Skill mix changes	X		
	Piva et al. (2005)	R&D expenditure	Employment (blue-collars, white-collars)			X
	Greenhalgh et al. (2001); Lachenmaier and Rottmann (2007); Yang and Lin (2008); Lachenmaier and Rottmann (2011)	R&D, patents	Employment	X		
	Hall et al. (2008); Harrison et al. (2008); Dachs and Peters (2014); Falk (2015)	Product and process innovations	Employment	X		
	Baccini and Cioni (2010)	Introduction of ICT	Demand for skilled workers			X
	Coad and Rao (2011)	R&D expenditure, patents applications	Total number of jobs	X		
	Meschi et al. (2011)	R&D expenditure, technological transfer from abroad, foreign ownership	Demand for skilled labor	X		
	Evangelista and Vezzani (2012)	Product and process innovations	Employment	X		
	Bogliacino et al. (2012); Ciriaci et al. (2016)	R&D expenditure	Employment	X		
	Kwon et al. (2015)	Product[5] and process[6] innovations	Employment	X		
	Meschi et al. (2016)	R&D expenditure; the obtained availability of a foreign patent or other appropriable devices developed abroad; investment in foreign machinery and equipment per worker	Employment (blue-collars, white-collars)	X		
		Investment in domestically produced machinery and equipment per worker	Employment (blue-collars, white-collars)		X	
	Haile et al. (2017)	The share of foreign ownership	Skilled and unskilled labor force demand	X (for skilled workers)		X (for unskilled workers)

2 The authors study manufacturing sector both at the firm and industry level.
3 The database for the empirical application consists of the data-set from the business survey and the investment survey of the IFO institut, München. Innovations are defined as novelties or essential improvements of the product or the production technique (Smolny 1998).
4 This research describes the dynamics of employment both at a firm and sector level.
5 Five items, e.g., "Product innovation conducted in my company has a positive impact on achieving industrial standards."
6 Five items, e.g., "Process innovation enhances product quality."

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