Impact of innovation on employment in quantitative terms: review of empirical literature based on microdata

Heijs, Joost and Arenas Díaz, Guillermo and Vergara Reyes, Delia Margarita

Complutense University of Madrid, Complutense University of Madrid, Instituto de Investigaciones Económicas UNAM

25 July 2019

Impact of Innovation on Employment in Quantitative Terms: Review of Empirical Literature Based on Microdata

Joost Heijs[a] , Guillermo Arenas Díaz[b], Delia Margarita Vergara Reyes[c]

[a] Department of Applied Economics, Structure and History. Complutense University of Madrid

[b] Ph.D. Student of Economics at Complutense University of Madrid

[c] Instituto de Investigaciones Económicas. UNAM

Abstract

Because of the alarming discussion about robotisation and the potential loss of jobs, the effect of technological change on employment is back at the center of social debate. This study reviews the empirical evidence of 44 micro-level studies on the quantitative impact of innovation on employment, offering a systematic review of the methodologies used, (control) variables and data sets. It tries to explain their contradictory results and shortcomings and summarize their conclusions, offering a new taxonomy of the studies. Although we analyze all types of studies, the main part of our review is focused on two basic models. The first one is the static input-oriented model of Van Reenen (1997) and Bogliacino et al. (2008 and 2014), which shows a positive effect of R&D expenditures on employment. The second one is the dynamic output-oriented model of Harrison et al. (2008), which shows a positive effect of product innovation on employment and contradictory effects for process innovation. Most studies confirm the expected negative effect of process innovation. However, others (especially those which analyze low-income countries and low- tech sectors) reflect non-significant relationships. Further on**,** some conclusions, final critical remarks about detected limitations and contradictions and possible future lines of research will be presented.

Keywords: innovation effects on employment, endogeneity, process and product innovation

JEL CLASSIFICATION:

D2

J23

L1

O31

O33

E-mail addresses: joost@ccee.ucm.es (Heijs J.), guillare@ucm.es (Arenas G.), verdel@unam.mx (Vergara Reyes D. M.)

∗Acknowledgements: The authors acknowledge funding support from PAPIIT, UNAM, project (IN302317), titled “Efectos de la política tecnológica en el comportamiento innovador de las empresas y el modelo en México: una aproximación econométrica”

1.- Introduction

The discussion about the effects of innovation on social welfare in terms of unemployment has historically been marked by sharp contradictions. Workers that lost their jobs believed that innovation destroys employment and organized themselves in movements like the case of the "machine breakers" or Luddites. However, such movements only achieved a slowdown of the diffusion of innovation and failed to stop technological progress in the long term (Hobsdawn, 1952). Process innovation was the most remarkable activity during the first industrial revolution with, as will be argued, an enormous impact on employment. Since that time, the impact of technological change on the labor market has always been an aspect which creates social controversy.

The historical empirical data shows drastic employment effects based on major innovations in the past. Industrialization in particular and the subsequent technological revolutions permitted an enormous increase of efficiency and/or productivity. For example, Jenkins's study (1994) indicates that the amount of cotton that is nowadays processed in only 40 working hours (using the most modern machines) required around 50,000 hours before the first industrial revolution. This example reflects the immense labor saving generated by the mechanization and automatization of production (process innovation) and is an interesting reference point for discussing the potential drastic employment effects of technical, advanced robots –in combination with artificial intelligence–. This trend implies a substantial intensification of the automation process[1] and it suggests a drastically effect on labor productivity, generating a negative effect on overall employment demand. McKinsey (2017) analyzed the effects of automatization –based on robots– on the global labor market across 54 countries and foresee a potential loss of around 40-50%[2]. These estimations sound alarming and again put the relationship between employment and innovation back at the center of political and public discussion.

Historically, the labor movement has underlined the negative effects of innovation on employment in terms of quality and quantity, especially during the periods of economic crisis while entrepreneurs underpin the benefits of technological change regarding efficiency, productivity and competitiveness. In fact, politicians and businessman are in general very confident about the positive role of compensation mechanisms[3], and suppose that the labor market will absorb –in the medium and long term– unemployed workers in new activities or because of the increase of the demand for "old" goods of some sectors due to the overall economic growth. They consider innovation as the main cause of economic growth and social well-being, and the loss of jobs or diminishing working hours are compensated by higher overall living standards. In fact, because of a higher overall production level, everybody could theoretically live better than before, but in the real world this does not happen.

The theoretical debate about the impact of innovation on employment at a macroeconomic level distinguishes several approaches. The first one is based on the neoclassical equilibrium model that highlights the compensation mechanisms, based on the free market

[1] Dorn, 2016; McKinsey, 2017; Arntz, et al., 2017; Acemoglu, et al. 2017

[2] The difference depends on the country or sector analyzed.

[3] This study reviews the empirical studies. For a broader review of the theoretical approach, see Vivarelli (2007) and (2014), Calvino et al. (2016), and Pianta (2003).

assumptions. These mechanisms guarantee the recovery of employment loss because of innovation in the long term. In fact, this theory argues that the negative effects of innovation on employment will be compensated automatically.

In the case of disequilibrium perspectives, there are alternative approaches like the Keynesian and Schumpeterian (Evolutionist) theories that recognize the problems in the labor market generated by lack of effective demand and technological progress, respectively. The disequilibrium-based models recognize, in a certain way, the concepts behind the compensation mechanisms. However, they do not believe in the automatic accomplishment and the consequence of these mechanisms in terms of full employment. On the contrary, the labor market is far from a flexible "free market situation" and several aspects impede a fast and flexible reaction[4]. They include minimum wages, powerful labor unions, legal state regulations, and slow adjustments to changes in demanded qualification of the available human capital. For Keynesians, unemployment is a temporal problem related to the business cycle and is caused by downturns in the economy and its business cycle. In Schumpeter's approach, so-called unemployment is not only an effect of the lower labor demand caused by process innovations and the depletion of old technologies. Schumpeter also identifies so-called "technical" unemployment caused by the discrepancy between the formation of workers expelled from traditional sectors and the requirements of human capital in emerging innovative sectors.

According to Dorn (2016)**,** an intuitive yet profoundly mistaken view of the labor market is that there is a fixed amount of work, which can be done by either humans or machines. According to this view —known to economists as the "lump of labor fallacy" (Walker, 2007, Schloss, 1891) – an increasing use of machines in the production process necessarily reduces the total work –or overall labor demand– available to humans. However, a number of economists[5] and policymakers emphasize that the labor market is dynamic and elastic, and they focus on ways to create employment.

The main goal of this article is to review 44 studies that analyzed the impact of innovation on employment in terms of quantity for different countries. We offer a systematic methodology in order to synthetized different aspects, such as: econometrical methodologies, dependent variables, input or output indicators of innovation, control variables, samples and subsamples, and other important aspects. This revision should help the authors interpret their results and especially help them to clarify or explain the possible contradictions in their results.

Following the introduction of the relationship between innovation and employment, the next section presents a short review of the main problems that exist when attempting to review the theories that explain the impact innovation on employment: the endogeneity problem. The next two sections –which are the central part of the article–, synthesize the empirical evidence offering a critical analysis of the econometric models used, the

[4] Although it is true that during the last crises, the labor market became more flexible, employers still have no freedom to dismiss their workers, lower salaries or apply negative changes to other working conditions.
[5] Vivarelli (2007) and (2014); Pianta (2003); Bogliacino et al. (2014); Harrison et al. (2008) and (2014); Dorn (2016); etc.),

appropriateness of the variables used, a synthesis of the results obtained, and the contradictions found in the studies. Finally, the last section offers conclusions and some final critical remarks about the limitations of the existing empirical evidence and future lines of research.

2.- Measuring the effect of innovation on employment: The endogeneity problem

The main methodological obstacle when measuring the effect of innovation on employment is the endogeneity problem. Its existence causes biased in the results of the classic econometric models. The coefficients might be under–or over–estimated[6]. Intuitively**,** it can be stated that endogeneity exists if "something" related to the dependent variable (Y) and also related to the independent variable (X) is not included in the model. That "something" can be related to important determinants of Y, which are not included in the model (omitted or non-observable variables). It can be caused by simultaneous relationships between independent variables (X) and dependent variables (Y) or by a variable that affects both the dependent (Y) and the independent (X) variables. That "something" can also be related to a sample problem.

From an econometric point of view, it can be stated that endogeneity exists if a correlation is detected between one of the explanatory variables and the error term. Three possible explanations for the endogeneity problem are: an unobserved or omitted variable, errors in variables and simultaneity[7] (Wooldridge, 2015). In the case of the studies that analyze the effect of innovation on employment the endogeneity is basically caused by measure errors and the omission of (unobservable) variables. An example of an endogeneity problem based on pure missing variables is offered by Harrison et al**.** (2008 and 2014). They argue that the variable of "percentage of sales due to new products" shows a correlation –with the error term in their model– because it does not include information on external shocks and it does not fully account for possible different prices of new and old products. Both aspects impact the employment of each type of the firms in different ways

A solution to the endogeneity problem can be the inclusion of instrumental variables (IV). Such variables would correct the model in relation to the possible bias generated by the endogenous explanatory variable. The IV should accomplish two assumptions. First, it should be causally related to the explanatory variable which is suspected to (X; sales growth due to new products) cause endogeneity –inclusion assumption–. Second, the IV should not have an independent causal relationship with the dependent variable of the main equation (Y; employment). In other words, the instrumental variable should be related to "X" and not to "Y" –exclusion assumption–. In this way, this variable would "randomize" the sample for the "X" and therefore IV resolve the endogeneity problem between X and Y. This means that all the influence of IV on employment (Y) is the result of an indirect effect caused through its impact on innovation (X). If this is the case, the model will estimate the

[6] In the case of Harrison et al. (2008 and 2014) the coefficient of g2 is underestimated with OLS.

[7] "Simultaneity" is a relation between two variables that happening at the same time. Especially within a systemic dynamic framework with a large number of interdependent aspects –like the dynamics in an economic structure- we find frequently such of mutual interdependent relationships

real causal effect of the explanatory variable (innovation) on the dependent variable (employment). The methodological box offers the formal representation of the endogeneity problem.

Two main estimators are applied to include IVs in the literature. One option is the application of an econometric adjustment, called the General Moment Method models (GMM), and a second type of model is the two-stage least squares (2SLS) estimator. Moreover, if researchers have panel data, they can use two types of instrumental methodologies. They use the lags of independent variables such as IVs[8], or they can opt for the use of specific observations of certain variables included in the data set. As will be discussed in section 3.3, the main problem of the last option is to find an accurate instrumental variable (IV) that is available in the data set, meets the statistical requirements, passes the econometric test of endogeneity and fulfills the conceptual requirements from a theoretical point of view. The different methodologies used in the empirical literature are synthesized in Table 2 and will be discussed in section 3.3.

3.- Particularities of the used data and the econometric models

As it can be observed in Table 1, we have reviewed 44 studies that analyzed the impact of innovation on employment. The following subsections offer the characteristics of the data sets used (3.1) followed by a taxonomy of the detected studies based on the specific methodological settings (3.2). In Section 3.3, we review the specific instrumental variables used to overcome the endogeneity problem analyzing their appropriateness, advantages and disadvantages.

3.1.- The characteristics of the data sets and dependent variables

Table 1 reflects some of the basic characteristics of the samples used in the studies. Looking to the type of country[9] it can be stated that only a few studies examined the effect of innovation on employment for developing countries (only 8 of the 44 studies) and many studies have focused in developed countries (only 36 of the 44 studies). The type of country is important for the interpretation of the results because the relationship between innovation and employment could be very different between both types of countries.

The second particularity of the sample that could affect the correct interpretation of the models is the exact type of firms included in the data set, especially in relation with the differences between sectors. In fact, only few studies offer models by subsamples and most of them simply distinguished between industry and the service sector[10]. In our opinion, this distinction is important because both sectors have very different characteristics. In the service sector, it is –or was– very difficult to "automatize" certain labor intensive activities, moreover in this sector it is often difficult to differentiate between product and process innovation. Therefore, mixing up the two types of firms in one sample could offer biased results. Other studies included sector-based subsamples following the aggregated OECD sectors classification by R&D intensity. However, taking into account the main objective of

[8] Thy use the lags of both innovation and control variables as IVs

[9] These countries are from Europe and Latin America

[10] Seven models were based on such subsamples in the case of Type 1 studies, four in Type 2 studies, and three in Type 3.

our study, the effect of innovation on employment, the aggregation of the sectors should also be based on the type of product or activity, like the taxonomy of Pavitt (1984), [11] and updated by Bogliacino and Pianta (2015). This taxonomy considers the sector differences of the importance of process and product innovations and the importance of R&D efforts implicitly and simultaneously. This would be important because the role of technology purchasing sectors is quite different from that of the producers of equipment and machinery.

Table 1. Some selected characteristics of the studies and the samples used

Dependent Variable	Whole sample	Type 1	Type 2a	Type 2b	Type 3a	Type 3c
Total number of studies	**44**	**11**	**9**	**8**	**8**	**8**
Total number of samples	**119**	**32**	**35**	**22**	**17**	**13**
Growth Rate Employment	87 (100)	11 (13)	35 (40)	22 (25)	10 (11)	9 (10)
Total Employment	32 (100)	21 (66)			7 (22)	4 (13)
Countries						
Developed countries	99 (100)	31 (31)	21 (21)	21 (21)	13 (13)	13 (13)
Developing countries	20 (100)	1 (5)	14 (70)	1 (5)	4 (20)	
Type of data						
Panel	68 (100)	32 (47)	11 (16)	10 (15)	8 (12)	7 (10)
Cross Section	50 (100)		24 (48)	12 (24)	9 (18)	5 (10)
Samples						
Total	43 (100)	10 (23)	9 (21)	10 (23)	7 (16)	7 (16)
Manufacturing Sector	27 (100)	5 (19)	11 (41)	4 (15)	3 (11)	4 (15)
Services Sector	19 (100)	2 (11)	9 (47)	6 (32)	2 (11)	
High-Tech Sector	14 (100)	7 (50)	3 (21)	1 (7)	2 (14)	1 (7)
Medium-Tech Sector	2 (100)	1 (50)			1 (50)	
Low-Tech Sector	14 (100)	7 (50)	3 (21)	1 (7)	2 (14)	1 (7)

Notes: the table reflects the different dependent variables used to measure employment (absolute employment or the growth of employment) Moreover, it captures some characteristics of the samples (developed or developing countries and subsamples) and it shows the type of data used (cross section or panel data).

3.2.- Methodological differences between the main models

The majority of reviewed studies include models based on instrumental variables in order to solve the endogeneity problem. The studies can be classified into three main groups whose distinction is based on their theoretical or methodological approaches and the way they operationalize innovative activities. For the first type of model, proposed by Van Reenen (1997) and adapted by Bogliacino et al. (2008, 2014), 11 studies were detected. It

[11] Pavitt distinguish among: (1) Supplier-dominated (firms from mostly traditional manufacturing sectors that almost only buy technologies. (2) Scale-intensive (mainly large firms producing basic materials and consumer durables). (3) Specialized suppliers: firms producing technology for other firms like machinery and instruments (4) Science-based: high-tech firms which rely on R&D and develop new products or processes.

can be considered a static input-oriented model that defines innovation in terms of its input (R&D expenditures). It uses a comparative static specification without lagged variables and using the number of employees as a dependent variable in the empirical model. Moreover it applies a pure econometric solution to solve the endogeneity problem by the introduction of lagged[12] observations as instrumental variables. It therefore requires data for several time moments (applying GMM estimators).

The second type of study (17) follows the dynamic output-oriented view of Harrison et al. (2008), including two output variables simultaneously in order to analyze the effect of the results of the innovation in terms of products and processes on employment. The first one measure the effect of product innovation on sales and the second is a dummy or dichotomy variable that reflects the introduction of process innovations (yes/no). It is the dynamism of the changes in the sales between old and new products and the use of the growth of employment as a dependent variable which make the model dynamic. In order to solve the endogeneity problem, the studies suggest several specific variables as possible instruments applying the 2sls estimator (see section 3.2).

A third group of a hotchpot of studies[13] is distinguished because of some methodological differences. It includes several studies from before 2000 that do not correct the endogeneity problem. Moreover, several of them use a heterogeneous set of several alternative variables (not or barely used by mainstream models) to operationalize innovation, like the growth of R&D expenditures (4 samples[14]), capital investment in R&D (3), R&D expenditures by employment (5), patents (3), and organizational innovation (6). In fact, only few studies include alternative variables to define innovation. Besides the Type 3 studies, the Type 2b studies also simultaneously included alternative forms of innovations like organizational innovations and the use of a dichotomy variable for the product or process innovation instead of the use of a dummy for only process innovation.

The two main models, and basically all the other ones, are similar in terms of theoretical assumptions that are based on the neoclassical perfect market structure and recognize the existence of the neoclassical compensation mechanisms[15]. Furthermore, the two approximations assume the existence of the "Hicks-neutral technology parameters." This assumption implies that the optimum relation between capital and labor is not altered by technological change. The difference of the models, in terms of econometric estimation, is based on two aspects.

Eleven of the 44 studies applied the Type 1 model developed by Van Reenen (1997) and Bogliacino et al. (2008, 2014) executes with a comparative static input-oriented model because it does not include any lags-and estimates a production function called "Constant

[12] The use of the lagged variables is compatible with the static character of the model because it only implies an adjustment in beta terms of the static variables.

[13] The studies marked as Type 3a use only dummy variables, while the Type 3b studies also include variables of the intensity of innovation.

[14] There are 16 studies in total.

[15] The other models are basically an adaptation of the two main frames, and none of them indicate that they take another position in relationship to the mentioned assumptions.

elasticity of substitution" (CES). They maximized the function in order to obtain the profits[16] that allow calculating the labor equation:

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r\&d_{i,t} + \beta_4 g_{i,t} + (\varepsilon_i + v_{i,t}) \quad (1)$$

All the variables of the model are in logarithms which make it possible to interpret them in terms of elasticities. $l_{i,t}$ is the employment, y is the output (sales as a proxy variable), w is the wage, $r\&d$ is the research and development (R&D) expenditure, g is the gross investment, ε_i is the idiosyncratic individual and time-invariant firm's fixed effect and $v_{i,t}$ is the usual error term (Bogliacino et al., 2014) [17].

For its part, the Type 2 model of Harrison et al. (2008 and 2014) –used by 17 studies- offers a dynamic output-oriented model which is based on using lags and differentiates for new and old products by using three production functions: one for the sales of old products in t=1 and t=2 (t= time) and another function for the sales of new products (only in t=2). The authors minimize the costs[18] of these first two functions in order to obtain the labor demand. Finally, they calculate the employment growth and replace it in the labor demands (see equation 2).

$$l_i - y_{1i} = \alpha_0 + \alpha_1 d_i + \beta y_{2i} + u_i \quad (2)$$

where l stands for the rate of employment growth over the period (between the year t=1 and t=2), y_1 and y_2 are the rates of output growth for old and for new products, and u is the unobserved random disturbance. The main advantage of the model is related to its components, which can be interpreted –from a conceptual point of view– in terms of specific efficiency gains, according to the types of innovation:

- The constant term reflect the increase of the efficiency of the production process. In theory, the efficiency is always expected to improve over time for a certain good. Therefore, the parameter α_0 is expected to be negative, representing the average efficiency growth in the production of the old products.
- The binary variable d picks up the additional effect of process innovations on employment related to old products by means of the efficiency parameter α_1. Variable d is equal to one if the firm has implemented a process innovation not associated with a product innovation (process innovation only).

- The parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2008, 2014). In fact, it shows the effect of product innovation on the employment.

[16] In microeconomics, the maximization of a function allows us to find other functions such as labor and capital demands (depending on the assumptions). One way to maximize the function is to take the derivatives of the functions with respect to labor or capital.

[17] It is important to mention that the last equation is proposed in the Bogliacino et al. work (2008, 2014) since Van Reenen's work (1997) did not utilize an input of innovation as an exogenous variable (research and development expenditure), but instead a measure of innovative output (new products and/or new process). However, it is the input model of Bogliacino et al. that is used more frequently used in the literature.

[18] Like maximization, minimizing the cost mathematically consists of taking the derivative with respect to one of the variables that forms the total cost. Economically, it gives information about the behavior –ceteris paribus– of one of the variables of the cost function.

As we stated earlier, this interpretation is a big advantage, although at the same it is almost impossible to modify the original model, adding new variables. To assure the correct interpretation of the model, the theoretical-methodological model developed by Harrison et al. (2008) should be followed rigidly.

Therefore, we classified the seventeen studies that used this model in two groups. As far as we could deduce form the articles, the studies were classified respecting exactly the original model as in Type 2a, while the Type 2b studies included variations that impeded the initial foreseen interpretation or did not explain the specifications of the models sufficiently.

Seeing this, the first difference between the two types of models is the way they capture the innovation effect on employment (as mentioned above and reflected in the equations). The Bogliacino et al. (2014) models imply an input orientation, conceptualizing the innovation by its input in terms of R&D efforts or expenditures. On the contrary**,** the model of Harrison et al. (2008) uses the output of innovation as the key element to analyze its impact on employment. Their model simultaneously includes a variable for the output in terms of product innovation (the sales growth due to new products) and a dummy variable on the introduction of only process innovation (yes or no). In general terms, the target of process innovation is to convert production to a more efficient activity by including labor-saving labor. In contrast, the development of new products looks to maintain and/or expand the existing market or generates new ones with the discussed positive potential effects on labor demand.

The second difference is in terms of the dependent variable that measures the creation or destruction of employment, the studies reviewed use, basically, two different variables: "total employment of the firm" (used in 32 samples)[19] and "growth rate of employment" (used in 87 samples). The studies based on the dynamic output approach (Type 2) use, basically, the growth rate of employment as an endogenous or dependent variable (57 samples), and those of the static input approach (Type 1) mostly use the total employment variable in absolute values (21 samples of the 32 mentioned)**.** The studies of Type 3, alternatively, use one of those two variables.

A third difference is the way they include the instrumental variables in the model. The dynamic**-**output-oriented models use as instrumental variables, basically, one or more specific variables available, taken from the data used, like the motives to innovate, cooperation in R&D, etc. (see section 3.3.2). For its part, the static-input-oriented model applies a pure econometric adjustment, called the General Moment Method model (GMM), which applies the lags of the variables as instrumental variables (see section 2).

3.3.- Different instrumental variables and methods applied by the empirical studies

As mentioned, the endogeneity of the model (caused by missing or unobservable variables because of a sample problem) is the main problem in estimating the impact of innovation on employment. In this section we review the different instrumental variables and methods applied by the empirical studies. Our recommendation is to skip to section 3.4. to the readers with lack of knowledge on the basic concepts of the econometric models, used for

[19] As mentioned, we analyzed 44 studies. However, most of them included several estimations by subsamples in terms of size of the firms, sector, country etc. In the following pages, we use the word "sample" for all 119 estimations carried out by the 44 studies.

the application of the method of instrumental variables, and the ones that is not interested in the methodological. In spite of, this section is just a general overview of the methods used, obviating a depth analysis about the specification and the advantages and disadvantages of the different models.

3.3.1. Different methods of instrumental variables applied by the empirical studies

Table 2 has two columns. The first one (called "methodology used") refers to the number of times that a specific econometric methodology is used in the studies reviewed. Most studies apply several methodologies and indicate which of them are the best, (in econometric terms because of more robust, efficient and less biased estimators) in order to interpret the results correctly. Therefore, the second column is included to show how many times each method is considered the best of the ones applied.[20]

Table 2. Empirical Methodologies

Methodology[21]	**Methodology Used** [a]	**Best Methodology**[b]	**Percent respect to Best Methodology**
Cross-Section data			
Ordinary Least Squares (OLS)	19	5[c]	26%
Model-Specific IV based on indicators included in the data set (2SLS)	16	14	74%
Panel Data			
OLS	12	3[c]	13%
Fixed Effects Models (FE)	12	4	42%
Specific IV based on indicators taken from the data set (2SLS based on a pooled panel data set)	8	6	46%
IV based on GMM models	14	12	
	81	44	

a It includes all the methodologies that are used in the articles no matter whether they are formally corrected in order to solve the endogeneity problem.
b It is constructed based on the arguments of the authors when they say that the methodology is the best to interpret. In the parentheses the percentages of the best methodologies are captured with respect to the methodology used
[C] The studies that interpret OSL as the best option are studies carried out before the development of the methods that solve the endogeneity problem.

Almost all studies included the classical model based on Ordinary Least Squares (OLS). However, its interpretation depends on the statistical assumptions[22], and if at least one of them is not satisfied, the model has to be adjusted adequately to a specific methodology. The inclusion of such models that do not solve the endogeneity problem is justified because they are required to test if the endogeneity problem exists, and such additional estimations analyze indirectly[23] the robustness of the final model.

The researchers that tried to measure the impact of innovation on employment before the development of "econometric models" were not able to solve the endogeneity problem, and therefore, they refer to the OSL as the "best methodology"[24]. The more recent studies apply

[20] A decision made by the author on econometric methodological arguments.
[21] This review does not intend to debate the differences, advantages and disadvantages of the different methods. The most commonly used models are the Two-Stage Least Squares (2SLS) (in the case of panel data) and the pooled OLS (for cross-section data) which uses IV, and also different versions of so-called GMM models (General Moment Method). For a review of the methods, see Wooldridge (2015) and Arrelano and Bond (1991).
[22] In short, the assumptions of the classical econometrical model are normality, homoskedasticity, non-autocorrelation, exogeneity and linearity (all of them are tested in the error term).
[23] If different models offer similar results, it can be expected that they are more robust.
[24] For 26% of the studies that used cross-section data and 13% of the panel data-based studies.

different kinds of methodologies[25] in order to correct the endogeneity problem, and their exact choice depends on the kind of data that is available (cross-section or panel data). In the case of static input-oriented models (Type1), the majority of the studies use panel data sets, and therefore they are able to apply methodologies such as GMM (they use the lags variables as instrumental variables) or fixed effects. By contrast, the authors that applied the dynamic output-oriented model (Type 2) used the Two Stage Least Squares model (2sls). Initially, they only had access to cross-section data because the European innovation surveys were not applied every year.

The dynamic-output-oriented models (Type 2 studies) based on the model of Harrison et al. (2008) use as instrumental variables basically one or more specific available variables taken from the data used, like the motives to innovate, cooperation in R&D, etc. 24 samples used such specific instrumental variables and 20 studies marked this methodology as the most appropriate one. For its part, the static-input-oriented model applies the lags of the variables as instrumental variables using the General Moment Method models (GMM) 14[26] of the 44 studies used the GMM in one or more of its variations, and 12 of them marked this model as the best method. The GMM model can be applied in case of an endogeneity problem among the explanatory variables, and if the number of observations over time (moments) is larger than the number of parameters that should be estimated.

3.3.2.- The specific used instrumental variables

As mentioned, the endogeneity of the model (caused by missing or unobservable variables and/or because of a sample problem) is the main problem in estimating the impact of innovation on employment. The solution of this typical econometric problem would be the use of instrumental variables. The main problem is to find an accurate instrumental variable (IV). Such a variable has to be a determinant of the "X" variable (the innovative behavior of the firm) and should have a zero correlation with the dependent variable (Y, the variation of the employment of the firm). Also, theoretical or conceptual arguments have to be discussed for each of the IV. It can be stated that most studies barely discuss their suitability from a theoretical point of view. Extremely difficult will be the search for theoretical arguments to assure that the IV only affects the X and does not have a direct effect on Y, especially because of the absence of good theoretical frameworks and the systemic character of economic and innovative systems. The studies offer some general comments and show that the test to confirm the aptness of the VIs is correct. The inherent systemic character of the economy and firms implies that a certain level of correlation will be found between very large numbers of variables that express very different aspects of a firm.

The instrumental variables observed in the reviewed studies can be grouped basically into three categories (see Table 3). The first and most used ones are IVs based on the importance of certain motives that drive the innovative activities of firms and of some of the sources of innovation. A second group of IVs was created by variables that reflect the

[25] Like 2SLS, GMM, fixed effects etc. Additionally if you use fixed effects, the model only controls the heterogeneity of the individuals and does not solve the endogeneity problem.
[26] Nine of the studies are marked as Type 1A studies based on the input indicator of R&D expenditures and 5 five studies are classified as Type C, D and E, using output indicators of innovation (product and/or process innovation).

innovative efforts or input, and the third one used some aspects of the results of the innovative activities. A fourth "group" includes some additional IVs that were used less frequently.

In the group of instrumental variables based on the importance of the motives and resources of innovation, the most used indicator (in 41 estimations) is "the increase of the range of goods and services"[27]. According to Harrison et al. (2014), this motive could be used as an IV because it measures the extent to which the firm's innovation is associated with an increase of demand for reasons other than changes in product prices and quality (Harrison et al., 2008). This variable, equal to all the ones in this group, is captured in qualitative form (valuing its importance on a five-point scale) based on the perception of the person that answers the surveys in relation to this specific objective. In fact, it does not reflect whether there is an increased range (goods and services) due to an improvement in demand or other factors. Moreover, it is not clear that, for smaller firms based on one or a few products, the answer to this motive can be considered relevant.

For the other instrumental variables of this fist group –based on the motives and sources of innovation[28]–, the authors do not offer clear theoretical reasons about why they are adequate. Most of them were used in combination with the first one and were justified by the fulfillment of the corresponding endogeneity tests of the econometric models.

The instrumental variables based on the intensity of R&D efforts (R&D or innovation expenditures/sales) are the most utilized (57 times, 20 of which in terms of a lagged value). This variable is used in the studies that follow the approach of Harrison et al. (2008)[29]. Those authors argue that R&D is a way to produce innovative output (process and product innovation), but it does not affect employment directly (Harrison et al., 2014). In order to test this causality, the effect of R&D on employment must only be caused through the endogenous variable of "sales growth due to new products". The problem is if the R&D expenditures variable is used directly in the structural equation, it is impossible to confirm or statically test that its effect is only through product innovation.

Another IV used in six studies (25 samples) is an indicator of "Continuous R&D engagement[30]". In the previous section, it was mentioned that this variable can measure some kind of innovative dynamism, although the impact of this variable in terms of innovations and new products might happen in a future time span (year). However, in our opinion, a similar value of this indicator can have a quite different meaning. Large firms with large R&D projects (of duration of several years) are more prone to do continuous R&D than smaller firms in less innovative sectors. Moreover, smaller firms could introduce innovations with some delay, and that implies that its effect on employment also will be delayed. Such a delay could be more remarkable in smaller firms that carry out R&D in an irregular way.

---

[27] Used in 41 estimations and especially in the dynamic output-oriented Type 2 models of Harrison et al. (66% of the studies of Type 2a and 34% of Type 2b).

[28] Like the motives "the improvement of the quality of the goods and services" and "increased market share" or the importance of "clients as a source of information" and therefore innovation.

[29] In these studies, this indicator is therefore not included as a control variable as in some other studies.

[30] Continuous R&D engagement: dummy variable which takes the value 1 if the firms report continuous engagement in intramural R&D activities during the period (1998-2000).

Table 3. The instrumental variables used

Variables	All samples	Type 1	Type 2a	Type 2b	Type 3a	Type 3b	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries
Motives and sources of innovation														
Motives: Increased Range (goods and services)	41		27 (66)	14 (34)			11 (27)	13 (32)	13 (32)	2 (5)		2 (5)	34 (83)	7 (17)
Motives: Improved quality	21		21 (100)				1 (5)	10 (48)	8 (38)	1 (5)		1 (5)	19 (90)	2 (10)
Motives: Increased market share	21		16 (76)	5 (24)			1 (5)	10 (48)	10 (48)				21 (100)	
Sources: New inputs utilization as an origin of the innovative idea. [a]	1			1 (100)			1 (100)							1 (100)
Sources: Scientific and technological opportunities [b]	3			3 (100)				2 (67)	1 (33)				3 (100)	
Sources: Clients as a source of information	21		19 (90)	2 (10)			1 (5)	10 (48)	10 (48)				20 (95)	1 (5)
Effort														
Innovation Intensity (R&D expenditure or Innovation/Sales)	37		19 (51)	14 (38)		4 (11)	10 (27)	17 (46)	10 (27)				37 (100)	
Lag of Innovation Intensity	20		16 (80)	4 (20)			4 (20)	8 (40)	8 (40)				20 (100)	
R&D expenditure	4			4 (100)			4 (100)						4 (100)	
Continuous R & D engagement [c]	25		18 (72)	3 (12)		4 (16)		14 (56)	11 (44)				25 (100)	
Results														
Innovation new to the market [d]	2			2 (100)				1 (50)	1 (50)				2 (100)	
Patents	5	1 (20)		4 (80)			1 (20)	2 (40)	2 (40)				5 (100)	
Others														
Firm knowledge of public support for innovation activities [e]	4		4 (100)				2 (50)			1 (25)		1 (25)		4 (100)
Increase in productive capacity[f]	1		1 (100)				1 (100)							1 (100)
Product life cycle dummies[g]	2		2 (100)							1 (50)		1 (50)		2 (100)
Obstacles to innovation averaged across firms in the same region	4		4 (100)				2 (50)			1 (25)		1 (25)		4 (100)
New markets[h]	4		4 (100)				2 (50)			1 (25)		1 (25)		4 (100)
Cooperation	8			8 (100)			4 (50)		2 (25)	1 (13)		1 (13)	8 (100)	

Notes: +=positive effect. ns=no significant effect. -=negative effect

a The instrument used is the degree of usage, on the part of the company, of new inputs as an origin of innovative ideas. This variable takes the value zero if the innovative idea, as declared by the firm, is not a result of the recent introduction of new inputs and takes values between 1 and 4 according to the level at which the company declares innovative ideas were originated in the usage of new inputs.

b Technological opportunities and if institutional sources like universities or other higher education institutions or government or public research institutes were of 'high' or 'medium' importance as sources of information for a firm's innovation activities.

c Continuous R&D engagement: dummy variable which takes the value 1 if the firms report continuous engagement in intramural R&D activities during the period (1998-2000).

d As the market share of goods and services introduced in 2002 and 2004 and were new to the firm's market.

e Whether the firm has some knowledge (but is not necessarily a user) of public support programs for innovation.

f The production of new goods would be related to the increase in productive capacity.

g Set of industry dummies to control for industry productivity shocks. This reinforces the finding of the absence of serial correlation in individual productivity shocks and it controls for the business cycle effect.

h This variable assesses the impact of innovation on the development of new markets for firms (coded between 0 to 3: 0 = irrelevant impact, 1= low, 2= medium, and 3 = high impact).

h Takes 1 if the firm has cooperated in innovation projects with other agents like suppliers, research institutions and competitors.

To overcome endogeneity between employment and R&D investments, a lagged value of the latter can be used to assure that the decision on R&D is in advance and independent of the decision to contract employment. Furthermore, the variable can be interpreted as a response of firms to external productivity shocks. Those authors suppose a direct relation between innovation intensity and sales growth due to new products. Fifty-one percent of the models of Type 2a use the lagged innovative effort as an instrumental variable; in the case of Type 2b studies, this percentage is 38%. The lag of the variables is used in 80% of the Type 2a models and in 20% for Type 2b estimations (see Table 3).

The studies summarized in Table 3 show a certain group of instrumental variables used in few studies. Some of them are mainly used in studies on Latin American countries**,** and include the firm's knowledge of public support for innovation activities (4)[31], increase in productive capacity (1), dummies for the life cycle of the product (2), importance of obstacles to innovation averaged across firms in the same region (4), and the use of new inputs as an origin of the innovative idea (1). Some other barely used IVs were applied in studies for developed countries: cooperation (8), scientific and technological opportunities as a source of innovation (3), innovation new to the market (2), and patents (5). It can be stated that especially the last two variables are more appropriate for developed countries because only a small group of firms in developing ones would have patents or introduced products new to the market. The authors that use those IVs do not offer the required theoretical justification. They justify instrumental variables based on econometric tests of the exclusion (Sargan Test) and inclusion restrictions.

As can be noticed, most of the time the theoretical justification of their instrumental variable is not clear and can often be put in doubt. Most authors take a count of the instrumental variables and their tests: the endogeneity test and the exclusion and inclusion restriction. Therefore**,** the use of these variables in the models depends only on statistical assumptions and therefore it should be reviewed more specifically. Finally, the studies that estimate some type of static oriented model (GMM) apply some kind of instrumental variable based on lags of the exogenous variables. That is why the majority of these studies have not reported the instruments. However, they show the test of exclusion.

4.- Empirical evidence at the firm level:

Once the methodological aspects are reviewed, in the following pages we analyze the empirical findings of the studies that have studied the effect of innovation on employment. We mention whether the detected differences or the contradictions of these results can be explained by the specific characteristics of the sample used: the type of country, sector, or time period or methodological aspects related to the models used.

This section starts with an overview of the studies' results, in terms of the employment changes induced by innovation. Section 4.2 discusses the need to include other explanatory variables in the models and the corresponding results. The control variables are used to isolate the effect of innovation from other causes that, from a theoretical and conceptual point of view, affect employment. In other words, they create *ceteris paribus* in relation to the effect of the variable of innovation

31 Number of firms that use each aforementioned instrumental variable is in parentheses.

4.1.- Results of the estimated models by types of dependent or endogenous variables

Some methodological limitations to interpreting the results

Two aspects have to be taken into account for the correct interpretation of the general results. A first main aspect is related to practical limitations in conceptualizing the different forms of "innovation". As mentioned, the studies mainly use three kinds of indicators as innovation: product innovation, process innovation and R&D expenditures. Theoretically, the firms can be classified by five types of firms in relation to the input and output in terms of innovations: (1) only product innovators; (2) product and process innovators; (3) only process innovators; (4) firms that carry out R&D and innovation but they did not introduce innovation in the market, and (5) the non-innovating firms that do not introduce product or process innovations and neither spend money on R&D or innovation.

Not all studies that apply output indicators used these distinctions, aggregating frequently the type 1 and 2 firms. In most studies, the firms that introduce process innovation in combination with product innovation are considered "product innovators", because product innovations habitually require process innovation simultaneously. In this case, it is not sure whether process innovation is required for the introduction of new products or it is related to more efficient production of old products, and therefore they are excluded as "pure" process innovators. Moreover, it can be stated that the difference between product and process innovation is not always clear, especially, as mentioned before, in the case of the service sector.On the hand, the type of study which uses the input in terms of R&D efforts normally does not include "process innovation" as an additional variable. Such a variable is included in only two of the 31 estimations and, surprisingly, in both cases the impact is contrary to the theory that shows a positive impact.

Empirical evidence based on the impact of product and process innovation

Table 4 shows that in global terms, the vast majority of the 44 studies confirm that product innovation has a positive effect on employment. In the studies that used the dynamic output-based models (Type 2 models in the tables), product innovation is operationalized as the "sales growth due to new products" and the expected impact on employment would be positive. In fact, in all the samples and subsamples (except one) that use a continuous variable for product innovation (like sales growth due to new products), a positive impact on employment was detected. This means that, if the firm's product composition in terms of sales included a higher percentage of new products, the firm shows a higher growth rate of its employment.

The studies of group 3a conceptualize the product innovations using a dummy variable (yes/no). The problem with such variables is that they offer only limited information on innovation and are not capable of offering a model that differentiates the level of impact of innovation on employment in terms of the firm's innovative level or intensity. The methodological decision to use dichotomy versus continuous output variables is important because it could led apparently to contradictory results. As mentioned, all studies that used a continuous variable for product innovation (except one) found a positive impact. While in the case of product innovation as a dichotomy variable, 6 out of 12 studies reflect a positive effect, and for the other half its impact on employment is statistically not significant (Table

4). It can be stressed that the non-significant effect is basically observed in samples of developing countries (Chile and Estonia), and especially in samples for medium- and low-tech sectors (in the case of Italy). In turn, the majority of the estimations confirm the expected negative effects of the process innovations on employment. The firms that carry out "only process innovation" were considered non-significant in 47 estimations, and in 20 samples the expected negative effect was confirmed, while in 11 studies a positive effect was observed.

In the case of process innovation only dummy variables can be used because it is almost impossible to quantify the number or intensity of process innovations. The results reflected in Table 3 show contradictory results. The variable "only process innovation" is used in 65 of the 119 estimations (taken from 36 studies). For around 60% of those estimations (47), a non-significant relation was detected between process innovation and employment. For another 5% of the samples (3), a positive effect was identified, while around 29% of the models (16) showed a negative statistical effect.

In the intention to explain these contradictory for process innovation results by looking at the different kinds of subsamples or countries, no clear results can be depicted. In both developed and developing countries, all three types of relationships were detected, and similar differences show the estimations of only manufacturing firms. In the case of the service sector, no models were detected that show a negative effect of "only" process innovation on employment. In fact, in one study a positive effect was observed for the service sector and a negative effect for manufacturing firms (Damijan et al. 2004), a fact that underpins the importance of to include additional estimations based on subsamples.

Empirical evidence based on other indicators of innovation

The studies that used the static input orientation used by Van Reenen and Bogliacino (see Table 4) show a positive impact of innovation –defined as the level of R&D expenditures– on the employment of firms. The subsamples used to analyze whether this positive relationship differs by sector or size do not always confirm this relationship. The effect essentially does not exist in the subsamples of low-tech sectors, while no real differences were detected by types of countries. For both cases –developing and developed countries– the majority of the models show a positive impact of innovation efforts on employment.

In fact, only a few studies include alternative variables that reflect other aspects of the innovation process. One of them is the inclusion of organizational innovations, which is used in five studies. The final effect of this variable on employment, as observed in the empirical evidence, is not clear. The 5 studies offer estimations for 18 different samples. Four estimations indicated a statistically significant positive impact, in 6 samples a negative effect was detected, and for 8 samples the organizational innovation was statistically non-significant. Looking at the differences by type of sample, no real pattern can be defined. Moreover, only 3 studies used the number of patents as a variable to measure the output of the innovation process obtaining some contradictory results. The lack of sufficient studies that use this variable impedes any further explanation of the results.

Table 4. Operationalization of the innovative level or attitude in order to measure its impact on employment and the found results

Variables	**All samples**	**Type 1**	**Type 2a**	**Type 2b**	**Type 3a**	**Type 3b**	**Total**	**Manufacturing**	**Services**	**High-Tech**	**Medium-Tech**	**Low-Tech**	**Developed Countries**	**Developing Countries**	**OLS**	**GMM**	**2SLS**	**FE**
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Innovative Effort:																		
R&D + i Expenditure	(15,12,4)	(15,12,4)					(6,3,0)	(2,2,1)	(2,0,0)	(4,1,2)	(1,0,0)	(0,6,1)	(14,12,4)			(7,4,0)	(0,5,4)	(8,2,0)
Lag of R&D+i Expenditure	(0,0,1)	(0,0,1)					(0,0,1)						(0,0,1)			(0,0,1)		
R&D expenditure per employee	(3,1,1)				(2,1,0)	(1,0,1)	(2,0,1)			(1,0,0)		(0,1,0)	(3,1,1)		(2,1,1)			
Growth: R&D Intensity	(3,1,0)					(3,1,0)	(2,0,0)			(1,0,0)		(0,1,0)	(3,1,0)		(1,0,0)			(2,1,0)
FBC expenditure for Innovation	(0,4,2)	(0,3,0)				(0,1,2)	(0,2,2)			(0,1,0)		(0,1,0)	(0,4,2)		(0,1,2)	(0,3,0)		
Results of Innovations:																		
New products and/or process	(2,9,2)	(1,0,0)		(0,9,2)		(1,0,0)	(2,5,0)	(0,2,1)	(0,2,1)				(2,9,2)		(1,0,0)	(1,0,2)	(0,9,0)	
New products	(6,6,0)	(1,0,0)		(0,1,0)	(5,5,0)		(4,2,0)	(1,0,0)		(1,1,0)	(0,1,0)	(0,2,0)	(5,1,0)	(0,5,0)	(3,1,0)	(2,4,0)	(0,1,0)	
Only process Innovation	(3,36,16)		(0,24,11)	(3,12,5)			(0,12,7)	(1,7,6)	(2,12,0)	(0,3,1)		(0,2,2)	(3,26,11)	(0,10,5)		(2,0,0)	(0,36,15)	(1,0,1)
Process Innovation	(8,11,4)	(2,0,0)		(0,1,1)	(6,10,1)	(0,0,2)	(6,2,3)	(0,3,1)	(0,3,0)	(0,2,0)	(1,0,0)	(1,1,0)	(4,10,4)	(3,1,0)	(3,3,1)	(4,4,0)	(0,4,1)	
Organization	(4,8,6)			(1,6,5)	(3,2,1)		(1,2,3)	(2,1,1)	(1,5,0)	(0,0,1)		(0,0,1)	(4,8,6)		(0,0,1)	(0,3,1)	(3,4,4)	(1,1,0)
Sales Growth due to New Products	(58,0,1)		(35,0,0)	(19,0,1)		(4,0,0)	(19,0,0)	(18,0,0)	(13,0,1)	(4,0,0)		(4,0,0)	(43,0,1)	(15,0,0)		(2,0,0)	(55,0,0)	(1,0,1)
Patents	(3,2,0)	(1,1,0)				(2,1,0)	(2,1,0)			(1,0,0)		(0,1,0)	(2,2,0)			(1,1,0)		(2,1,0)
% Sales due to New Products	(5,2,0)			(2,0,0)	(1,1,0)	(2,1,0)	(2,1,0)	(2,0,0)	(1,1,0)				(5,2,0)		(2,1,0)	(1,1,0)	(2,0,0)	

Notes: +=positive effect. ns=no significant effect. -=negative effect.

Concluding remarks on the results

To conclude, there are two dominating analytical models that analyze the impact of innovation on employment and their main difference is in the way they conceptualize innovative activity and create the instrumental variables (IVs). The studies that follow Bogliacino's and Van Reenen's static output-oriented model include only innovation inputs (R&D expenditure), obviating the output. In the second case, the studies that apply the dynamic output-oriented model of Harrison et al**.** (2008) use the obtained output (products and process innovation, and the impact of new products on sales) and use specific observed IVs.

Looking at the variables used**,** two important aspects have to be discussed. The first is the difference between the studies based only on binary (dummy) variables on innovative input or output versus the use of continuous variables. The last type (like R&D expenditures by sales or the percentage of sales by new products) permits to consider the intensity of the R&D activities. Those studies that use only dichotomic variables or dummies to operationalize innovation also simplify the relationship between innovation and employment**,** comparing non-innovating firms with innovating ones. However, it sounds logical that the effect of innovation on employment can be quite different for more innovative firms.

The appropriateness of the use of patents as a good indicator for the output of innovation is suspicious because this way of protecting intellectual property is used by a minority of innovative firms, the propensity to patent is very different for each of the productive sectors, and not all patents are transformed in products commercialized in the market.

Another important discussion in relation to the operationalization of innovation is the possible delay of its impact on employment. In the case of R&D expenditures or patents, it seems to be clear that their effects in terms of the introduction of new products or processes can take some time[32]. However, using output variables[33] related to new products, the effect on employment would be immediate. In some studies, like Lachenmeyer et al. (2011), lags are applied to the new products and processes. This application offers better adjustments of the results, but the authors do not explain why they use a time lag or the exact number of years of the lag. No theoretical assumptions exist on this subject, although the lag probably varies by type of firm of different sectors, sizes, or technical areas. The drop back lag will especially be higher in the case of sectors that require specific quality control or security measures certified by the public government or official accredited laboratories, or activities that require the creation of complex prototypes.

The main shortcoming of the use of the input variable R&D spending is its limited appropriateness for a large number of firms whose innovations are based on engineering or innovations based on ad hoc ideas. Of course, R&D spenders will probably obtain innovations more often. However, this does not mean that the rest of the firms do not introduce innovations. In fact, a large number of specific sectors obtain their innovation from their providers. Moreover, the impact of (often incremental) product or process innovations that are obtained by other non-R&D activities like engineering or those innovations purchased in the market (incorporated innovations in capital goods) can have very important impacts on the employment of firms. As a consequence, measuring the impact of innovation on employment by R&D expenditures is limited. Using this methodology would imply a simplification of the differences

[32] As an example, the patents of medicines and the introduction of drugs in the market can take three to four years (DiMasi 2003).

[33] Like dummy variables as the introduction of new services, products or processes (yes/no) or the percentage of sales.

between innovative and non-innovative firms. Especially in less innovative countries, R&D is just a small part of innovative activities. To summarize, using R&D expenditures leaves out a substantial part of innovations introduced by firms. Therefore, if you want to use an input, it would be better to use expenditures on innovation, which are supposed to be used for projects closer to the markets.

4.2.- The use of control variables to isolate the effect of innovation from other determinants

If someone wants to estimate the net effect of innovation on employment, their model should include additional explanatory variables of employment in order to have better control of the effect of innovation from other determinants, creating "ceteris paribus" condition. In fact, most studies used a varied set of control variables that can affect employment at the firm level, but they do not offer clear theoretical arguments to justify the inclusion of these variables. These include the wage level, investments in and stock of capital (capital intensity of the firm), size by sales, sector differences and geographical location. In this section, we offer a short overview of the control variables used and why they are important.

The variable "sales" controls the model by decomposing the increase of employment attributed to process or product innovations versus the change in employment caused by an increase of the total overall demand. In other words, it has to be pointed out which part of the sales increased because of process or product innovation and which part because of the overall changes in the demand caused by, among others, overall economic growth cycles, new export markets, variation in wages and prices and so on. Moreover, sales are used as an indicator to control the effects of innovation by the firm size. Larger firms normally show a higher variation in terms of the absolute number of employees than smaller firms. This problem can be solved by including an indicator of the firm size or by using the growth rate of employment. This last option is a way to standardize the variation of employment by head count. In fact, size controls for different aspects, the market power of firms among others. It also takes into account the possible advantages of scale and scoops and differences in the type of innovation carried out by firms of different dimensions (incremental versus radical innovation).

As can be observed in Table 5, "sales" or "added value" (in absolute terms) is frequently used in the reviewed studies (24 times) as a proxy of firms' output. Theoretically, a positive relationship is expected, and this is confirmed without any exception by all the studies. This means a firm with more productive output will have, *ceteris paribus*, more employment according to the neoclassical theory. As showed in the table, especially the static input-oriented models of Bogliacino et al. (2008) include this variable (19 of 24 studies)[34]. Another way to control the model for the size of the firm is the number of employees of the firm. Eight studies –all of them based on the dynamic output model– used dummy variables based on the intervals of size by employment or sales. On the other hand, growth of sales is used in only three studies, all of which analyze developed countries and belong to the Type 3 studies.

The variable "investment in capital" controls the effect of innovation for a possible bias of the model for the increase of demand due to market tendencies. Capital investment (used in thirty-five estimations) can be correlated with different situations or reasons such as new investments. A first option could be that firms broaden their capital stock as an answer to increasing demand for their "old products," buying similar machines. In this case, an increase in employment is expected because of the capital investments and is not related to their innovation activities. Another probability is that firms buy new machines to

[34]Observing Table 5, someone might suspect that the studies on developing countries do not take into account this variable. However, this is a reflection of the fact that none of those studies use the Harrison et al. (2008) model and therefore do not use this variable.

modernize their capital stock, substituting old machines with modern and more productive ones to produce the same number of old products in a more efficient way; this is considered a process innovation[35]. A third option is that firms invest in new machines adapted to the production requirement of the new product innovation. The relationship between capital investment and employment found in the reviewed studies is, in general, positive. Twenty-one estimations showed a statistically significant positive sign between both variables. However, in seven samples, the corresponding coefficient was not significant, and in another seven, a negative impact on employment was detected. Analyzing the characteristics of the samples, it can be stated that the negative relation is observed more frequently in developed than in developing countries (see Table 4).

The majority of the studies or estimations include dummies of time (60), industry (85), sector (15), country (31) and size (24). In Table 4, it is not possible to show the signs of the dummy variables because a large number of the reviewed papers only mention whether they use them or not[36]**.** Moreover**,** the exact definition of apparently the same dummies is often quite different[37]. Observing the use of some specific dichotomy variables**,** it can be mentioned that the studies based on Bogliacino et al. (2008, 2014) introduced, in almost all estimations, sector dummies or a dichotomy variable that distinguishes between the industrial and the service sector. A large number of studies that follow the model of Harrison et al**.** (2008) also used dummies to separate services versus industries (9) or even distinguish between a broad number of different sectors (10).

It is clear that changes of employment not only depend on the firm's innovative behavior but are directly related to economic growth cycles or the overall economic context. Therefore, the studies that used panel data for different years has to control such cyclical differences and therefore include time dummies. Without any doubt, it is also important to control the relation between innovation and employment for sectoral differences because the productivity and therefore employment intensity of sectors differ clearly. Secondly, the expected effects of innovation, economic cycles and so on can be quite different in specific sectors, especially in the case where you use the absolute number of employees as a dependent variable. Moreover, the level of innovation or the position of a good in the product cycle implies differential impact of innovation on employment. In the case of mature, well-standardized products, a possible process innovation will not affect employment drastically, while the introductions of machines to produce non-standardized products elaborated almost manually could imply an enormous loss of employment[38]. Thirdly, the overall economic cycle measured indirectly by the time variable can be quite different for some specific sectors.

[35] The first option –broadening the stock of capital for extra demand– often implies the purchase of modern machines which are more productive than the old ones. In this case, it is a combination of the first two options.

36 Moreover, if several mutual excluding dummy variables are used, some categories are excluded to overcome the collinearity problem. The sign of the betas are interpreted in relation to the "score" of the excluded category, the studies used a different "reference dummy".

[37] For example**,** in the case of size intervals and even in the case of sectors**,** the aggregation procedure differs frequently between the studies**.**

[38] Such marginal decreasing returns in productivity gains by "incremental" process innovation is showed by Jenkins' (1994) example of the production of cotton: each new machine implies a lower impact in terms of productivity gains and therefore less loss of jobs**.**

Table 5. Control variables used in order to isolate the effect of the innovation form other determinants of employment

Variables	All samples	Type 1	Type 2a	Type 2b	Type 3a	Type 3b	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Characteristics of the firm:														
Lag of Employment	28/2/3	(21,1,1)			(7,0,2)	(0,1,0)	10/2/3	3/0/0	3/0/0	5/0/0	2/0/0	5/0/0	23/2/3	5/0/0
Employment Size	1/0/4				(1,0,2)	(0,0,2)	0/0/3			1/0/0		0/0/1	1/0/4	
Sales and added value size	24/0/0	(19,0,0)			(1,0,0)	(4,0,0)	9/0/0	2/0/0	2/0/0	5/0/0	1/0/0	5/0/0	24/0/0	
Investment	21/7/7	(15,3,3)		(0,0,3)	(2,4,1)	(4,0,0)	8/2/2	3/0/2	2/1/1	4/1/1	1/1/0	3/2/1	19/4/6	2/3/1
Wage level	0/3/37	(0,3,19)	(0,0,6)		(0,0,6)	(0,0,6)	0/1/15	0/0/3	0/0/3	0/1/7	0/1/1	0/0/8	0/3/26	0/0/11
Salary growth	0/1/1				(0,1,0)	(0,0,1)	0/1/1						0/1/1	
Foreign ownership	1/15/8		(1,8,6)	(0,6,2)		(0,1,0)	1/8/3	0/0/1	0/1/2	0/3/1		0/3/1	0/7/4	1/8/4
Located in the central region	0/9/0		(0,9,0)				0/5/0			0/2/0		0/2/0		0/9/0
Market and Firm Dynamics														
Export Growth	1/1/0					(1,1,0)	1/1/0						1/1/0	
Sales Growth	3/0/0				(3,0,0)		1/0/0	1/0/0	1/0/0				3/0/0	
Productivity Growth	0/0/1					(0,0,1)	0/0/1						0/0/1	
Market Dynamics (GDP, expanding/contracting market based on demand)	3/5/2	(1,1,0)		(1,2,1)	(0,1,1)	(1,1,0)	3/5/2						3/5/2	
Innovative Behavior														
Distribution of Innovation (Design, know-how and engineer expenditure)	3/1/0				(2,1,0)	(1,0,0)	2/0/0			1/0/0		0/1/0	3/1/0	
Motivation: cost reduction	0/1/0					(0,1,0)	0/1/0						0/1/0	
Dummy Variables														
Technological sector dummies[39]	15	9	0	0	4	2	7	1	1	3	0	3	15	0
Sectors by productive activities[40]	84	10	35	22	12	5	26	24	17	8	1	8	65	19
Time	60	27	11	10	6	6	24	8	4	11	2	11	47	13
Size	24	9	2	8	5	0	6	6	4	4	0	4	24	0
Country	31	10	2	12	5	2	10	6	8	3	1	3	31	0

Notes: +=positive effect. ns=no significant effect. -=negative effect.
*GDP, expanding/contracting market based on demand, ** Engineer expenditure

[39] Aggregating the sectors into a few groups based on the OECD classification of low-, medium-, and high-tech sectors or the taxonomy of Pavitt (1984) based on sectoral innovative behavior.
[40] Including a large number of sectors by Statistical Classification of Economic Activities of the EC or OECD.

Another control variable frequently used is the costs of employment or its increase,[41] which is a basic variable to explain the level of employment. Higher or increasing salaries should, theoretically, generate a change towards a more capital-intensive production system based on process innovation and capital investments. This last variable has, as shown, a negative relation to labor demand. Therefore, the expected effect of the wage level on employment is negative. This variable –cost of employment– is used forty times (in thirty-seven estimations, a negative effect is detected, and only three models showed a non-significant beta coefficient). The types of studies that mostly used this variable are the static input models (Type 1 studies) based on Bogliacino et al. (2010, 2014). In the case of the model of Harrison et al. (2008), only a few studies (6) use wage level as a control variable, basically the studies with data on Latin American countries.

The rest of the control variables included in the models are used less frequently. Several of them indicate some aspects of the dynamics of the markets on the aggregate level (growing versus stable markets) and of the internal dynamic of the business of the firms (growth of exports, sales or improvement of productivity). Such variables are basically used by the studies in Types 2d and 3b. The growth of sales and exports would reflect the dynamism of their own internal market. However, the growth of sales can be the result of business stealing or the loss or gain of market shares. Therefore, other ways to operationalize the market dynamism like the GDP growth are also used. It is supposed that the growth of the GDP would imply a growing market, and such increasing demand implies a positive impact on employment. Surprisingly, only three studies reflect this positive impact of GDP growth, while two studies show a negative impact, and in five estimations the relationship is statistically non-significant.

The Latin American studies that applied the dynamic output-oriented model of Harrison et al. (2008) include two extra interesting control variables, the location of the firm in the central versus peripheral region and the possible role of foreign ownership of the firm. Although the presence of foreign capital of the firm is, in the majority of the studies, statistically non-significant, the inclusion of the variable is very important in countries where the attraction of foreign investment is one of their main targets of the national economic policy in order to create economic growth and generate employment. Moreover, a few studies introduce some extra variable on innovation to control for innovative behavior. In this case, it is the distribution of R&D expenditures for their main objectives and one of the motives of innovation: cost reduction. If this is an important motive, it could be supposed that new processes could be developed in order to reduce employment, and therefore that the firm is carrying out process innovations.

5.- Effects on employment: conclusions and final comments

In this review, we offered an in-depth analysis of a large number of studies that examined the quantitative impact of innovation on employment, based on microeconomic firm- level data in different countries. As always, in the case of empirical studies, the exact definition

[41] Sometimes measured directly using the wage level mentioned by firms, and sometimes based on the costs of personnel (including wages).

of the models depends on the availability of an appropriate data set and the way that the existing variables express the different conceptual particularities of "innovation". In this last section, we offer some conclusions about the types of models, the methodological problems and the main challenges and requirement of future studies.

5.1.- Main methodological findings in relation to the models used in the empirical analysis

We distinguish two mainstream types of models. The first one is the static input-oriented model developed initially by Van Reenen (1997) and Bogliacino et al. (2014). In order to measure innovation activities, their models include, because of the lack of the availability of other more appropriate indicators, expenditures on R&D. One of the main criticisms of this indicator is that it is based on the input of innovative activities and does not take into account the success of R&D projects. It can be stated that innovation is an uncertain high-risk activity in which technical and commercial barriers can be an obstacle for a successful introduction of new products in the market or the use of new processes. Moreover, this input indicator does not allow us to discriminate whether the firm strategy is cost reduction-target, based on either process innovation or the introduction of new or improved products, in other words, product innovations. Another important critique is that the use of only R&D activities and several other activities related to product or process innovation are excluded from the analysis, like engineering, product design, organizational changes, and other innovative activities. First of all, innovative firms with such alternative innovative activities that do not do R&D are included as "non-innovative firms" in the analysis. Secondly, R&D intensity can be very different from the intensity in innovation expenditures, which also could bias the results. The advantages of R&D expenditures as an indicator is that they correspond to innovation activities considered more complex, higher forms of innovation, and doing R&D apparently implies higher involvement of the firm (Kleinknecht et al., 2002). However, they would exclude incremental innovations based on merely small changes with no real added value in terms of the upgraded better product (change of colors, design, etc.). The results of the studies that use R&D expenditure as an indicator of innovation showed different effects on employment. Most studies found a positive effect on employment (21 studies), although some offered evidence of a non-significant relationship (14 studies) for some specific sectors or other subsamples[42].

The appearance of national innovation surveys offered the possibility to use new indicators related to the output of innovation, offering two alternative and complementary basic indicators. First, several reviewed studies used qualitative dichotomous indicators (yes/no) in order to measure the effect of the introduction of new product and process innovations on employment. Other studies used the variable that measures the intensity of the product innovation within the overall product portfolio of the firm, reflected by the percentage of sales related to new innovative products. In fact, the innovation surveys made it possible to develop the dynamic output-oriented model presented by Harrison et al., (2014) who look at the differentiated effects of product and process innovations. Moreover, nowadays several countries offer information in form of a panel data set, which makes it possible to analyze some tendencies over time.

[42] Counting the numbers of models with different effects says nothing about the quality of the studies. However, in this case, the overwhelming majority of the studies indicate the same trend.

Two main differences between the two types of models were highlighted. In the first place, the static input-oriented model[43] considers that the firm operates in a market of perfect competition and it maximizes its profits under a "Constant Elasticity of Substitution" function in order to obtain the labor demand in terms of quantity (total employment). We called the model static because it uses the number of employees (not growth rate) as a dependent variable in the empirical model and it does not include any lags in the model.

The dynamic output model of Harrison et al. proposes three simultaneous production functions at different moments, distinguishing between the momentum T1 with only old products and the T2, in which old and new products can coexist. This model minimizes the cost functions and applies some mathematical treatments, estimating the labor demand function by using its growth rate as a dependent variable. It is the dynamism of the changes in the sales between old and new products and the use of the growth of employment as a dependent variable which make the model dynamic.

5.2.- Main results of the models in terms of effect of innovation on employment

In this review of the empirical results, we concentrated our analysis on two basic models. It was observed that the results of all the reviewed models (67) estimations (belonging to 44 different studies) showed a positive relationship between product innovation and employment. This effect is found independently by the exact operationalization of the output variable in terms of a binary indicator for product innovation whether they use the percentage of sales related to new products. This result is in line with the theoretical argument where it is assumed that a new product could generate or expand markets and, therefore, create new employment in the emerging productive sectors.

The expected negative effect of process innovation on employment was not always confirmed. In 20 models, a negative effect was detected, for 47 models, the detected effect was not significant, and some studies even showed an increase of employment due to process innovation. According to the theory, the impact of process innovation implies an increase of efficiency in labor productivity, which should imply the loss of jobs.

For the correct interpretation of the results it should be stated that introduction of process innovation can have different contradictory effects mechanisms of compensation. On the one hand, it can generate a loss of employment due to higher productivity, but on the same time, if such lower costs are transferred into lower prices, the total demand could be increased implying that the loss of employment would be eased. In addition, it must not be forgotten that the analysis are carried out at the micro level, studying the effect of the innovation on the company that performs it. Having this in mind it can be stated that besides the existence of the compensation mechanism by increasing the global demand in the market, companies that introduce process innovations could capture part of the market of national or international competitors (business stealing effect).

Therefore, we tried to find some explanations for these contradictory effects, looking at the specific settings of the studies. Apparently, the contradiction of the results cannot be explained by the differences in the conceptual and methodological frameworks. The

[43] Bogliacino et al. (2012), Piva et al. (2005), Pellegrino et al. (2017).

incongruities were found in all subgroups of studies classified by the type of firm included in the sample, the type of country (developed or developing countries) or the type of sector (industry versus service sector). They were also found in the subgroup of studies with similar methodological settings like the specific instrumental variables used or the inclusion of different control variables. However, in the case of Latin American countries, the positive effect between employment and process innovation is found more frequently. Maybe such countries are at the beginning of the industrialization process or the modernization of their production sector, and in such cases, the most innovative firms show higher overall growth in which the loss of employment due to efficiency is compensated by the gain of market shares. However, future studies should insist on a better explanation of this fact[44].

Critical remarks and shortcomings

In order to interpret the results correctly, it is important to take into account the multiple conceptual and methodological problems. In conceptual terms, it can be stated that the empirical studies are very limited because they only pay attention to the direct micro effects within each of the innovative firms and do not consider the possible indirect effects on other firms or on the global macro-economic international labor market.

Another important shortcoming of the existing empirical evidence, based on the microdata at the firm level, is that it reflects only individual and/or partial effects, while the interdependencies between firms or the impact on the (global) productive system as a whole is not analyzed. It seems that innovative firms create more employment. However, this increase can be based on the existence of a growing market in combination with an increasing market share. Also, it can be partially or totally based on an effect of their behavior on stable or decreasing markets in the form of "business stealing", absorbing markets from other less innovative or non-innovative firms that therefore show a decrease in their employment level. In this case, the net effects of innovative firms on employment, in a sector, a country or internationally, might be null or even negative. To conclude, it might be the creation of new employment in any country or sector may implicate its destruction in others, because it is obtained at the expense of competitors without analyzing whether there is a net effect on aggregate industry (Pianta, 2005; Katsoulacos, 1986). Again, as mentioned by Greenan and Guellec (2000), the positive effects of a firm may disappear if you repeat the same analysis with sectorial-level data. Another shortcoming in the same sense is the fact that the majority of the studies analyze firms in developed countries with high wages. However, they do not consider the indirect impact due to structural changes and delocalization of labor-intensive production on countries with low wages.

Maybe the most important methodological shortcoming or problem of the existing studies is the assumption of the Hicks-neutral technology parameter. One can hardly believe that the ratio between capital and labor before the introduction of new technology is equal. However, at this moment, no satisfying methodological solution is available, so its use is the only way to assure a technical, correct labor function that allows the estimation of unbiased empirical models. Another methodological shortcoming is that many studies analyze only the short-term effects, and these differ from medium- and long-term ones. This means that many studies are not able to prove the compensation mechanisms which are based on the long term and refer to macroeconomic labor effects. Therefore, it is impossible to associate the indicators of innovation conceptually in the firms with each of the different compensation mechanisms.

In view of the foregoing, we showed that the results of empirical studies are inconclusive, and several aspects should be solved for a "to the point" overall systemic analysis. According to Vivarelli (2007), "economists cannot propose a clear-cut diagnosis about the employment impact of innovation, either theoretically or empirically". There is agreement on the fact that technological progress creates welfare. Nevertheless, the destruction of employment is hidden in the back part of the evolution of population, the redistribution of employment (reduction of the workday and partial employment), or sectorial or geographical relocation.

These problems should be considered for future studies. For example, nowadays there are data available to prove the effect of innovation on labor composition. Although there are still limitations in the available data, the innovation surveys include information on the skills and education level of workers. These specific aspects could be analyzed by both of the main methodological approaches reviewed. Another important aspect that can probably be solved in the future is the effect of innovation on employment for developing countries. Some of these countries have improved the data related to innovation (Latin American countries specifically), implementing innovation surveys and including some countries that already offer a (short) panel data set.

Finally, the analysis in the long run (in terms of empirical models) depends on the availability of the appropriate data. This problem is difficult to overcome because it requires a historical series that allows us to isolate the effect of innovation on employment from other potential explanatory variables to assure an accurate conclusion in the long run.

References

Aboal, D., Garda, P., Lanzilotta, B., & Perera, M. (2015). Innovation, firm size, technology intensity, and employment generation: Evidence from the Uruguayan manufacturing sector. *Emerging Markets Finance and Trade, 51*(1), 3-26.

Acemoglu, D., & Restrepo, P. (2017**)**. Robots and jobs: Evidence from US labor markets. NBER Working Paper 23285**.** Retrieved from http://www.nber.org/papers/w23285

Alonso-Borrego, C., & Collado, D. (2002). Innovation and job creation and destruction. *Recherches Économiques De Louvain, 68*(1), 148-168.

Alvarez, R., Benavente, J. M., Campusano, R., & Cuevas, C. (2011). *Employment Generation, Firm Size, and Innovation in Chile.*

Antonucci, T., & Pianta, M. (2002). Employment effects of product and process innovation in Europe. *International Review of Applied Economics, 16*(3), 295-307.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The **R**eview of **E**conomic **S**tudies*, 58(2), 277-297.

Autor, David. "The Polarization of Job Opportunities in the U.S. Labor Market." The Hamilton Project, April 2010**.**

Benavente, J. M., & Lauterbach, R. (2008). Technological innovation and employment: Complements or substitutes? *The European Journal of Development Research, 20*(2), 318-329.

Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labor within US manufacturing: Evidence from the annual survey of manufactures. *The Quarterly Journal of Economics, 109*(2), 367-397.

Blanchflower, D. G., & Burgess, S. M. (1996). Job creation and job destruction in Great Britain in the 1980s. *ILR Review, 50*(1), 17-38.

Blanchflower, D. G., & Burgess, S. M. (1999). New technology and jobs: Comparative evidence from a two-country study. *Conference n Technology, Firm Performance and Employment, National Academy of Sciences, Washington DC, May1995***.**

Blanchflower, D. G., Millard, N., & Oswald, A. J. (1991). Unionism and employment behavior. *The Economic Journal, 101*(407), 815-834.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised Pavitt classes. *Research Policy, 39*(6), 799-809.

Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European microdata. *Economics Letters, 116*(1), 56-59.

Bogliacino, F., Piva, M., & Vivarelli, M. (2014). *Technology and employment: The job creation effect of business R&D***.** *Università cattolica del Sacro Cuore.*

Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers, 51*(2), 96-113.

Bogliacino, F., & Pianta, M. (2016**)**. The Pavitt taxonomy, revisited: patterns of innovation in manufacturing and services**.** *Economía Política*, 33: 153-180.

Brouwer, E., Kleinknecht, A., & Reijnen, J. O. (1993). Employment growth and innovation at the firm level. *Journal of Evolutionary Economics, 3*(2), 153-159.

Calvino, F., & Virgillito, M. E. (2018). The innovation-employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, 32(1), 83-117.

Crespi, G., & Tacsir, E. (2011). Effects of innovation on employment in Latin America. *Science and Innovation Policy, 2011 Atlanta Conference on,* pp. 1-11.

Dachs, B., Hud, M., Koehler, C., & Peters, B. (2016). Employment effects of innovation over the business cycle: Evidence from European countries. *Mannheim: ZEW Discussion Paper,* (16-076)**.**

Dachs, B., & Peters, B. (2014). Innovation, employment growth, and foreign ownership of firms: A European perspective. *Research Policy, 43*(1), 214-232.

Damijan, J., Kostevc, Č., & Stare, M. (2014). Impact of innovation on employment and skill upgrading. SIMPATIC 7th EU Project, Working paper n°7.

DiMasi, J. A., Hansen, R. W., & Grabowski, H. G. (2003). The price of innovation: new estimates of drug development costs. Journal of health economics, 22(2), 151-185.

Dosi, G. and R. R. Nelson (2010). Technical change and industrial dynamics as evolutionary processes. In B. H. Hall and N. Rosenberg (Eds.)**.** *Handbook of the Economics of Innovation*, Volume 1, pp. 51 -127. Amsterdam: North-Holland.

Dosi, G., D. Moschella, E. Pugliese, & F. Tamagni (2015). Productivity, market selection, and corporate growth: comparative evidence across US and Europe. *Small Business Economics* 45 (3).

Dorn, D. (2016). The rise of the machines: How computers have changed work. UBS International Center of Economics in Society at the University of Zurich.

Edquist, C., Hommen, L., & McKelvey, M. D. (2001). *Innovation and employment: Process versus product innovation***.** United Kingdom: Edward Elgar Publishing.

Elejalde, S., Giuliodori, D., & Stucchi, R. (2011). *Employment Generation, Firm Size and Innovation: Microeconometric Evidence from Argentina, IDB Technical Notes, No.IDB-TN-313. Washington, DC: IDB.*

Entorf, H., & Pohlmeier, W. (1990). *Innovation, employment and export activity: Evidence from firm-level data.* In: Forens JP, Ivaldi M, Laffont n, Laisney F (eds) Microeconometrics: surveys and applications. Oxford, 394-415

Evangelista, R., & Savona, M. (2003). Innovation, employment and skills in services. firm and sectoral evidence. *Structural Change and Economic Dynamics, 14*(4), 449-474.

Evangelista, R., & Vezzani, A. (2012). The impact of technological and organizational innovations on employment in European firms. *Industrial and Corporate Change, 21*(4), 871-899.

Falk, M., & Hagsten, E. (2017). Employment impacts of market novelty sales: Evidence for nine European countries. *Eurasian Business Review,* 1-19.

Fioravante, D. G., & Maldonado, W. F. L. (2008). Impacts of technological innovation on employment: The Brazilian manufacturing case. Paper presented in the IV Globelics Conference at Mexico City, September 22-24

Garcia, A., Jaumandreu, J., & Rodriguez, C. (2004). Innovation and jobs: Evidence from manufacturing firms. UC3M, http://www.eco.uc3m.es/IEEF.

Grabowski, H., Vernon, J., & DiMasi, J. A. (2002). Returns on research and development for 1990s new drug introductions. *Pharmacoeconomics*, 20(3), 11-29.

Graetz, G., & Michaels, G. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review*, 107(5), 168-73.

Greenan, N., & Guellec, D. (2000). Technological innovation and employment reallocation. *Labor, 14*(4), 547-590.

Greenhalgh, C., Longland, M., & Bosworth, D. (2001). Technological activity and employment in a panel of UK firms. *Scottish Journal of Political Economy, 48*(3), 260-282.

Groshen, E**.** L., & Potter, S. Has Structural Change Contributed to a Jobless Recovery? *Federal Reserve Bank of New York Current Issues*, August 2003. Vol. 9, No. 8, pp. 1-7.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: Evidence from Italian microdata. *Industrial and Corporate Change*, 17(4), 813-839.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2008). Does Innovation Stimulate Employment? A Firm-Level Analysis using Comparable Micro-Data from Four European Countries. NBER Working Paper 14216.Cambridge MA: NBER.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35, 29-43.

Hildenbrand, W. (1981). Short-run production functions based on microdata. *Econometrica***,** 49 (5), 1095 -1125.

Hobsdawn, E. J. (1952). The machine breakers. Past & Present, (1), 57-70. Oxford Journals, Oxford University Press

Jaumandreu, J. (2003). Does innovation spur employment? A firm-level analysis using Spanish CIS data. *Universidad Carlos III de Madrid*, 17(4), 813-839.

Jenkins, D. T. (1994). *Industrial revolutions: The textile industries***.** Hoboken, NJ: Wiley-Blackwell.

Katsoulacos, Y. S. (1986). *The employment effect of technical change: A theoretical study of new technology and the labor market*. Wheatsheaf, London.

Keynes, J. M. (1973). The general theory of employment, interest and money. In ***T**he Collected Writings of John Maynard Keynes*. London: Macmillan. First edition 1936.

Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002). The non-trivial choice between innovation indicators. *Economics of Innovation and **N**ew **T**echnology*, 11(2), 109-121.

Klette, J., & Førre, S. E. (1995). Innovation and job creation in a small open economy**:** Evidence from Norwegian manufacturing plants 1982–92. *Economics of Innovation and New Technology*, 5(2-4), 247-272.

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, 29(2), 210-220.

Leitner, S. M., Pöschl, J., & Stehrer, R. (2010). Change begets change: Employment effects of technological and non-technological Innovations A comparison across countries. *Dynamics*, (67)**.**

Lucchese, M., & Pianta, M. (2012). Innovation and employment in economic cycles. *Comparative Economic Studies*, 54(2), 341-359.

Mairesse, J., Wu, Y., Zhao, Y., & Zhen, F. (2014). Employment growth and innovation in China: A firm-level comparison across regions, industries, ownership types and size classes. International Journal of Industrial Organization, 35, 29-43.

Manyika, J., Chui, Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017)**.** *A future that works: **A**utomation, employment and productivity* (McKinsey Global Institute)**.** Retrieved from http://apo.org.au/node/72505.

Matuzeviciute, K., Butkus, M., & Karaliute, A. (2017). Do technological innovations affect unemployment? Some empirical evidence from European countries. *Economies*, 5(4), 48.

Meriküll, J. (2010). The impact of innovation on employment: Firm-and industry-level evidence from a catching-up economy. *Eastern European Economics*, 48(2), 25-38.

Meyer-Krahmer, F. (1992). The effects of new technologies on employment. *Economics of Innovation and New Technology*, 2(2), 131-149.

Mill, J. S. (1976). *On politics and society. Glasgow: Fontana Press.*

Pellegrino, G., Piva, M., & Vivarelli, M. (2017). Are robots stealing our jobs? Bonn: IZA. IZA Discussion Paper 10540.

Peters, B. (2005). Employment effects of different innovation activities: Microeconometric evidence for Germany. ZEW Discussion Paper 04-73. Mannheim.

Peters, B., Hud, M., Dachs, B., & Köhler, C. (2017). Employment effects of innovations over the business cycle: Firm-level evidence from European countries. ZEW Discussion Papers, No. 16-076, Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim

Pianta, M. (2000). The employment impact of product and process innovations. In M. Pianta & M. Vivarelli (Eds.), *The **e**mployment **i**mpact of **i**nnovation: Evidence and **p**olicy* (pp. 77-95). Location: Routledge.

Pianta, M. (2005). Innovation and employment. In D. M. J. Fagerberg & R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 568-598). UK: Oxford University Press.

Pianta, M., & Lucchese, M. (2012). Innovation and Employment in Economic Cycles, Comparative Economic Studies, 54(2), 341-359.

Pianta, M., & Vivarelli, M. (Eds.). (2003). *The employment impact of innovation: Evidence and policy***.** London, England: Routledge.

Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of Economics*, 86(1), 65-83.

Piva, M., & Vivarelli, M. (2018). Technological change and employment: Is Europe ready for the challenge? *Eurasian Business Review*, 1-20.

Rojas Pizarro, F. B. (2013). Innovación y empleo en las empresas manufactureras españolas. Documentos De Trabajo De La Facultad De Ciencias Económicas y Empresariales, Nº.7, 201341 Pags, (7). Madrid:UCM.

Schumpeter, J. A. (1939). *Business* ***c****ycles*. New York: McGraw-Hill.

Schloss, D. F. (1891). Why working-men dislike piece-work. *The Economic* ***R****eview*, 1891-1914, 1(3), 311-326.

Smolny, W. (1998). Innovations, prices and employment: A theoretical model and an empirical application for west German manufacturing firms. *The Journal of Industrial Economics*, 46(3), 359-381.

Smolny, W. (2002). Employment adjustment at the firm level. A theoretical model and an empirical investigation for west German manufacturing firms. *Labor*, 16(1), 65-88.

Unesco. (2005). *UNESCO science report: The current state of science around the world***.** UNESCO Publ.

Van Reenen, J. (1997). Employment and technological innovation: Evidence from UK manufacturing firms. *Journal of Labor Economics*, 15(2), 255-284.

Vivarelli, M. (2007)**.** Innovation and employment: A survey**.** Discussion Paper No. 2621, Institute for the Study of Labor, Alemania.

Vivarelli, M. (2012). Innovation, employment and skills in advanced and developing countries: A survey of the literature. Journal of Economic Issues, 48(1), 123-154.

Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, 48(1), 123-154.

Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in Italian manufacturing industry. *Research Policy*, 25(7), 1013-1026.

Walker, T. (2007). Why economists dislike a lump of labor. *Review of Social Economy*, 65(3), 279-291.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Toronto, Canada: Nelson Education.

Yang, C., & Lin, C. A. (2008). Developing employment effects of innovations: Microeconometric evidence from Taiwan. *The Developing Economies*, 46(2), 109-134.

Yu, X., Dosi, G., Lei J., & Nuvolari, A. (2015). Institutional change and productivity growth in China's manufacturing: the microeconomics of knowledge accumulation and “creative restructuring “. *Industrial and Corporate Change***,** 24 (3), 565-602.

Appendix

A) Methodological box

Formalizing this problem in form of econometric point of view, endogeneity is generated because the simple OLS model violates the "exogeneity" assumption of the independent variables. To reflect this problem in technical terms, the simple regression model can be written as:

$$y = \beta_0 + \beta_1 x + u \quad (3)$$

In order to control for the possible presence of endogeneity in the model, it is necessary to confirm whether $cov(x, u) \neq 0$. If correlation between X and U (the error term) exists, it will generate an endogeneity problem that, if ignored, causes a bias and inconsistency of estimated parameters (in this case**,** of all the beta parameters).

When the exogeneity assumption is not accomplished, the instrumental variables method[1] is one of the alternative suitable solutions. It is necessary to add some additional information (the instrumental variables z) that satisfies the following properties. The *zetas* must not be correlated with u -$cov(z, u) = 0$- (the so-called exclusion restriction) and z has to be correlated with x $cov(z, x) \neq 0$ (the inclusion restriction). If the added variable satisfies both assumptions mentioned earlier, it can be called an instrumental variable for x.

According to Wooldridge (2015), the exclusion restriction (Z is not related with Y) cannot be generally tested. In the majority of the cases, we must maintain the assumption, demanding arguments based on economic and innovative behavior or introspection. In contrast, the inclusion restriction can be tested (given a random sample) estimating a regression between x and z (see equation 4). In the case where $\pi_1 \neq 0$, it is possible to affirm that the inclusion restriction (Z affects X) is achieved.

$$x = \pi_0 + \pi_1 z + v \quad (4)$$