UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

"The relationship between innovation and employment: firm-level effects and a value chain framework"

"La relación entre innovación y empleo: efectos a nivel empresa y un enfoque de cadena de valor"

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Guillermo Arenas Díaz

Directores

Joost Heijs
Andrés Barge Gil

Madrid

UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

"The relationship between innovation and employment: firm-level effects and a value chain framework"

"La relación entre innovación y empleo: efectos a nivel empresa y un enfoque de cadena de valor"

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Guillermo Arenas Díaz

Directores

Joost Heijs
Andrés Barge Gil

Madrid

UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

“The relationship between innovation and employment: firm-level effects and a value chain framework”

“La relación entre innovación y empleo: efectos a nivel empresa y un enfoque de cadena de valor”

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADO POR

Guillermo Arenas Díaz

Directores

Joost Heijs Andrés Barge Gil

Madrid, 2021

COMPLUTENSE UNIVERSITY OF MADRID
FACULTY OF ECONOMICS AND BUSINESS

DOCTORAL THESIS

"The relationship between innovation and employment: firm-level effects and a value chain framework"

By:

Guillermo Arenas Díaz

Thesis to obtain the Ph.D. degree

Advisors

Joost Heijs Andrés Barge Gil

Madrid, 2021

Para mis padres y hermana
Don Mike, Rosy, y Any, con mucho amor para ustedes

Acknowledgments

The beginning of this trip was difficult. However, it is one of the most exciting things I have ever done. During this process, many people have helped me to improve not only the academic aspects but my personal growth as well.

At the outset, I would like to thank Joost Heijs for believing in me, even when you ignored the results. Thank you, Joost, for your patience and for giving me a place in the IAIF.

In second place, I wish to thank Andrés Barge Gil, who has been an inspiration for me. He always motivates me to move forward. Even when I could not do anymore, he gave me stamina to continue fighting. I have learned so much from you. I will try to apply your recommendations and your vision of how research is supposed to be. You always challenge me to surpass my own limits.

I would also, like to especially thank two researchers who have impacted my Ph.D. journey: Mikel Buesa, and Elena Huergo. Even though they were not my supervisors, they always tried to help with my theoretical doubts and in many other aspects. I will never forget the coffee time, learning about economics, politics, and literature. It was an enormous pleasure to listen to you.

There were other researchers involved in this adventure. If I missed someone, please forgive me. I would like to thank Delia Margarita Reyes, Alberto Marzucchi, and Alex J. Guerrero for their comments during my thesis elaboration. Also, I would like to thank my thesis reviewers, Gabrielle Pellegrino and Chiara Marzocchi. Your comments and recommendations were constructive in improving the thesis quality.

Finally, I would like to thank my family for supporting me all the time. Don Mike, Rosy, and Any, I do not have words for all the help you gave me. This work is also yours because you taught me how to face life, even when things are not so good.

Agradecimientos

El comienzo de este viaje fue difícil. Sin embargo, es una de las cosas más emocionantes que he hecho. Durante este proceso, muchas personas me han ayudado a mejorar no solo los aspectos académicos sino también mi crecimiento personal.

En primer lugar, me gustaría agradecer a Joost Heijs por creer en mí, incluso cuando ignoraste los resultados. Gracias Joost por tu paciencia y por darme un lugar en la IAIF.

En segundo lugar, quiero agradecer a Andrés Barge Gil, quien ha sido una inspiración para mí. Siempre me motiva a seguir adelante. Incluso cuando no podía hacer más, me dio energía para seguir luchando. He aprendido mucho de ti. Intentaré aplicar tus recomendaciones y visión de cómo se supone que debe ser la investigación. Siempre me desafías a superar mis propios límites.

También me gustaría agradecer especialmente a dos investigadores que han influido en mi doctorado: Mikel Buesa y Elena Huergo. Aunque no eran mis supervisores, siempre intentaron ayudarme con mis dudas teóricas y en muchos otros aspectos. Nunca olvidaré la hora del café, aprendiendo sobre economía, política y literatura. Fue un enorme placer escucharlos.

Hubo otros investigadores involucrados en esta aventura. Si alguien me hace falta, pido una disculpa. Me gustaría agradecer a Delia Margarita Reyes, Alberto Marzucchi y Alex J. Guerrero por sus comentarios durante la elaboración de mi tesis. Además, me gustaría agradecer a mis revisores de tesis, Gabrielle Pellegrino y Chiara Marzocchi. Sus comentarios y recomendaciones fueron constructivos para mejorar la calidad de la tesis.

Finalmente, me gustaría agradecer a mi familia por apoyarme en todo momento. Don Mike, Rosy y Any, no tengo palabras por toda la ayuda que me brindaron. Este trabajo también es suyo ya que me han enseñado a afrontar la vida, incluso cuando las cosas no van tan bien.

Part of this thesis was elaborated with the participation of two PAPIIT projects.

Parte de esta tesis fue elaborada con la participación de dos proyectos PAPIIT.

- PAPIIT IN302317 “Efectos de la política tecnológica en el comportamiento innovador de las empresas y empleo en México: una aproximación econométrica” (enero 2017- diciembre 2018).
- PAPIIT IN302620 “Nuevas formas de aplicación del PSM para analizar el impacto de las ayudas públicas a la I+D empresarial en México: un estudio microeconómico” (enero 2020-diciembre 2021).

Contents

List of Tables

List of Figures

List of Boxes

Summary

Historically, sharp contradictions have marked the discussion about the effects of innovation on unemployment. It is easy to see that new industries created a large number of jobs. Autor (2015) argues that, historically, new industries have hired far more people than they have put out of work. Although follow the Schumpeter's (1947) idea of creative destruction jobs frequently associated with process innovation are destroyed, but at the same time, others generally related to product innovation are created (see Vivarelli, 2014). The creative destruction theory also applies to the types of workers. Innovation often negatively affects the demand for unskilled work, but it is complementary with skilled workers, according to Skill-Biased Technology Change (SBTC).

Nowadays, robotization generates an intense debate on employment effects. It allows, in conjunction with artificial intelligence, a substantial intensification of the automation process and therefore implies a drastic impact on labor productivity, generating a different effect on overall employment demand (Acemoglu & Restrepo, 2017; Arntz, Gregory, & Zierahn, 2017; Dorn, 2015). However, these studies do not take into account the potential positive effects of the introduction of new products, which could generate new markets and stimulate employment again.

As a result of this debate, the empirical examination of the innovation-employment nexus from a microeconomic point of view has gained renewed interest recently (Bogliacino et al., 2014; Dorn, 2015; Harrison et al., 2008, 2014; Vivarelli, 2007, 2014; Vivarelli & Pianta, 2003). This thesis contributes to this literature in three different ways.

First, it provides a review of these studies, with particular attention on the underlying models, the empirical methodologies, the results achieved, and the limitations encountered, which motivates our second and third contributions. Second, it offers a novel empirical analysis of the effect of product and process innovation on high-skilled and low-skilled workers in a period of economic turmoil. Third, it extends previous models to analyze the effect of downstream, upstream, and intra-industry product innovation on the employment of high-skilled and low-skilled workers.

Considering the above mentioned, Chapter 1 discusses the theoretical framework of the relationship between innovation and employment at a macroeconomic level. Chapter 2 develops a review of the empirical studies that have analyzed the effects of innovation on employment at a microeconomic level. The first two chapters lead the following research questions that are empirically addressed in Chapter 3 and 4:

1.- *Does innovation have differential labor effects on low- or high-skilled workers during bad times?*

2.- What are the broader impacts of the innovations introduced by firms in the downstream, upstream, and the same sectors to which the focal firm belongs on the employment of the focal firm for general, high- amd low-skilled workers?

To analyze these aspects, we use Spanish data from the "Panel de Innovación Tecnológica" (PITEC) on over 27,800 observations for manufacturing firms from 2006 to 2014 and make use of the structural model of Harrison et al. (2014).

Chapter 3 presents the empirical model that analyzes the effects of product and process innovation on different types of workers, high- and low-skilled, during bad times. Also, it analyzes whether the effects of product and process innovation on high- and low-skilled workers are pervasive across industries or whether there are some features specific to high- or low-tech industries. The main findings suggest a positive effect of innovation on employment during bad times, although this effect is remarkably larger for high-skilled than for low-skilled workers. These results hold across industries and are exacerbated in high-tech industries. These results implicitly reflect that innovation, especially product innovation, favors a bias towards the demand of high-skilled employment to the detriment of low-skilled workers.

Chapter 4 goes one step forward because it includes an extension of the basic model developed by Harrison et al. (2014) with the aim to answer the employment effects within a value chain model. This extended model considers the labor effects of new product innovations introduced by the upstream, downstream, and same sector (UDS). We use the extended HJMP model adding the data from the national input-output tables to trace the inter- and intra-sectoral flows. The overall results of this analysis are also differentiated for different types of workers.

The result of the estimations of Chapter 4 for the same sector effects suggests that, holding firm innovation constant, being located in an industry with more product innovation has a negative effect on firms' employment. Contrarily, if firms in downstream and upstream industries are more product-innovative, a positive impact on the employment of the focal firm is found. For different types of workers, the results of the estimations suggest that high-skilled employment is not affected by innovation outside of the firm, so the effect previously reported is entirely driven by low-skilled workers.

The last part of this study offers some final remarks on the conclusions, indicates several limitations of the analysis presented, and states future lines of research for overcoming constraints.

Resumen

Históricamente, las fuertes contradicciones han marcado el debate sobre los efectos de la innovación en el empleo. Es fácil observar que las nuevas industrias crearon un gran número de puestos de trabajo. Autor (2015) argumenta que, históricamente, las nuevas industrias han contratado a mucha más gente de las que se han quedado sin puestos de trabajo. Aunque siguiendo un proceso de destrucción creativa (Schumpeter, 1947), los empleos asociados con la innovación de procesos son destruidos, pero al mismo tiempo, se crean otros generalmente relacionados con la innovación de productos (véase Vivarelli, 2014). La teoría de la destrucción creativa también se aplica a los tipos de trabajadores. La innovación a menudo afecta negativamente a la demanda de trabajo no cualificado, pero es complementaria con los trabajadores cualificados, según Skill-Biased Technology Change (SBTC).

Hoy en día, la robotización permite, junto con la inteligencia artificial, una intensificación sustancial del proceso de automatización y, por lo tanto, implica un impacto drástico en la productividad laboral, generando un efecto diferenciado en la demanda general de empleo (Acemoglu &Restrepo, 2017; Arntz, Gregory, & Zierahn, 2017; Dorn, 2015).

Como resultado de este debate, el análisis empírico de la relación innovación-empleo desde un punto de vista microeconómico ha ganado interés recientemente (Bogliacino et al.,

2014; Dorn, 2015; Harrison et al., 2008, 2014; Vivarelli, 2007, 2014; Vivarelli & Pianta, 2003). Esta tesis contribuye a esta literatura de tres maneras diferentes.

En primer lugar, proporciona una revisión de estos estudios, con especial atención a los modelos subyacentes, las metodologías empíricas, los resultados obtenidos y las limitaciones encontradas, lo que motiva a la segunda y tercera contribución. En segundo lugar, ofrece un nuevo análisis empírico del efecto de la innovación de productos y procesos en trabajadores altamente cualificados y poco cualificados en un período de crisis. En tercer lugar, amplía los modelos anteriores para analizar el efecto de la innovación de productos aguas abajo, aguas arriba e intra-industria en el empleo de trabajadores altamente cualificados y poco cualificados.

Teniendo en cuenta lo mencionado anteriormente, el Capítulo 1 examina el marco teórico de la relación entre la innovación y el empleo a nivel macroeconómico. El Capítulo 2 desarrolla una revisión empírica de los estudios que han analizado los efectos de la innovación en el empleo a nivel microeconómico. Los dos primeros capítulos llevan a las siguientes preguntas de investigación que se tratan de responder empíricamente en los capítulos 3 y 4:

1.- *¿La innovación tiene efectos laborales diferenciales en los trabajadores de baja o alta cualificación en los tiempos de crisis?*

2.- ¿Cuáles son los impactos más amplios de las innovaciones introducidas por las empresas aguas arriba y aguas abajo, y de los mismos sectores a los que pertenece la empresa focal en el empleo general, altamente cualificado y bajamente cualificado?

Para analizar estos aspectos, utilizamos datos del "Panel de Innovación Tecnológica" (PITEC) sobre más de 27.800 observaciones para empresas manufactureras de 2006 a 2014 de España y hacemos uso del modelo estructural de Harrison et al. (2014).

El Capítulo 3 presenta el modelo empírico que analiza los efectos de la innovación de productos y procesos en diferentes tipos de trabajadores, altamente y poco cualificados, en tiempos de crisis. Además, analiza si los efectos de la innovación de productos y procesos en los trabajadores de alta y baja cualificación son generalizados en todas las industrias o si hay algunas características específicas para las industrias de alta o baja tecnología. Los principales hallazgos sugieren un efecto positivo de la innovación en el empleo en tiempos de crisis, aunque este efecto es notablemente mayor para los trabajadores altamente cualificados que para los trabajadores poco cualificados. Estos resultados se mantienen en todas las industrias y se exacerban en las industrias de alta tecnología. Estos resultados reflejan implícitamente que la innovación, especialmente la innovación de productos favorece un sesgo hacia la demanda de empleo altamente cualificado en detrimento de los trabajadores poco cualificados.

El Capítulo 4 da un paso adelante porque incluye una ampliación del modelo básico desarrollado por Harrison et al. (2014) con el objetivo de responder a los efectos del empleo dentro de un modelo de cadena de valor. Este modelo ampliado considera los efectos laborales de las innovaciones de nuevos productos introducidas por el sector aguas arriba, aguas abajo, y del mismo sector (UDS). Se utiliza el modelo HJMP extendido añadiendo los datos de las tablas nacionales de input-output para rastrear los flujos inter y dentro del sector. Los resultados generales de este análisis también se diferencian para diferentes tipos de trabajadores.

Los resultados de las estimaciones del Capítulo 4 sugieren que el empleo de cada empresa, manteniendo constante sus resultados innovadores, se ve afectado negativamente por la innovación de productos de las empresas del mismo sector, pero positivamente por la innovación de producto de las empresas de las industrias aguas abajo. Para los diferentes tipos de trabajadores, los resultados de las estimaciones sugieren que el empleo altamente cualificado no se ve afectado por la innovación fuera de la empresa, por lo que el efecto reportado anteriormente está totalmente impulsado por trabajadores poco cualificados.

La última parte de este estudio ofrece algunas observaciones finales sobre las conclusiones, indica varias limitaciones del análisis presentado y establece futuras líneas de investigación para superar las limitaciones.

Preamble

Historically, sharp contradictions have marked the discussion about the effects of innovation on unemployment. Workers that lost their jobs believed that innovation destroyed employment and organized themselves in movements like the case of the "machine breakers"[1] or Luddites. However, such actions only achieved a slowdown of the diffusion of innovation and failed to stop technological progress in the long term (Hobsdawn, 1952). Especially at the beginning of industrialization and during periods of economic crisis, the negative impact of innovation on employment is highlighted in the social debate on the future of society. At other moments in history, innovation and the correlated productivity increase were considered the main cause of economic growth and social well-being.

It is easy to see that new industries created a large number of jobs. Autor (2015) argues that, historically, new industries have hired far more people than they have put out of work. The employment effects of innovation follow the same track as Schumpeter's (1947) idea of creative destruction, where new activities, goods and forms of organization appear while others disappear. In this sense, some jobs frequently associated with process innovation are destroyed, but at the same time, others generally related to product innovation are created (see Vivarelli, 2014). The creative destruction theory also applies to the types of workers. Innovation often negatively affects the demand for unskilled work, but it is complementary with skilled workers, according to Skill-Biased Technology Change (SBTC).

As mentioned, since the beginning of the industrial revolution, the labor movement (workers, as an example, the Luddite movement) has underlined the harmful effects of

[1] See Hobsdawn (1952).

innovation on employment. At the same time, some entrepreneurs underpin the benefits of technological change regarding efficiency, productivity, competitiveness, and new markets while other firms disappear in this process (Schumpeter, 1947). Classical economists such as Ricardo and Marx are, in general, confident about the positive role of compensation mechanisms, which are the countervailing forces against the direct job- destroying effects of new machines[2]. Notably, the classical vision truly believes that the labor market will absorb unemployed workers in new activities (Freeman & Soete, 1994).

Anyhow, the initial stage of industrialization, which can be considered mainly a form of process innovation, permitted an enormous increase in efficiency and 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. It implies, *ceteris paribus*, that for every 1250 workers employed then, only one person is employed today. Another example is agricultural production, where labor productivity has multiplied by a factor of 2400 since the beginning of the twentieth century (UNESCO, 2005). The two examples reflect the immense labor-saving effect generated by the mechanization of production. Nevertheless, these examples do not take into account the positive impact on employment generated by the sectors that created the new technologies. They are an interesting reference point for discussing the employment effects of advanced robots.

Nowadays, robotization generates an intense debate on employment effects. It allows, in conjunction with artificial intelligence, a substantial intensification of the automation process and therefore implies a drastic impact on labor productivity, generating a different

[2]See the next section for a review of this topic. For a broader review of the theoretical approach, see Calvino & Virgillito (2018); Vivarelli (2007, 2014); Vivarelli & Pianta (2003).

effect on overall employment demand (Acemoglu & Restrepo, 2017; Arntz, Gregory, & Zierahn, 2017; Dorn, 2015). The Mckinsey Global Institute analyzed the effects of automation on the global labor market across 54 countries. It estimated that the percentages of employment that could be automated is around 40-50%[3] of current jobs. However, this study does not take into account the potential positive effects of the introduction of new products, which could generate new markets and stimulate employment again. These estimations sound alarming and again place the relationship between jobs and innovation back at the center of political and public discussion.

Anyhow, automation depends not only on the availability of new technology, but also on factors that influence the absorptive capabilities of robotization (Arntz et al., 2017): the technical capacity of firms, the availability or lack of qualified human capital, the costs of employment in comparison with the new technologies and the expected benefits of automation not related to labor costs (such as steadier product quality and productivity and more labor security), legal regulation and social acceptance.

Dorn (2015) states that an intuitive yet profoundly mistaken view of the labor market exists. It is often supposed that the labor market is based on 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" (Schloss, 1981; Walker, 2007), an increasing use of machines in the production process necessarily reduces the total work, or overall labor demand, available to humans. However, some economists and policymakers emphasize that the

[3] The difference depends on the country or sector analyzed. The estimated loss of employment in percentages are 52% in the case of the United States (25.5 million employees), 51% for China (395.3 million employees), 48% for Germany (20.5 million workers), 56% for Japan (35.6 million workers), 43% for the UK (11.9 million employees), and 48% for Spain (8.7 million workers). Specifically, in Mexico, 52% of the employment may be replaced by robots, which means 25 million workers (64% in the industrial sector).

labor market is dynamic and elastic, and that the focus should be on ways and policies for the creation of employment. The fallacy exists because some economists, entrepreneurs, representatives of labor unions and policymakers do not recognize the effect of mechanisms that can compensate for the loss of jobs or the elasticity of demand.

Anyhow, despite the supposed negative employment effects of process innovation, a higher overall production level implies that everybody might theoretically live better than before. As stated by Stiglitz in terms of the income distribution, “while the skilled workers could compensate the unskilled workers, such compensation seldom occurs,” and if “the losers are those at the bottom of the income distribution, then innovation can contribute to growing inequality” (Stiglitz, 2015: pg.3).

As a result of this debate, the empirical examination of the innovation-employment nexus from a microeconomic point of view has gained renewed interest recently (Bogliacino et al., 2014; Dorn, 2015; Harrison et al., 2008, 2014; Vivarelli, 2007, 2014; Vivarelli & Pianta, 2003). This thesis contributes to this literature in three different ways.

First, it provides a review of these studies, with particular attention on the underlying models, the empirical methodologies, the results achieved, and the limitations encountered, which motivates our second and third contributions. Second, it offers a novel empirical analysis of the effect of product and process innovation on high-skilled and low-skilled workers in a period of economic turmoil. Third, it extends previous models to analyze the effect of downstream, upstream, and intra-industry product innovation on the employment of high-skilled and low-skilled workers.

The structure of this Ph.D. thesis is as follows. Chapter 1 presents a short review of the main theories that try to explain the relationship between innovation and employment. In the first part of this chapter, a summary of the main macroeconomic arguments related to innovation and jobs is exposed. Then, in Section 1.1, compensation mechanisms are explained based on the classical schools of economic thought according to the ideas of Ricardo and Say. Section 1.2 summarizes the debate about the relationship between innovation and employment based on the ideas of Keynes and Schumpeter. Section 1.3 describes the direct and indirect effects of product innovation on employment. Section 1.4 discusses the relationship between innovation and labor composition, Skilled-Biased Technological Change and Routine-Biased Technological Change. Section 1.5 presents some general conclusions about this chapter.

Chapter 2 develops a literature review of 44 studies that have analyzed the effects on innovation on employment at the firm-level. Section 2.1 reviews the two main models in the empirical literature to prove the existence and intensity of the relationship between innovation and employment at the firm-level. The first type of study is the output-oriented model based on the work of Harrison, Jaumandreu, Mairesse, and Peters (2014). The second main type is the input model based on Bogliacino, Piva and Viarelli (2012, 2014), followed by a brief discussion of the main concern for this model, the endogeneity problem. This problem would generate biased estimations. Therefore, Section 2.2. pays special attention to the methods used by each type of study to overcome this problem. Section 2.3. debates the differences, advantages and shortcomings of both approaches. A survey of the extensive empirical evidence at the firm-level is presented in Section 2.4 in terms of characteristics of the data, the variables that measure innovation, control variables, and instrumental variables. The main conclusion for this review is that previous empirical evidence clearly shows that product innovation positively affects the employment of the same firm. In contrast, the effect of process innovation is ambiguous. In the last section, the conclusions and limitations of the models are presented. The following questions based on the limitations are explored in subsequent chapters.

1.- *Does innovation have differential labor effects on low- or high-skilled workers during bad times?*

2.- What are the broader impacts of the innovations introduced by firms in the downstream, upstream, and the same sectors to which the focal firm belongs on the employment of the focal firm?

To analyze these aspects, we use Spanish data from the "Panel de Innovación Tecnológica" (PITEC) on over 27,800 observations for manufacturing firms from 2006 to 2014 and make use of the structural model of Harrison et al. (2014). They analyze the differentiated effects of product and process innovation on employment.

Chapter 3 presents the empirical model that analyzes the effects of product and process innovation on different types of workers, high- and low-skilled, during bad times[4]. It has been observed that the crisis more intensely affected unskilled employment, taking into account that, at least in Spain, 4.5 million jobs were lost between 2007 and 2013. However, the total number of employees with a university degree remained more or less stable during this period (ILO, 2015). Also, it analyzes whether the effects of product and process innovation on high- and low- skilled workers are pervasive across industries or whether there are some features specific to high- or low-tech industries.

[4] It can be highlighted that part of this chapter is published as: Díaz, G. A., Barge-Gil, A., &Heijs, J. (2020). The effect of innovation on skilled and unskilled workers during bad times. *Structural Change and Economic Dynamics*, *52*, 141-158.

Section 3.1. introduces some basic notions of the impact of innovation on employment, and the skill composition is presented. Section 3.2 offers some stylized facts on the firm-level, showing the descriptive statistics of some of the relevant variables on innovation by Spanish firms. Section 3.3 shows a summary of the methodology of Harrison et al. (2014), followed by a part that offers a review of the relevant empirical evidence. The method, data, and the results of estimations are shown in Sections 3.5 and 3.6. Finally, the conclusions are presented in the last part of the chapter.

The main findings suggest a positive effect of innovation on employment during bad times, although this effect is remarkably larger for high-skilled than for low-skilled workers. These results hold across industries and are exacerbated in high-tech industries. These results implicitly reflect that innovation, especially product innovation, favors a bias towards the demand of high-skilled employment to the detriment of low-skilled workers.

Chapter 4 goes one step forward because it includes an extension of the basic model developed by Harrison et al. (2014) with the aim to answer the third research question: *What are the broader effects of the innovations introduced by firms located in the downstream and upstream sectors and in the same sector to which the firm belongs on the employment of the focal firm?* This extended model considers the labor effects of new product innovations introduced by the upstream, downstream, and same sector (UDS). The overall results of this analysis are also differentiated for different types of workers.

Section 4.1. introduces and motivates the work. Section 4.2 briefly discusses the aspects of linkages and the expected labor impact on the innovation of the focal firm. It is followed by a synthesis of the empirical strands that use a similar analytical approach to estimate the role of the UDS. We use the data from the national input-output tables to trace the inter-and intra-sectoral flows. Section 4.3 explains the specifications of the extended HJMP model. It highlights the construction of the indicators used to measure the employment effect of the forward and backward linkages and of the index that reflects the new product flows of the firms in the same sector. It also explains how these three indicators are integrated in the model. Section 4.4 offers a descriptive analysis of the variable used. Section 4.5 presents the results of the estimated models. Section 4.6. provides the main conclusions of the work.

The result of the estimations of Chapter 4 suggests that, holding firm innovation constant, being located in an industry with more product innovation has a negative effect on firms' employment. Contrarily, if firms in downstream and upstream industries are more product-innovative, a positive impact on the employment of the focal firm is found. For different types of workers, the results of the estimations suggest that high-skilled employment is not affected by innovation outside of the firm, so the effect previously reported is entirely driven by low-skilled workers.

The last part of the document offers some final remarks on the conclusions, indicates several limitations of the analysis presented, and states future lines of research for overcoming constraints.

The content of the chapters has benefited from the remarks expressed during the discussion of the draft versions of the preliminary models presented at several seminars and congresses. A previous version of Chapter 2 was introduced at the "XVII Congreso Latino-Iberoamericano de GestiónTecnológica (ALTEC)." In the case of Chapter 3, the paper was thoroughly revised by the anonymous evaluators of the journal *Structural Change and Economic Dynamics*. Their remarks helped to improve different aspects of the work. The previous versions of Chapter 2 were presented at the “IV Workshop: Knowledge, Innovation and Internationalization Strategies,” “XIII Labour Economics Meeting,” and “XXXIV Jornadas de Economía Industrial.” Finally, Chapter 4 was presented at the Science Policy Research Unit (SPRU) at the University of Sussex (Wednesday seminars) and the “7th European Conference on Corporate R&D and Innovation CONCORDI 2019.” All the comments and suggestions have improved the quality of each chapter.

Chapter 1.- Innovation and its effect on employment: a theoretical and historical approach

Introduction

The impact of innovation on employment has been debated since the Industrial Revolution, and there is a great deal of literature on the subject (Pianta, 2005). Although it is not easy to distinguish between product and processes innovation, Vivarelli (2014) established a very practical working definition[5]. Product innovation might generate new products and markets that stimulate demand, output and employment while process innovation refers to the opportunity to produce the same output with fewer workers, and it directly reduces the labor required by the market. The first authors who wrote about this broadly analyzed the direct and indirect effects of product and process innovation.

Vivarelli (1995) states that "In the first half of the 19th century, economists put forward a theory that Marx later called the compensation theory (see Marx, 1867)". However, the ideas behind most of these so-called compensation mechanisms were developed mainly by the classical authors that described in detail the market mechanism that reabsorbs the unemployment generated by new machines, especially authors like Mill, 1848; Pigou, 1933; Ricardo, 1821; and Say, 1803. It is essential to mention that the basic concepts behind these mechanisms are macroeconomic. The high unemployment at the end of the19th century put the discussion of these mechanisms back in the center of the general debate on employment.

[5] According to Vivarelli (2014), by definition, technological change allows people to produce the same amount of goods with fewer production factors, namely capital and labor. Interestingly enough, "technological unemployment" occurs as a direct effect of innovation irrespective of its intrinsic nature. This definition is associated particularly with process innovation.

According to Freeman & Soete (1994), the classical economists assume that new technologies cause unemployment because of the incapacity of the labor market to absorb the increase of the output generated by those technological changes. Also, there is not enough capital supply to absorb the displaced labor force. Contrarily, the neoclassical economists –Marshall, Gourvitch, and so on – mentioned that the existence of a price that clears the market solves the two problems discussed above based on the well-known "Say's Law."[6] Gourvitch (1940) states that "there is a system of prices where an excessive production cannot exist of all the goods, neither an excessive supply of themselves." The substitution of the factors, which is the principal distinction between classical and neoclassical economists, leads to a better combination of capital and labor through price mechanisms (wages and interest rates, respectively). As a consequence, there is no possibility of overproduction or unemployment in the absence of price rigidities such as a legal minimum wage. The idea behind the substitution offers the solution to the second problem: insufficient capital supply. The price mechanism that clears the market assures equilibrium between capital and labor (Freeman & Soete, 1994).[7]

Moreover, there is another group of authors that deny the assumptions of the classical and neoclassical schools yet recognize the existence of compensatory mechanisms. They developed alternative theoretical frameworks to analyze the relationship between innovation and employment like the Evolutionary, Keynesian, Structural and Regulationist theories.

---

[6] Say's Law assumes that supply generates its own demand: *"A product is no sooner created than it, from that instant, affords a market for other products to the full extent of its own value"* (Say, 1803).

[7] According to Vivarelli (1995), some stylized facts define the models of the neoclassical school: comparative statics (short-term), microeconomic approach (one good), perfect competition (prices flexibility and market clearing), flexibility coefficients (substitutivity between capital and labor), and disembodied technical change.

In the case of the heterodox perspectives, alternative approaches like the Keynesian and Schumpeterian (Evolutionist) recognize the problems in the labor market generated by a lack of sufficient demand and technological process, respectively. It is important to mention that both visions (Classical and Neoclassical versus Keynesian and Schumpeterian approaches) coincide in some ideas or outcomes included in the compensation mechanisms. However, they integrate theoretically completely different frameworks based on radically different assumptions. For example, according to Freeman and Soete (1994), Keynesians deny the idea that equilibrium necessarily implies the exitance of full employment[8]. Although Say's Law is valid in the case of full employment, it does not apply in the case of sub-employment.

One of the main arguments against the neoclassical vision is the assumption of full employment.[9] Keynes (1936) states that "… in a dynamic society, there will always be some resources not used." The Keynesian theory does not pay specific attention to the impact of technical progress on economic development. However, in this vision, public investments should be oriented to activities or infrastructure that can improve the overall productivity of most of the agents once the economy recovers. In such a context, investment in innovation can be crucial. As mentioned by Freemanand Soete (1987), Perez (2002), Schumpeter (1939) and others, the new technological revolutions will

[8]This idea is the main difference between the Keynesian economists and neoclassical economists.

[9]For Keynesians, unemployment is a temporal problem related to the business cycle and is caused by downturns in the economy and its business cycle. Therefore, the problem related to so-called cyclical unemployment cannot be solved in the market (it is a problem of demand). According to Calvino & Virgillito (2018), the negative expectations of future profits generate a low level of aggregate demand; this results in a lack of private investment and decrease of employment. To overcome this trend and in order to push the economy towards a recovery phase, the government should incentivize the aggregate demand. This provokes a new positive period of investment expectations (the result of this is an increase of employment).

trigger a new economic upswing[10] because the innovation and business cycles are clearly intertwined.

In Schumpeter's approach, unemployment is not only an effect of the lower labor demand caused by process innovations and the depletion of old technologies (Boianovsky & Trautwein, 2010). Schumpeter (1939) 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. The accumulative character of capabilities necessary to manage the new technologies requires new skills in the labor force (Rosenberg, 1976) that can only be obtained by an intensive long-term learning process.

The discussion mentioned above shows that the economists of the different schools of thought historically pay attention mainly to the effect of process innovation on employment. Although a worry exists about the possibility of labor-saving impact, in the short run, the same authors recognize the existence of the compensation mechanism that mitigates the initial loss of employment derived from process innovation. The literature identified five so-called "compensation mechanisms" (Pianta, 2005; Vivarelli, 2007, 2014; Vivarelli & Pianta, 2003): new machines, decrease of prices, new investment, increase in incomes, and decrease of wages.

New products have sometimes been considered another indirect compensation mechanism from process innovation. However, Vivarelli (1995), based on the first type of Schumpeter’s taxonomy, states that product innovations are not compensation mechanisms

[10] See also Freeman & Soete (1987), Schumpeter (1939) and particularly the book of Carlota Perez (2002), *Technological Revolutions and Financial Capital: The Dynamics of Bubbles and Golden Ages*. The author analyzes the relationships between investments in R&D, the rise of new key technologies and the economic crisis.

in a strict sense. Compared with other compensation mechanisms, this develops a completely different aspect of technical change. New products build entirely new industries which are able to generate a huge number of new jobs.

According to Calvino & Virgillito (2018), although initially these different compensation mechanisms were developed by the classical school, they can be discussed from the various theoretical perspectives mentioned above. Some economists, such as Freeman et al. (1982) and Vivarelli (1995, 2012, 2014), have proposed a classification that depends on pass-through channels that trigger the transmission chain of economic effects of the compensation mechanisms. In the following pages, we discuss each of them briefly.

1.1.- The compensation mechanisms

1.1.1.- Compensation via the new sector of machinery, equipment and tools

A first compensation mechanism with a direct effect on employment is the extra labor required for the rise of the machine and tool sector introduced by the classical literature (Say, 1803). In other words, the new industrial sector emerged to design and produce new machines, generate new employment to produce tools and provide technical service and training, and maintain the machinery. According to Say (1803), while process innovation expels employment in the sectors that use new machines and tools, there is a compensation mechanism that generates jobs in a new sector that produces the required machines and equipment goods.

Although this mechanism has not received too much attention lately, Marx (1867) commented on it. In the first place, Marx discussed the relative profitability of the dismissed workers because of the new machines: *"... the machine can only be employed* *profitably if it is the (annual) product of far fewer men than it replaces"* (Marx, 1969: pg. 552). *"Although machinery necessarily throws men out of work in those industries into which it is introduced, it may, notwithstanding this, bring about an increase of employment in other industries. This effect, however, has nothing in common with the so-called theory of compensation. Since every article produced by a machine is cheaper than a similar article produced by hand, we deduce the following infallible law: if the total quantity of the article produced by machinery–is equal to the total quantity of the article previously produced by a handicraft or by manufacture, and now made by machinery, then the total labor expended is diminished. The new labor spent on the instruments of labor, on the machinery, on the coal, and so on, must necessarily be less than the labor displaced by the use of the machinery; otherwise, the product of the machine would be as dear, or dearer, than the product of the manual labor"* (Marx 1867).

Vivarelli (1995) states the value of the new machines has to be lower than the value of the workers that are displaced. As a result, this mechanism is only partial because the volume of work embodied in creating these new machines is lower than the replaced work. In the second place, Marx (1969) also states that labor-saving technologies spread in the capital goods sector, and this substantially weakens the power of compensation mechanisms. In other words, labor-saving technologies will also be introduced in the sector of machinery (Vivarelli, 2014). In the third place, there are authors (Bogliacino et al., 2014; Freeman et al., 1982; Vivarelli, 1995) that assure that *"... new machines can be put into effect either through additional investments (new products) or simply by substituting the obsolete ones (scrapping them). In the latter case, which is the most frequent one, there is no compensation taking place"* (Calvino & Virgillito, 2018).

1.1.2.- Compensation via decrease of prices

The obtained cost advantages of process innovations can be used in three forms. The first one would be a reduction of prices[11], which is a long-term effect in the case of a competitive market. In this case, the quantity of the demand would be stimulated, requiring a higher level of production that implies the creation of the corresponding new jobs (Say's Law). Steuart (1767) states that *"the introduction of machines is found to reduce prices in a surprising manner. And if they have the effect of taking bread from hundreds formerly employed in performing their simple operations, they have that also of giving bread to thousands."*

However, there is a specific weakness of this compensatory effect. A direct impact is that a labor-saving technology implies the loss of purchasing power of the dismissed workers and, therefore, a decrease in aggregate demands (Mill, 1848). It means that an increase in the demand due to lower prices has to neutralize or overcome, in the medium/long term, the initial loss of the overall aggregate demand due to a higher level of unemployment. According to Vivarelli (2012), three market conditions are necessary to assure that this mechanism functions. First of all, a significant price-demand elasticity should exist to assure a growing demand for the goods and services that are affected by the price reduction. Second, a high relevance of these commodities is essential in workers' consumption bundles to assure a sufficient demand effect. Third, perfect competition based on a (non-oligopolistic) market structure is needed. The demand only increases when those three conditions are simultaneously fulfilled.

[11] The other two are the increase of salaries and the increase of profits (see the next two compensation mechanisms.

1.1.3.- Compensation via new investment

A second option to employ the obtained cost benefits would be to increase the overall profits of firms. Within the classical view (specifically Ricardo), cost reduction could be used, in the short term, to increase the benefits, which automatically lead to new investments and therefore create new jobs, thus partially compensating the loss of employment. As Vivarelli (1995) states, *"during the competitive gap between the decrease in costs and the consequent fall in prices, extra profits are accumulated; these profits are invested, and so new products and jobs are created."*

This supposed effect is also related to Say's Law, which predicts that all profits will be used for new investments. Nonetheless, in the economic reality**,** this effect is not automatic, and it depends on the evolution of the markets, the expected profits, and the individual decisions of businesspeople. Additionally, if these new investments are oriented to capital-intensive activities, the negative effect in terms of loss of employment would persist or could even, in the long run, be higher. Vivarelli (2012) states that theoretical analysis has to consider the animal spirits and expectations of economic agents, which can delay the translation of additional profits into effective investments or demand (see Freeman & Soete, 1987; Pasinetti, 1981; Pianta, 2005; Vivarelli, 1995).

1.1.4.- Compensation via increase in incomes

In a third case, the direction of cost benefits in terms of productivity gains might be an increase in the salaries of workers. The effect would provoke an increase of aggregate demand by offering opportunities for firms to invest, and, as a consequence, this would imply the creation of new jobs. The limitations of this indirect impact on employment are also discussed later within the theoretical approach of Keynes and Schumpeter.

1.1.5.- Compensation via decrease of wages

A neoclassical compensation mechanism (Vivarelli, 2007) is the reduction of wages provoked by the decrease of labor demand as a consequence of a higher level of efficiency or productivity. This decrease generates more unemployment and, as a consequence, a downturn in the level of salaries. Such decreasing labor costs would, from the neoclassical perspective, induce business people to orient their investments to more labor-intensive technologies and therefore hire more new workers (Hicks, 1932: pg.56; Pigou, 1933: pg.526; Wicksell, 1961: pg.137).

Considering that this mechanism takes the principle of factor substitution (Calvino & Virgillito, 2018), it can be stated that several situations impede the consequential automatic functioning of this mechanism. Firstly, once the firm has mastered the technique (in terms of new technology) and bought the machinery, it is difficult to reverse its use and substitute it with labor (see Dosi & Nelson, 2013). Secondly, it assumes perfect factor substitution and therefore requires a homogeneous demand in terms of human capital, which does not exist (Schumpeter, 1939). Thirdly, contrary to what the theory predicts, empirical studies (Dosi et al., 2015; Hildenbrand, 1981; Yu et al., 2015) offer no evidence in favor of the absence of factor substitutability (Calvino & Virgillito, 2018; Vivarelli, 2012).

1.2.- Innovation and employment from a Keynesian and Schumpeterian perspective

In this section, a short review of the Keynesian and Schumpeterian visons is made. Keynes highlights the role played by the business cycles of crisis and prosperity and Schumpeter highlights the absence of the neoclassical "homogeneity" of the labor forces or supply which causes "technological unemployment".

From a classical, neoclassical and Keynesian perspective**,** higher salaries would stimulate an increase of aggregate demand, offering opportunities for firms to invest, and, as a consequence, this would imply the creation of new jobs. Even if such investments exist, it is not clear that they are in labor-intensive sectors.

Starting with Keynes, as just mentioned, productivity gains can be used to increase the level of the salaries of workers that remained in the firms. However, the classical and neoclassical theories do not take into account the differences in the adjustments of the salaries in the moments of economic periods of upswings or downswings or of the functioning of the mechanism in labor markets with an overall high unemployment level. The adjustments in terms of lower salaries (in real terms) would function in a situation of full employment[12].

As an alternative vision, Schumpeter states that technological progress is the main element in the dynamics of the economic cycle, and it is the main difference between Schumpeter's ideas versus neoclassical and Keynesians economists. The technical transformations generate what he called technological unemployment, and it has a cyclical character (Freeman & Soete, 1994). Schumpeter (1939), based on the Kondratieff Wave, states that the cycles are successions of technological transformations in the economic system that require profound structural changes, including the demand of jobs in quantitative and qualitative terms. Schumpeter called this phenomenon creative-destruction process or successive industrial revolutions.

[12] However, from the 1950s to the 1970s, when the Fordism model was applied, and almost full employment existed, at least in the most economically advanced countries, it did not work, especially because labor unions were strong enough to negotiate wages. Nowadays, the labor force is more fragmented, and with a large supply or potential workers in the labor market, workers are less able to lay collective claims. Therefore, this compensation mechanism has been greatly weakened in the new institutional context of unemployment (Vivarelli, 2012).

In fact, several recoveries of the downward cycles were partially based on "jobless growth".[13] Almost no empirical evidence on its exact causes exists[14]. However, the structural changes of the production sector and polarization of the types of required jobs (technical unemployment) are mentioned as possible causes (Autor, 2010; Groshen & Potter, 2003).

1.3.- The direct effect of new products on employment

The creation of new products can imply the birth of entirely new economic branches where additional markets and products can appear. In other words, the introduction of new branches and products can stimulate consumption, demand and employment (Calvino & Virgillito, 2018).

All the schools of economic thought agree with the labor-creating effects of product innovation. For instance, the classical economist (Say, 1803) recognized the labor-intensive impact of product innovation. Even Marx, who was among the most critical of employment effects of innovations, admitted the positive effect of product innovation and its benefits that are produced because of the technological change (Marx, 1867). Nowadays, the positive effect of new products is also emphasized by more recent authors (Freeman et al., 1982; Freeman & Soete, 1987, 1994; Pianta, 2005; Vivarelli, 1995) that have analyzed the relationship. These authors state that product innovation can open a way of development all new goods (Vivarelli, 2014).

[13] Like Japan in the 1990s and the USA in the 1980s and in the last decade. For a theoretical framework of jobless growth, see Caballero & Hammour (1997).
[14] However, the few empirical data on this subject reject the idea that jobless growth is caused by innovation (Graetz & Michaels, 2017).

During the introduction phase of an innovation, new products and processes are not standardized, and as a result, the production of new products are more labor-intensive (Utterback & Suárez, 1993). However, not all new products have the same labor intensiveness. For example, the introduction of the automobile had a much higher labor-intensive effect than the diffusion of home computers (see Vivarelli, 2012). Therefore, the employment effect of new products can differ by sector and by type of product. According to Vivarelli (2014), the real positive employment effect of new products may be limited, especially in high-tech sectors.

Although the positive labor effect based on new products has its limit, it appears to be the most powerful counterbalancing factor of technological change. According to Peters, Hud, Dachs, & Köhler (2017) and Vivarelli (2014), some indirect effects can mitigate the positive employment effects of new products[15]; the new generation of an old product could imply a cannibalization effect where the new product replaces the old product. In this situation, the final employment effect depends on the differences between the labor intensity for the production process of the new and old products.[16]

In addition, from a general equilibrium perspective, the gain of jobs in a certain firm could be compensated with a loss of jobs in other firms and the net employment effect will be zero. Finally, if the new product is only a continuous innovation (incremental) in order to avoid the imitation of competitors and it does not imply the increase of market size, the effect of innovation on employment will be small (Heijs et al., 2016).

[15]The previous indirect effects are based on radical innovation (for example, the substitution of vinyl records with compact discs) or incremental innovation (for example, planned obsolescence) (see Heijs et al., 2016).

[16] As will be seen in the next chapter, the labor-friendly effect of product innovation is particularly obvious at the microlevel analysis.

1.4.- The effects of innovation on labor composition in terms of skills and education

Besides the overall effect of innovation on employment, this part tries to assess the quantitative and qualitative impact of innovation on skilled versus unskilled jobs. As was mentioned above, Schumpeter's concept of creative destruction has relevance in terms of employment because while one type of job is created, others are destroyed. Two different aspects can be mentioned in relation to the differences between the new and the old jobs. First of all, the skills required by the new jobs can be quite different from the ones that the expelled workers from the old replaced industries have. Even the introduction of new technologies introduced in certain jobs that are not destroyed could be difficult for older workers to learn. Schumpeter (1939) denominates this situation "technical unemployment," which he considers an unavoidable by-product of capitalist development, albeit a temporary situation that will disappear in the long run.

Another important aspect of the relationship between innovation and employment is the skills required. This paragraph indicates some reasons that might explain the increasing demand of skilled (or more highly educated) labor in absolute terms. Welch (1970) mentions three basic causes. The first is structural change in the composition of the production sector towards high-tech industries observed in the most advanced countries. These industries, which are the most skill-intensive, grow faster than low-tech manufacturing sectors, creating more high skilled jobs. Their fast growth is due to the fact that the products of these high-tech sectors have higher income-demand elasticities, changing the composition of the consumption (because of the rising income), because richer citizens demand more innovative products (Porter, 1993). Also, process innovation increases productivity and therefore average income per capita with a similar stimulating effect on the demand of high-tech products. Secondly, the increasing use of non-labor input factors can generate, *ceteris paribus***,** a positive bias towards the demand of skilled labor. In particular, capital investments substitute unskilled labor activities more frequently. In this case, it is not the technology that causes the lower demand of unskilled workers. Nevertheless, the real cause would be the increase of capital intensity. Thirdly, technical change effects on productivity are not neutral between skill classes.[17] *"It may be that increments in technology result in increments in the relative productivity of labor that is positively related to skill level"* (Welch, 1970: p.38).

The effect of innovation on employment in qualitative terms has been further analyzed, leading to the well-known skill-biased technological change (SBTC) hypothesis. This idea, already mentioned by Nelson & Phelps (1966), Griliches (1969) and Welch (1970), implies that the introduction of new technologies requires workers with new suitable capabilities and skills. The SBTC hypothesis suggests that new technologies and the required skills are intrinsically complementary, so it favors the hiring of skilled over unskilled workers by increasing their relative productivity (Violante, 2008). This hypothesis has been complemented with the routine-biased technological change (RBTC) hypothesis (Autor et al., 2008; Goos et al., 2014; Jaimovich & Siu, 2018), which places the emphasis on the routine versus cognitive contents of the tasks and argues that most of the new technologies would replace workers that perform routine tasks. The presence of a labor-saving and skill-biased process innovation can generate unemployment among unskilled workers. The recent consensus of empirical studies is that technical change favors more skilled workers, replacing tasks previously performed by the unskilled, and

[17] However**,** even a strict neutral technological change would increase skilled labor demand more (Vivarelli, 2007; Welch, 1970).

exacerbates inequality (Acemoglu, 2002; Acemoglu et al., 2020; Acemoglu & Restrepo, 2018; Dorn, 2015).

It can be highlighted that some of the SBTC/RBTC studies analyze the impact of a specific technology – ICT, computers and so on Vivarelli (2014) states in his literature review that the main member countries of the Organization for Economic Cooperation and Development (OECD) showed a significant change in the composition of the labor force in favor of the skilled component of the labor force. However, there is no robust evidence yet on the differential effect of product and process innovation on the different types of workers. The following work aims to contribute in this regard.

Another approach is the labor polarization hypothesis. According to this theory, workers can be classified by their level of skills and the type of task (routine vs non-routine and abstract vs manual) in high, medium- and low-skilled workers. The labor polarization theory implies that the demand for high- and low-skilled workers will increase while the jobs of medium-skilled workers will be displaced. Dorn (2015) states this phenomenon happens because medium-skilled workers execute routine task-intensive occupations which are more likely to be replaced by new machines while occupations specializing in abstract or manual tasks cannot be readily replaced by machines (high- and low-skilled workers). Both RBTC and labor polarization are based on the type of task that workers execute (for an in-depth conceptual discussion, see Autor & Dorn, 2013; Autor et al., 2008; Autor et al. 2003; Dorn, 2015). However, at an empirical level, it is quite complicated to test this hypothesis because of a lack of appropriate information.[18]

[18] In fact, the polarization of employment is not analyzed because of a lack of appropriate data in the database used in this thesis.

1.5.- Conclusions

The theoretical literature offers several alternative possibilities regarding the relationship between innovation and employment and shows different effects by types of innovation: product or process innovation. While process innovation is understood as those novelties that are focused on saving labor, which implies a negative effect on employment, product innovation is based on substantially improved or totally new features of products (Vivarelli, 2014).

Another conclusion is that all the schools of economic thought agree with the existence of the above-mentioned compensation mechanisms. However, they differ on the functioning of the mechanisms, the recovery of the initial negative effect of process innovation on employment, and their ability to compensate for lost jobs.

The classical and neoclassical analyses state that the compensation mechanisms are automatic processes that will always recover the initial loss of employment and assure full employment. Nevertheless, other schools like the Keynesian and Schumpeterian mention several of their shortcomings and deny the basic assumptions of the neoclassical school. Keynesians argue that unemployment is a temporal problem related to the business cycle, especially in the moment of economic downturns. Schumpeter denies the expected "perfect" functioning of the mechanism that in the long run always assures full employment. He especially refutes the existence of a perfect market. Apart from that, the Schumpeterian assumes that a part of the unemployment is caused by the discrepancy between the formation of workers expelled from traditional sectors and the requirements of human capital in emerging innovative sectors. He called the lack of jobs for these obsolete workers technical unemployment.

Although the perspective of direct and indirect effects of innovation on employment is different among the economic visions, there is no disagreement that they exist. It is important to mention that the theoretical background of these effects is macroeconomic. Therefore, the empirical test of the existence of the effects at a macroeconomic level is extremely difficult, and most studies try to shed some light on their existence using data at the firm-level. In particular, the worldwide appearance of innovation surveys with detailed firm-level data as well as innovation activities and employment made it possible to carry out specific studies on the relationship between both aspects. In fact, the empirical models developed in this Ph.D. thesis are based on the Spanish Innovation Survey.

The last remark is that innovation affects employment not only in quantitative terms but also in qualitative terms. In other words, technological change also has an impact on labor composition. In this chapter, the skilled-biased technological change (SBTC) hypothesis is explained briefly to clarify possible reasons for the unequal impact of innovation by type of job in terms of skills and education levels. According to this hypothesis, the new technology is complementary to skilled workers, not reducing skilled employment and even increasing it, while the new technology substitutes unskilled employment. Routine-biased technological change (RBTC) complements the former hypothesis. RBTC highlights the difference between routine and cognitive tasks, assuming that workers that execute routine tasks will be more likely to be replaced by machines or new technology.

Chapter 2. Firm-level empirical evidence of the relationship between innovation and employment

Introduction

As observed in Chapter 1, at the theoretical or conceptual level, several mechanisms behind the effects of innovation on employment can be identified. However, the conversion of these analytical concepts in measurable indicators is still a big problem. First of all, the measurement of innovation results at the firm-level was until the1990s a scarce activity, and the few innovation surveys were not publicly available to researchers. Therefore, most studies before that period were done at the regional, national or sector level.[19] It was difficult for those aggregate-level studies to isolate the impact of innovation on labor from other possible determinants like economic growth cycles or international economic shocks, among others.

There is some general agreement about the feature of some specific innovation concepts and how to measure them. For example, there is a set of manuals on several aspects of R&D and innovation[20] that offer a clear indication of what is considered process and product innovation and how to measure it. However, combining these practical aspects with more abstract theoretical concepts like compensation mechanisms to define the final impact of innovation on employment is much more complicated. It is already difficult to separate the overall employment effects based on innovation from the impact of other possible

[19] Some of the first articles that try to measure the effects of innovation on employment are Katsoulacos, (1986) and Stewart (1974).

[20] The first of them, known as the Frascati Manual, was published in 1963 by the OECD. It was based on a draft report by Christopher Freeman and further developed by OECD experts together with the national experts of the NESTI group (National Experts on Science and Technology Indicators). The first version of the Frascati Manual in 1963 is officially known as The Proposed Standard Practice for Surveys of Research and Experimental Development. Since that moment, several series of official documents and manuals have been developed, each of them discussing the measurement of different aspects, and they are frequently updated. These include the manual on R&D (Frascati Manual), innovation (Oslo Manual), human resources (Canberra Manual), technology, balance of payments, and patents as indicators of science and technology.

determinants. Once the innovation-related impact on employment is identified, the problem is to assign them to each of the compensation mechanisms. The empirical studies are constrained by the availability of the required data and its quality. For instance, at a macro-level, it is difficult to find a proper aggregate proxy of technology change (Vivarelli, 2014).

The improvement of innovation surveys, especially in Europe, makes the firm-level analysis more suitable and trustworthy. However, as will be stated, empirical studies are only able to estimate the separate impact of the direct and indirect mechanisms. An additional problem in calculating the exact effect of innovation on employment on the firm-level is the fact that such studies do not take into account technological spillovers. In other words, to analyze the impact of R&D on employment at the firm-level, not only their own innovation effects should be considered, but also the innovation of other firms used directly or indirectly by the focal firm, especially the providers.

The main goal of this chapter is to review the empirical studies that analyzed the relationship between innovation and employment at the firm-level. In the central part of this chapter, a broad review on the methodological aspects of the models and the way they overcome the endogeneity problem will be offered, followed by a review of the empirical results of the existing empirical literature. Among others, the endogeneity problem is – besides the problem of defining and measuring the right indicators on innovation– maybe the most important methodological obstacle to measuring the effect of innovation on employment. The existence of such a problem in regression models causes biased results. As will be explained, a generally accepted solution to the endogeneity problem can be the inclusion of instrumental variables (IV) frequently used in the studies reviewed for this chapter.

A broad effort was made to identify the maximum number of existing empirical studies on this subject. In fact, 44 articles were found, offering an empirical analysis of the impact of innovation on employment from a microeconomic point of view, and for this chapter, all of them have been reviewed. They can be classified into two main groups, a distinction based on their theoretical or methodological approaches and the way they operationalize innovative activities. The following sections offer a taxonomy of the studies found on the specific methodological settings based on two of the three main groups.[21]

The first group –Type 1– includes 17 studies (see section 2.1.1) that follow the output-oriented view of Rupert Harrison, Jordi Jaumandreu, Jacques Mairesse and Bettina Peters (2014)[22]. This Type 1 or HJMP model simultaneously includes two output variables of innovation to analyze their effect on employment. According to Dachs & Peters (2014), this type of model has several advantages. First, it is possible to disentangle some of the theoretical employment effects mentioned in Chapter 1. Second, the differentiated relationship between employment growth and innovation output (only process innovation and sales growth due to new products) can be measured. Third, the data from the innovation surveys –implemented in a large number of countries and based on the aforementioned Frascati and the Oslo Manual– make it suitable to apply and reply to the model in a large number of different environments.

[21]A third group of a hotchpot of studies is distinguished because of large methodological differences. It includes several studies from before 2000 that do not always take into account the endogeneity problem. Moreover, several of them use a heterogeneous set of methodologies and several alternative variables (not or barely used by mainstream models) to operationalize innovation, like the growth of R&D expenditures (four samples). In this overview, the structure and background of these studies are not explained in detail although they are included in the second part of the chapter, where the empirical results are presented.

[22] The structural model of Harrison et al. (2014) is based on previous works of Harrison et al. (2008); Jaumandreu (2003); and Peters (2005). All of them are working papers. We are going to use Harrison et al. (2014) for the rest of the thesis because it is the article published in a journal.

For the second group of models –Type 2– proposed by Van Reenen (1997) and adapted by Bogliacino, Piva, and Vivarelli (2012), and Bogliacino et al., (2014), eight[23] studies were found, and their features are discussed in section 2.1.2. Their approach can be considered an input-oriented model that defines the employment effects of innovation in terms of its input (R&D expenditures). Pellegrino & Vivarelli (2017) state that the model makes it possible to analyze the link between technology changes (R&D and innovation) and employment through a stochastic version of a standard labor demand function, augmented by the inclusion of the innovation factor.

In the next sections, the two main strands of methodological approaches are reviewed. Section 2 presents the empirical specification of both models, and their possible interpretation in terms of "economic" and/or theoretical concepts is discussed. Section 2.2.1 offers the methodological discussion of the endogeneity problem, and also explains the methodological aspects of instrumental variables as a solution to this problem, followed by a section on the analysis of the empirical features of the instrumental variables used by both types of studies. Section 2.3 compares the different aspects of the two main models, analyzing the methodological and conceptual differences and the similarities between them. In Section 2.4 of this chapter, a review of the main results of the existing empirical evidence will be offered. Section 2.4.1 summarizes the data sets and the overall (economic) setting of the 44 empirical firm-level studies found and a review of the exact definition of the variables used to capture the innovation effects on employment by each of the types. Section 2.4.2 shows the empirical findings in terms of the labor effect of innovation. This section discusses the similarities and contradictions in the labor effects observed in the 44

[23] Type 2 or BVP model.

studies and the possible causes of the ambiguous results. Other essential aspects of the empirical studies (reviewed in Section 2.4.3) are the indicators that are called control variables. Several studies add additional variables to control the effect of innovation on employment from other possible causes that affect labor demand at the firm-level. In other words, these studies use such variables to isolate employment effects caused by innovation, creating a kind of ceteris paribus situation. However, some studies, especially the Type 1 model proposed by Harrison et al. (2014), do not require such control variables[24]. In this case, the additional (control) variables are included to observe the employment effects of some specific aspects. In Section 2.4.4, an overview about the appropriateness and the (dis)advantages of the different instrumental variables applied in the studies will be offered. In the last section (2.5), some brief general conclusions are presented.

2.1.- The two main strands or empirical models developed for firm-level analysis

2.1.1.- Model Type 1: Econometric specification of the model of Harrison et al. (2014).

The first empirical approach that will be explained is the model of Rupert Harrison, Jordi Jaumandreu, Jacques Mairesse, and Bettina Peters (the Type 1 or HJMP model). This structural model is conceived to test the labor-creating and labor-destroying effects of innovations on employment growth (Peters et al., 2017). As mentioned, the model establishes a theoretical link between firm-level employment growth and innovation output in terms of the sales growth generated by product innovations (new or improved products) and the efficiency gains attributable to process innovations (new or improved processes).

In the HJMP model, it is assumed that a firm can produce old and new products. We identify those firms with i=1 (old) and i=2 (new). Two periods of time, t=1 and t=2, are

[24]See the structural equation in Section 2.1.1.

established (a firm can introduce new products between them). In the first period, all the products are old (Y_{11}). However, in the second period, firms can produce either a combination of new (Y_{22}) and old (Y_{12}) products, or only old ones in the case that the firm has not introduced any new products between the two moments of observation (Harrison et al., 2014).

It is assumed that capital (K), labor (L), and intermediate inputs (M) present constant returns to scale in the production of technology. Also, the production function can be divided into two separable equations with different technological productivity (Hicks-neutral parameter θ).

$$Y_{it} = \theta_{it} F(K_{it}, L_{it}, M_{it}) e^{\eta + \omega_{it}} (2.1)$$

Furthermore, η is a fixed effect that captures the idiosyncrasy of the firm. The last parameter represents all the factors –non-observables– that make a firm more productive than the average firm using the same technology (in this case θ). ω represents unanticipated productivity shocks[25] ($E(\omega_{it}) = 0$).

According to Harrison et al. (2014), firms invest in research and development to generate product and process innovation. One of the objectives could be the improvement of the efficiency of the production of both old and new products. An interesting aspect of the model is that it also computes the change in the efficiency of producing old products θ_{12}/θ_{11}, and also the relative efficiency of producing old and new products θ_{22}/θ_{11}.

To calculate the employment equation, it is assumed that the decisions of inputs (employment, capital, and intermediate inputs) are made to minimize cost, taking into

[25] The parameter captures all the non-observable changes of the productivity function that are not related to technological change, for example, industrial organization, work problems and so on.

account individual productivity effects η and productivity shocks ω. Given the technology, the cost function takes the form:

$$C(w_{it}, Y_{it}, \theta_{it}) = c(w_{it})\frac{Y_{it}}{\theta_{it}e^{\eta+\omega_{it}}} + F_i \qquad (2.2)$$

where $\frac{c(w)}{\theta_{it}e^{\eta+\omega_{it}}}$ is the marginal cost, which is in function of the price w, and F is the fixed cost. Applying Shephard's lemma, the labor demand equation can be expressed for old products as

$$L_{1t} = c_{wL}(w_{1t})\frac{Y_{1t}}{\theta_{1t}e^{\eta+\omega_{1t}}} \qquad (2.3)$$

In the same way, the labor equation of new products is

$$L_{22} = c_{wL}(w_{22})\frac{Y_{22}}{\theta_{22}e^{\eta+\omega_{22}}} \qquad (2.4)$$

The expression $c_{wL}(.)$ represents the derivative of $c(.)$ with respect to the wage. It is supposed that the price of inputs is constant in all the years $c_{wL}(w_{11}) = c_{wL}(w_{12}) = c_{wL}(w_{22})$. Decomposing employment growth into two years t=1 and t=2:

$$\frac{\Delta L}{L} = \frac{L_{12}+L_{22}-L_{11}}{L_{11}} = \frac{L_{12}-L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \simeq ln\frac{L_{12}}{L_{11}} + \frac{L_{22}}{L_{11}} \qquad (2.5)$$

In theory, the growth rate of new products is defined as L_{22}/L_{11}. Replacing equations (2.3) and (2.4) in (2.5), and applying logarithms gives us the equation

$$\frac{\Delta L}{L} \cong -(\ln\theta_{12} - \ln\theta_{11}) + (lnY_{12} - \ln Y_{11}) + \frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11}) \qquad (2.6)$$

According to Harrison et al. (2014), equation (6) describes the growth of employment in four terms: firstly, the change in the efficiency of old products in the production process $-(\ln\theta_{12} - \ln\theta_{11})$; secondly, the rate of change of the demand of old products $(lnY_{12} - \ln Y_{11})$; thirdly, the increase of production related to new products $\frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}}$; and finally, the impacts of non-technological perturbation of productivity $-(\omega_{12} - \omega_{11})$. Equation (2.6) can be represented in the following form:

$$l = \alpha_0 + \alpha_1 d + y_1 + \beta y_2 + u \quad (2.7)$$

where l stands for the employment growth rate 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 ($u = -(\omega_{12} - \omega_{11}) + \xi$[26]). The parameter α_0 represents (minus) the average efficiency growth in the production of the old product. The binary variable d picks up the additional effect of process innovations 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). Finally, the parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2014). As can be seen in equation (2.7), the coefficient of $y_1$is equal to one. Therefore, this equation can be written as the following regression:

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \quad (2.8)$$

Equation (2.8) is the function to estimate. It is expected that the efficiency of new processes increases more for innovative firms because of spillovers and other factors. In other words, according to Harrison et al. (2014), the ratio $(\Theta_{21}/\Theta_{22})$ determines the impact of product innovation on employment growth or relative efficiency in producing old and new products. The ratio is less than the unity if the new products are produced more efficiently than old products.

[26]ξ represents many errors that are not correlated.

However, Harrison et al. (2014) state that they do not directly have output of either old or new products, $y_1$or y_2, respectively. The authors only observe the increase of sales in the dataset. This variable may include the effect of different prices for both new and old products. In the former, the authors only have the nominal growth of old products. As can be seen, both problems are related to the unavailability of firm prices. To solve this problem, the authors will use the prices at the industrial level (π) to deflate the growth of sales due to old products (substitute $g_1$for y_1). Furthermore, the authors of this methodology substitute g_2 for y_2 because they observe sales growth due to new products (Harrison et al., 2014). Taking into account these changes, we obtain equation (2.9):

$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i$(2.9)

The components of the models are the main advantage. They can be interpreted –from a conceptual point of view– in terms of specific efficiency gains according to the types of innovation. Their economic meaning, as already mentioned above, intertwined during the explanation of the different equations can be summarized by explaining the interpretation of each aspect and its expected sign:

- **The constant term reflects the increase in the efficiency of the production process**. In theory, the efficiency is always expected to improve over time for a particular good. Therefore, the parameter α_0 expects to be negative, representing the average efficiency growth in the production of the old products. In other words, it represents the increase of productivity without product and process innovation.
- The binary **variable *d* picks up the additional effect of process innovations on employment** related to old products by means of the efficiency parameterα_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 expected sign on employment growth is negative because firms that only introduce process innovation probably focus their technological progress in terms of cost reduction. The objective would be the increase of the (labor) productivity for the manufacturing of the old products by labor-saving technologies.

- **The parameter β captures the relative efficiency of the production of old and new products** (Harrison et al., 2014). In fact, it shows the effect of product innovation on employment. Also, as was mentioned, this parameter captured the relative efficiency between old and new products. If the value of the parameter is less than 1, it means that the new products are produced more efficiently than the old products. Therefore, the magnitude of the parameter matters.

2.1.2.- Model Type 2: Econometric specification of the model of Bogliacino et al. (2012).

A second main strand of studies is based on the model proposed by Van Reenen (1997) and adapted by Vivarelli (2007) and Bogliacino et al. (2012, 2014). According to Bogliacino et al. (2012), the adopted methodology takes into account the sticky and path-dependent nature of a firm's demand labor due to institutional factors such as labor protection and high adjustment costs in hiring and firing. The empirical specification uses a CES function (see equation 2.10), considering a competitive firm. It is supposed that the firm maximizes its profits.

$$Y = A[(\alpha L)^{\rho} + (\beta K)^{\rho}]^{\frac{1}{\rho}} \qquad (2.10)$$

where Y is the output, L is the labor input, and K is the capital input. A is a measure of the potential Hicks-neutral technological change. α and β capture the reaction of labor and capital to a technological shock. Finally, ρ has values between 0 and 1 ($0 < \rho < 1$). Taking into account that P is the price of output and W is the cost of labor, it is possible to find equation (2.10), which is the equation of profits(Π).

$$\Pi = \left(A[(\alpha L)^{\rho} + (\beta K)^{\rho}]^{\frac{1}{\rho}}\right) P - (WL) \qquad (2.11)$$

Maximizing the equation (2.11) leads to the following demand (in logarithm form).

$$\ln(L) = \ln(Y) - \sigma \ln\left(\frac{W}{P}\right) + (\sigma - 1)\ln(\alpha) \qquad (2.12)$$

where the elasticity of substitution between capital and labor is $\sigma = 1/(1-\rho)$. According to Bogliacino et al. (2012), the stochastic version of (2.12), augmented by including innovation for a panel of firms (i) over time (t) is[27]:

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r\&d_{i,t} + \beta_4 g_{i,t} + (\varepsilon_i + v_{i,t}) \qquad (2.13)$$

All the variables of the model are in logarithms, which makes it possible to interpret their coefficients as 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). It is important to mention that the last equation is proposed in the Bogliacino et al. work (2012, 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 (patents, new products and/or new processes).

According to Bogliacino et al. (2012), it is more appropriate to change the equation (2.13), which is a static specification, for a dynamic specification in order to take into account the dynamic of employment; see equation (2.14).

[27]See Van Reenen (1997) for a similar approach.

$$l_{i,t} = \propto l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r\&d_{i,t} + \beta_4 g_{i,t} + (\varepsilon_i + v_{i,t}) \qquad (2.14)$$

2.2.- Treatment of the endogeneity problem by the two main approaches

2.2.1. Endogeneity problem: a methodologic approach

When the models have to be estimated, the main goal is to address the endogeneity problem. In this section, a formalization of this problem from an econometric point of view is presented. Three possible explanations for the endogeneity problem are an unobserved or omitted variable, errors in variables, and simultaneity[28](Wooldridge, 2015). To reflect this problem in technical terms, the simple regression model can be written as:

$$y = \beta_0 + \beta_1 x + u \qquad (2.15)$$

The existence of correlation between X and U (the error term) would indicate the presence of an endogeneity problem that, if ignored, causes a bias and inconsistency of estimated parameters. When the exogeneity assumption is not accomplished, the instrumental variables method is one of the alternative suitable solutions. This method consists of the use of some additional information (the instrumental variable *z*) that satisfies the following properties. The *z* must not be correlated with u –$cov(z,u) = 0$– (the 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, "z" can be called an instrumental variable for x.

The exclusion restriction (Z is not related to Y) cannot be generally tested when the model is perfectly identified (it means the number of instruments is equal to the number of

[28]"Simultaneity" is a relation between two variables that happen 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 frequently find such mutual interdependent relationships.

explanatory endogenous variables). In other words, the exclusion restriction can only be tested if the number of instruments is higher than the number of explanatory endogenous variables (over-identification). In contrast, the inclusion restriction can be tested (given a random sample) by estimating a regression between x and z[29] (see equation 2.16). In the case where $\pi_1 \neq 0$, it is possible to affirm that the inclusion restriction (Z affects X) is achieved.

$$x = \pi_0 + \pi_1 z + v \qquad (2.16)$$

2.2.2.- Causes and treatment of the endogeneity problem in the two main models

In the case of Harrison's model, the endogeneity problem appears because of the structural specification. According to Harrison et al. (2014), in the specification of equation (9), the parameter β associated with the variable sales growth due to new products (g_2) is biased for two reasons. First, there is a problem of measurement (error in variables) in g_2. Second, there is a correlation of $y_2$with productivity shocks and because of its necessary replacement by g_2 for lack of firm-level price information. Moreover, there is another problem related to g_1. If there is a divergence between the prices of the firm and the industry, it will cause an identification problem. In other words, we would underestimate the displacement effect of process innovation. Harrison et al. (2014) assume that in the absence of firm-level price information, we can only identify an impact of process innovation on the employment net of (direct) compensating firm-level price variation[30]. Therefore, they use the introduction of the so-called instrumental variables in the regression

[29] In multiple models, this regression includes also all the other exogenous variables.
[30] For more information about these problems, see Harrison et al. (2008, 2014).

model as a solution to resolve the endogeneity problem[31]. More precisely, it is necessary to seek instruments for g_2.

It is not easy to find instrumental variables that satisfy the inclusion and exclusion requirement. Harrison et al. (2014) recommend some variables to be used as instruments. Their preferred instrument is "increased range of products," although they check robustness by trying other instruments, such as an increased market share, improved quality of products, clients as a source of information and others.[32]

Also, the model characterized as Type 2 (Bogliacino et al., 2012, 2014; Van Reenen, 1997) faces the endogeneity problem for several reasons. The first one is related to the endogeneity characteristic of the $l_{i,t-1}$. This variable is obviously correlated with the fixed effect ε_i. Therefore, Ordinary Least Squares (OLS) is a biased and an inconsistent estimator. Furthermore, OLS does not take into account the unobservable individual effects, which are likely correlated with the explanatory variables.

To solve the last problem, Bogliacino et al. (2012, 2014) proposed, first, to compute the within-group estimator using the fixed effects estimator. The second solution that the authors proposed is to take the first difference to equation 2.13.

$$\Delta l_{i,t} = \propto \Delta l_{i,t-1} + \beta_1 \Delta y_{i,t} + \beta_2 \Delta w_{i,t} + \beta_3 \Delta r\&d_{i,t} + \beta_4 \Delta g_{i,t} + \Delta v_{i,t} \qquad (2.17)$$

However, the specification of equation (2.17) still has the endogeneity problem because there is a correlation between $\Delta l_{i,t-1}$ and $\Delta v_{i,t}$. To deal with the endogeneity problem of $\Delta l_{i,t-1}$, the standard approach is the methodology proposed by Arellano & Bond (1991).

[31] This issue was discussed in Section 2.4.4.1.
[32] To see more details on the (dis)advantages of these instrumental variables, see the table of instrumental variables in the empirical studies (Chapter 2, Section 2.4.4).

The authors introduced the methodology called the First-Difference Generalized Method of Moments (GMM-DIF) as a suitable tool for dealing with the endogeneity of the lagged dependent variable. The instrumental variables of this methodology for the equations in differences are the lags of the levels of the endogenous independent variables. However, these instruments are likely weak instruments, so Blundell and Bond (1998) propose to extend this approach by using the so-called System Generalized Method of Moments (GMM-SYS). The idea is to have a system of equations composed by the equation in differences and by the equation in levels. The endogenous variables in the differenced equation is again instrumented using lags of the levels of the endogenous independent variables while the endogenous variable in the level equation is instrumented using the lags of the differences of the endogenous independent variables (Blundell & Bond, 1998). According to Bogliacino et al. (2012), developing the GMM-SYS estimator is more appropriate in the case of high persistency of the dependent variable.

However, the recent literature shows that when the number of individuals is low in the panel data, the GMM estimators are poor. Many of these studies that adopted methodology Type 2 present this characteristic. For this reason, some authors took the Least Square Dummy Variable Corrected (LSDVC) estimator as a solution to the problem of the low number of individuals. Bogliacino et al. (2012) state that this methodology is initialized by a dynamic panel estimate (in their case that provided by the GMM-SYS, given the high persistency of our dependent variable) and then relies on a recursive correction of the bias of the fixed effects estimator.

2.3.- Differences between the two types of models

The first and the most important difference is the type of variable to measure the innovation. The HJMP model uses the output innovation to measure the effects of innovation, which allows the disentangling of the effect of product innovation from the impact of process innovation. The HJMP model includes a variable for sales in terms of product innovation (sales growth due to new products) and a dummy variable on the introduction of only process innovation (yes or no).[33] On the other hand, the BVP models use an input indicator of innovation –the importance of this difference will be explained more broadly in the following paragraphs– conceptualizing the innovation by its input in terms of R&D efforts or expenditures.

The second difference is that in the original specification on the HJMP model, it is not necessary to include control variables, while in the BVPs, such variables are required to fulfill the assumptions to create a ceteris paribus situation in which the effects of innovation are isolated from other explanatory factors. The most frequently used control variables in model Type 2 are added value, real wage, and gross investment. However, as will be seen in the next sections, some studies, independent of the group, introduced alternative control variables.

The most important advantage of the innovation output models –Type 1– (based on new product and new process) is that such output variables measure the results of the innovation process and allow disentangling the effect from product versus process innovation. Moreover, as explained, several elements of the equation explain some of the effects

[33] 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 potential positive effects on labor demand.

reflected by the theoretical compensation mechanisms like the direct effects of product and process innovation. Finally, the innovation surveys such as CIS and PITEC give all the necessary information to apply this methodology easily (Dachs & Peters, 2014; Peters et al., 2017).

The disadvantage of the input model –Type 2– is the use of the innovation inputs, which makes it impossible to interpret the results in terms of the specific compensation mechanisms. They can only estimate the correlation between innovation and employment, and the effects are the net outcomes of the complex interactions of different forces on employment. One advantage of this methodology is that it represents all costs relating to the development of new products and services incurred during the year (Bogliacino et al., 2012).

Finally, there is a hotchpot of studies that do not show similarities with these two types of studies, in terms of methodology or variables used. They use several alternative variables and methodologies (not or barely used by mainstream models) to operationalize innovation, like the growth of R&D expenditures, capital investment in R&D, R&D expenditures by employment, patents, and organizational innovation. In fact, only a few studies include alternative variables to define innovation. As a last remark, it can be stated that the third group of a hotchpot of studies also includes several studies from before 2000 that do not correct the endogeneity problem.

2.4.- Comparison of the specific characteristics and the main results of the empirical studies

In the previous sections, an overview on the two main strands of methodological approaches was offered in order to analyze the employment effects of innovation and to address the endogeneity problem when estimating the models. In this section, a more practical approach is offered to compare some specific characteristics based on an inventory of a large number of aspects. After reflecting the differences in the data sets and contextual settings, some remarks on the methodological differences, the results obtained, and the use of control variables will be made. This section also includes a critical discussion on the use of instrumental variables and especially the theoretical justification and the (dis)advantages of the specific IV used in the studies.

The inventory of the 44 reviewed studies[34] is presented in a set of tables using the structure of the three types of studies mentioned. In other words, not only the totals for the 44 studies are offered but also the sub-samples by types of studies[35] in order to compare the differences observed for Type 1 (the HJMP-based models), Type 2 (the BVPs), and Type 3 (other models).

Moreover, it can be stated that the tables reflect, in the majority of occasions, the number of models that do not coincide with the number of studies. Most of the 44 studies not only offer one model but also estimate alternative models using different sub-samples. For instance, a study may estimate models for the total sample, for the manufacturing sector or for the services sector, for high-, medium-, and low-tech sectors, and so on. The tables pick up the results, not only for one estimation, but for all the estimations in each study.

[34]See in the appendix Table 2.1.a

[35]This part of the chapter is a product of research in the project "Efectos de la política tecnológica en el comportamiento innovador de las empresas y el empleo en México: una aproximación econométrica" (DGAPA, project PAPIIT IN2317) carried out by researchers of the Universidad Complutense de Madrid and the Universidad Nacional Autónoma de México. One of the tasks was the creation of an inventory of the existing studies on employment effects of innovation. The detailed data for each study (in Excel files) is available online http://ru.iiec.unam.mx/4530/. An earlier version of this review of this section is published as a working paper by Heijs, J., Arenas Díaz, G., & Vergara Reyes, D. M. (2019) "Impact of innovation on employment in quantitative terms: review of empirical literature based on microdata."

2.4.1.- Data sets and overall (economic) setting of the study

Table 2.1. reflects some of the basic characteristics of the samples used in the articles. As can be expected, the data sets used are very heterogeneous in terms of the country, model, data set, and the type of firm and the sector it belongs to. As mentioned, the structural model of HJMP –Type 1– uses employment growth (89 estimations) as the dependent variable while Bogliacino's models –Type 2– use employment in levels (21 estimations). In the case of the Type 3 model, 36% of the estimations apply employment growth and 34% employment in levels, while at other moments, alternative measures on employment are used.

In terms of countries, 110 estimations were made for developed countries while 42 estimations for developing countries. It might be because developed countries introduce more innovations than developed countries. In the case of Type 1, 52 estimations belong to developed countries, while 37 estimations correspond to developing countries. For Type 2, 20 estimations were made for developed countries and only one estimation for developing countries. Finally, there were 38 Type 3 estimates for developed countries and four for developing countries.

For type of data, 83 estimations were made using panel data while 69 were made using cross-section data. It is important to mention that the HJMP model –Type 1– was developed using cross-section data (54 estimations). However, the improvement of the innovation surveys led to applying it also using panel data (35 estimations). In the case of Type 2, there are no estimations using cross-section data, but 21 estimations were made with panel data. For Type 3, 15 studies were estimated with cross-section data, while 27 were made with panel data.

Table 2.1. Some selected characteristics of the groups

	Whole sample	Type 1	Type 2	Type 3
Total number of studies	44	17	8	19
Total number of estimations	152	89	21	42
Dependent Variable				
Growth Rate Employment	120 (100%)	89 (74%)	--	31 (26%)
Total Employment	32 (100%)	--	21 (66%)	11 (34%)
Countries				
Developed countries	110 (100%)	52 (47%)	20 (18%)	38 (35%)
Developing countries	42 (100%)	37 (88%)	1 (2%)	4 (10%)
Type of data				
Panel	83 (100%)	35 (42%)	21 (25%)	27 (33%)
Cross Section	69 (100%)	54 (78%)	--	15 (22%)
Sub-samples				
Total	35 (100%)	13 (37%)	8 (23%)	14 (40%)
Manufacturing Sector	35 (100%)	22 (63%)	2 (6%)	11 (31%)
Services Sector	22 (100%)	16 (73%)	2 (9%)	4 (18%)
High-Tech Sector	13 (100%)	4 (31%)	4 (31%)	5 (38%)
Medium-Tech Sector	2 (100%)	--	1 (50%)	1 (50%)
Low-Tech Sector	13 (100%)	4 (31%)	4 (31%)	5 (38%)
Methodologies				
OLS	13 (100%)	--	--	13 (100%)
2SLS	100 (100%)	83 (83%)	--	17 (17%)
FE	17 (100%)	4 (24%)	10 (59%)	3 (18%)
GMM	22 (100%)	2 (9%)	11 (50%)	9 (41%)

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).

Only a few sub-samples will be shown in this chapter[36]: the total, the manufacturing sector, the services sector, the high-tech sector, the medium-tech sector, and the low-tech sector. In the case of Type 1, 22 studies were estimated for the manufacturing sector, 16 for the services sector, four for the high-tech sector, and four for the low-tech sector. This is an interesting result because few studies have analyzed the effects of innovation on employment in different technological sectors such as high, medium, and low-tech sectors. Similar results were found for Types 2 and Type 3: manufacturing sector (2 and 11), services sector (2 and 4), high-tech sector (4 and 5), medium-tech sector (1 and 1), and low-tech sector (4 and 5), respectively.

Finally, Table 2.1. also reflects the methodologies used in the studies. For Type 1, there are no estimations with Ordinary Least Squares (OLS), 83 estimations were with two stages least squares (2SLS), 4 were estimated with fixed effects, and 2 were estimated with general method of moments (GMM). In the case of Type 2, there are no estimations with either OLS or 2SLS. The studies that belong to this group were estimated with FE (10 times) and GMM (11 times). For Type 3, OLS was used 13 times, 2SLS was used 17 times, FE and GMM were used 3 and 9 times, respectively. These results are according to the explanation of the methodology when the approaches try to fix the endogeneity problem. For instance, the studies that belong to group Type 1 apply 2SLS, while the studies of group Type 2 use GMM. Moreover, it can be stated that the third group of a hotchpot of

[36] The total sub-samples found in the different studies are~~,~~ Large Firms, Large Manufacturing Sector firm, Large Manufacturing firm Skilled , Large Manufacturing firm Unskilled, High-tech Sector, High-tech Sector skilled, High-tech Sector unskilled, Low-tech Sector, Low-tech Sector skilled, Low-tech Sector unskilled, Small Firm, Skilled, Manufacturing Sector, Small Manufacturing firm, Small Manufacturing firm skilled, Small Manufacturing firm unskilled, Medium-tech sector, Services sector, Total, Unskilled. In this chapter, we only present some of them, but they are taken into account once we sum up the results in the case of the "whole sample", Type 1, Type 2, and Type 3.

studies also includes several studies from before 2000 that do not correct the endogeneity problem.

2.4.2- The impact of innovation on employment

The results of innovation on employment will be presented in this part. The structure of this section is as follows. First, the results of the innovation of the Type 1 studies are shown. Second, the results of Type 2 studies are presented. Finally, the results of the estimation of group Type 3 are given. Each table of results has different categories (sub-samples): total, manufacture, services, high-tech, medium-tech, low-tech, developed countries, developing countries, OLS, 2SLS, FE, GMM.

Model Type 1 refers to the empirical model of HJMP, considering two innovation output variables (see Table 2.2.). The first one is sales growth due to new products, and the second one is only process innovation. However, other studies based on the HJMP model have been tested with new output-innovation variables, such as new products (dummy variable), process innovation (dummy variable), and organizational innovation (dummy variable). All these variables are available in the innovation surveys as dichotomic variables.

In the case of sales growth due to new products, the 89 estimations of Type 1 show a positive and significant effect on employment. Even in the case of creating specific sets of firms –the estimations for certain sub-samples– the positive effect of this variable is permanent. In other words, in each of the sub-samples, a positive effect for product innovation is obtained for sub-samples, for manufacturing and services sectors or for high- and low-tech sectors, and also for data of different types of countries, developed and developing. The majority of the estimations are made by 2SLS, but alternative econometric methodologies (FE and GMM) also confirm the positive effects of product innovation on employment. These are important findings because it suggests that product innovation has a strong and permanent labor-creating effect.

In the case of only process innovation –a dummy variable that defines whether the firm has introduced process innovation but not product innovation[37] – different results are found. The empirical model of HJMP expects a negative effect on employment for firms that have introduced only process innovation. Nevertheless, only 35 estimations confirmed such a labor-saving effect. For 20 estimations, the coefficients obtained were not statistically significant, and for 35 estimations, even a positive impact of doing "only process innovation" on employment was detected. In most of the cases, positive effects were found for studies that analyze developing countries (25). However, similar results are also found for some developed countries [38](seven) (Harrison et al., 2014). Accordingly, the empirical evidence about the effect of process innovation on employment is inconclusive.

Several alternative variables were used in order to analyze the labor effects of certain types of innovations and to test the robustness of the model, such as product innovation, process innovation, and organization. However, the number of Type 1 studies –only three– that use such variables is too small to draw clear conclusions. Most of them show some contradictory results. For example, the variable organizational innovation shows a positive effect on four occasions, a non-significant relationship three times, and a negative one 13 times (only in three studies). All these cases were applied for data sets for firms in developed countries.

[37] This is the way the model identifies the direct effect of process innovation on employment.
[38] The results include the names of all developed countries for which such effects are detected.

Table 2.2. Operationalization of the innovative level or attitude in order to measure its impact on employment and the results found: Type 1

Characteristics of the firm:	Type 1	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)		(+/ns/-)	(+/ns/-)	(+/ns/-)		(+/ns/-)	(+/ns/-)	(+/ns/-)
Innovative firm													
R&D + i expenditure	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Lag of R&D+i expenditure	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
R&D expenditure per employee	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Growth: R&D intensity	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
FBC expenditure for innovation	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Results of innovations:													
New products	**(1,0,0)**	**(1,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**--**	**(0,0,0)**	**(0,0,0)**	**(1,0,0)**	**--**	**(1,0,0)**	**(0,0,0)**	**(0,0,0)**
Only process innovation	**(32,20,35)**	**(3,1,9)**	**(6,7,8)**	**(3,11,1)**	**(1,1,2)**	**--**	**(2,0,2)**	**(7,20,23)**	**(25,0,12)**	**--**	**(28,20,33)**	**(2,0,2)**	**(2,0,0)**
Process innovation	**(0,1,1)**	**(0,0,0)**	**(0,0,1)**	**(0,1,0)**	**(0,0,0)**	**--**	**(0,0,0)**	**(0,1,1)**	**(0,0,0)**	**--**	**(0,1,1)**	**(0,0,0)**	**(0,0,0)**
Organization	**(4,3,13)**	**(1,0,3)**	**(1,0,1)**	**(1,3,0)**	**(0,0,1)**	**--**	**(0,0,1)**	**(4,3,13)**	**(0,0,0)**	**--**	**(2,2,12)**	**(2,0,0)**	**(0,1,1)**
Sales growth due to new products	**(89,0,0)**	**(13,0,0)**	**(22,0,0)**	**(16,0,0)**	**(4,0,0)**	**--**	**(4,0,0)**	**(52,0,0)**	**(37,0,0)**	**--**	**(83,0,0)**	**(4,0,0)**	**(2,0,0)**
Patents	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)

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

In summary, the Type 1 empirical studies detect a strong and positive effect of sales growth due to new products while there is not a general consensus about the effect of only process innovation on employment. The introduction of other variables does not affect the results of the main output-innovative variables.

The Type 2 studies use the methodology proposed by Van Reenen (1997) and adapted by Bogliacino et al. (2012, 2014). As mentioned, their models are based on the input-variables on innovation. In fact, the variable used is R&D expenditure, which they consider a proxy variable of innovation. However, it is not the only innovation variable. This model allows the simultaneous inclusion of other variables that reflect innovations like patents.

As can be seen in Table 2.3., the majority of the estimations found positive employment effects of R&D expenditure (17 times), while only three estimations showed statistically non-significant coefficients. These results also confirm the labor-creation effect of R&D expenditure as a proxy of product innovation. The positive effect is confirmed for several types of firms by analyzing the relationship by the sub-samples, manufacturing sector (twice) and service sector (twice), high-tech (four), medium-tech (once), and low-tech (twice) sectors.

Table 2.3. Operationalization of the innovative level or attitude in order to measure its impact on employment and the results found: Type 2

Characteristics of the firm:	Type 2	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)			(+/ns/-)	(+/ns/-)
Innovative effort:													
R&D + i expenditures	**(17,3,0)**	**(6,1,0)**	**(2,0,0)**	**(2,0,0)**	**(4,0,0)**	**(1,0,0)**	**(2,2,0)**	**(16,3,0)**	**(1,0,0)**	**--**	**--**	**(10,0,0)**	**(7,3,0)**
Lag of R&D+i expenditure	**(0,0,1)**	**(0,0,1)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,1)**	**(0,0,0)**	**--**	**--**	**(0,0,0)**	**(0,0,1)**
R&D expenditures per employee	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**--**	**--**	**(0,0,0)**	**(0,0,0)**
Growth: R&D intensity	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**(0,0,0)**	**--**	**--**	**(0,0,0)**	**(0,0,0)**
FBC expenditures for innovation	**(0,3,0)**	**(0,1,0)**	**(0,0,0)**	**(0,0,0)**	**(0,1,0)**	**(0,0,0)**	**(0,1,0)**	**(0,3,0)**	**(0,0,0)**	**--**	**--**	**(0,0,0)**	**(0,3,0)**
Results of innovations:													
New products	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	--	--	(0,0,0)	(1,0,0)
Only process innovation	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Process innovation	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	--	--	(0,0,0)	(1,0,0)
Organization	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Sales growth due to new products	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Patents	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	--	--	(0,0,0)	(1,0,0)

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

One study, Pellegrino et al., (2017), introduces gross fixed capital expenditure as a proxy variable of process innovation though the effect is non-significant. This variable was used in three different estimations for the total sample, for the high-tech sector, and for the low-tech sector. As can be seen in Table 2.3., two other variables are used in the original model elaborated by Van Reenen, J. (1997), and they are classified as results of innovation (new products and patents). The author found a positive effect of these variables. To conclude, the Type 2 studies reflect, in general, a positive effect of R&D expenditure on the firm level of employment.

The last group is Type 3, which includes a mix of different variables and methodologies that try to measure the effects of innovation on employment (see Table 2.4.). Beginning with the output-innovation variables, the majority of the estimations of the variables that capture the effect of product innovation are positive, for instance, sales growth due to new products (nine), new products (six), and patents (two). It confirms that even with other methodologies, there is a labor-creative effect of product innovation.

In line with Type 1 studies, the estimations of the effects of process innovation do not offer clear, conclusive results. Most models, 13 estimations, showed a positive labor effect. However, four estimations did not find any significant relationship, and other four estimations detected a negative effect on labor. Therefore, the empirical evidence does not always assure the labor-saving effect of process innovation. The majority of the estimations were for developed countries. The positive effect of product and process were detected 16 and 10 times, the non-significant effects of product and process innovation were detected four and three times, and the negative effects of product and process innovation were detected zero and four times.

Table 2.4. Operationalization of the innovative level or attitude in order to measure its impact on employment and the results found: Type 3

Characteristics of the firm:	Type 3	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Innovative effort:													
R&D + i expenditure	(1,6,4)	(1,1,0)	(0,2,1)	(0,0,0)	(0,1,2)	(0,0,0)	(0,2,1)	(1,6,4)	(0,0,0)	(1,0,0)	(0,5,4)	(0,0,0)	(0,1,0)
Lag of R&D+i expenditure	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
R&D expenditure per employee	(4,0,1)	(1,0,1)	(0,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(4,0,1)	(0,0,0)	(4,0,1)	(0,0,0)	(0,0,0)	(0,0,0)
Growth: R&D intensity	(2,1,1)	(1,0,1)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(0,1,0)	(2,1,1)	(0,0,0)	(0,0,1)	(0,0,0)	(2,1,0)	(0,0,0)
FBC expenditure for innovation	(0,1,2)	(0,1,2)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,1,2)	(0,0,0)	(0,1,2)	(0,0,0)	(0,0,0)	(0,0,0)
Results of innovations:													
New products	(6,4,0)	(2,1,0)	(1,0,0)	(1,0,0)	(0,1,0)	(0,1,0)	(0,1,0)	(6,0,0)	(0,4,0)	(5,0,0)	(0,0,0)	(0,0,0)	(1,4,0)
Only process innovation	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
Process innovation	(13,4,4)	(6,1,1)	(1,1,2)	(2,1,1)	(0,1,0)	(1,0,0)	(1,0,0)	(10,3,4)	(3,1,0)	(6,1,2)	(3,1,0)	(0,0,0)	(4,2,2)
Organization	(5,0,2)	(1,0,1)	(2,0,0)	(2,0,1)	(0,0,0)	(0,0,0)	(0,0,0)	(5,0,2)	(0,0,0)	(0,0,1)	(4,0,0)	(0,0,0)	(1,0,1)
Sales growth due to new products	(9,0,0)	(3,0,0)	(5,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(9,0,0)	(0,0,0)	(3,0,0)	(4,0,0)	(0,0,0)	(2,0,0)
Patents	(2,2,0)	(1,1,0)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(0,1,0)	(2,2,0)	(0,0,0)	(0,0,0)	(0,0,0)	(2,1,0)	(0,1,0)

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

Furthermore, the result of estimations of input-innovation variables are not clear, either. For instance, the estimations with R&D expenditures have different results (one is positive, six are non-significant, and four are negative). These negative and non-significant findings belong to the high- and low- tech sectors sub-samples. However, another variable called R&D expenditure per employee has a positive effect on employment (four times). Similar results are found for the growth variable: R&D intensity.

In summary, the Type 3 models suggest the positive effect of product innovation in the case of output-innovation variables, even in the case of input-innovative variables, and the estimations show a positive effect for R&D expenditure per employee (this is not the case for R&D expenditure). Again, there is not a consensus on the empirical estimations about the effects of process innovation on employment.

2.4.3.- The use of control variables to isolate the innovation effects from other determinants of employment

A large number of studies include additional variables that could affect innovation and employment. Some models like the Type 2 ones integrate such variables because it increases the precision of the estimations. In fact, most studies used a varied set of control variables that can affect employment at the firm-level. 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 original study of HJMP and most of the Type 1 models do not require the inclusion of control variables. In this case, such variables are not necessary because the model isolates the effect of innovation on employment with a structural equation, including the two variables mentioned (product and process innovation). However, several studies based on this model (see Table 2.5.) introduced some additional variables in order to analyze the effects of innovation in combination with the presence of such variables, or to analyze the effects of such variables controlled for the product and process innovations.

For example, an indicator of investment was used in two studies. Benavente & Lauterbach (2008) state this variable might be an important factor in determining productivity growth, and therefore a negative sign of this variable is expected. It is supposed that investment increases labor productivity, and this means fewer workers per output. This variable has been used in three estimations, and they confirmed the expected negative effect on employment (see Table 2.5.).

Another important factor that can affect employment growth might be the level of wages, used as a control variable in two studies (Aboal et al., 2015; Alvarez., 2011) that present estimations for developing countries, Uruguay and Chile. According to Aboal et al. (2015), the behavior of firms' managers and workers could also exacerbate or reduce the displacement effect and weaken or increase the compensation effects[39]. The wage is an indicator of this phenomenon. As can be seen in Table 2.5., the variable was used in six estimations and all of them reflected a negative effect on employment.

[39]For example, a firm's market power and workers' wage bargaining power could reduce the size of price reductions linked to cost savings from innovation and therefore weaken the positive employment effects of innovation (Aboal et al., 2015).

Table 2.5. Control variables: Type 1 models

Variables	Type 1	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Characteristics of the firm:													
Lag of employment	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Employment size	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Sales and added value size	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Investment	(0,0,3)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,0)	--	(0,0,0)	(0,0,2)	(0,0,1)	--	(0,0,3)	(0,0,0)	(0,0,0)
Wage level	(0,0,6)	(0,0,2)	(0,0,0)	(0,0,0)	(0,0,2)	--	(0,0,2)	(0,0,0)	(0,0,6)	--	(0,0,6)	(0,0,0)	(0,0,0)
Salary growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Foreign ownership	(10,3,19)	(3,0,3)	(3,0,2)	(0,1,2)	(1,1,1)	--	(1,1,1)	(3,3,12)	(7,0,7)	--	(10,3,19)	(0,0,0)	(0,0,0)
Located in the central region	(7,0,2)	(1,0,0)	(2,0,1)	(0,0,0)	(1,0,0)	--	(0,0,1)	(0,0,0)	(7,0,2)	--	(7,0,2)	(0,0,0)	(0,0,0)
Market and Firm Dynamics													
Export growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Sales growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Productivity growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(0,0,0)	(0,0,0)
Market dynamics (GDP, expanding/contracting market based on demand)	(8,0,4)	(2,0,2)	(0,0,0)	(0,0,0)	(0,0,0)	--	(0,0,0)	(8,0,4)	(0,0,0)	--	(8,0,4)	(0,0,0)	(0,0,0)
Dummy Variables						--				--			
Technological sector dummies	0	0	0	0	0	--	0	0	0	--	0	0	0
Sectors by productive activities	89	13	22	16	3	--	4	52	37	--	83	4	2
Time	35	7	6	4	2	--	3	23	12	--	31	4	0
Size	18	4	1	3	0	--	1	18	0	--	18	0	0
Country	24	4	4	6	0	--	1	24	0	--	18	4	2

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

The most used control variable is foreign ownership (22 times). This variable has been used in both developed and developing countries, testing for different sectors. Two main reasons can justify it. First, the studies that have used this variable assess the differentiated innovation effects on employment for the types of owners in developed countries (Dachs et al., 2016; Dachs & Peters, 2014; Peters et al., 2017). Second, in the case of developing countries, a substantial part of the overall investment in the production sector is executed by foreign firms. Therefore, the researchers that analyze the reality of such countries are interested in their role in employment growth (Aboal et al., 2015; Alvarez et al., 2011; Crespi & Tacsir, 2012). Anyhow, the empirical evidence of the role of this variable in employment is not conclusive. Some models show a positive impact (10), a few studies reflect a non-significant relationship (3), and most models obtained a negative effect (19). Therefore, extra analysis is required to determine how real the effect is and in what circumstances a positive or negative effect will be obtained.

Located in the central region is a variable used only in estimations that correspond to developing countries (Alvarez et al., 2011; Crespi & Tacsir, 2012). As for the inclusion of the foreign ownership variable, the authors of these articles do not give a theoretical reason for introducing the variable into the models. However, one possibility might be the importance of the location of firms in developing countries. The existence of potential spillovers is much more important in large urban and industrial areas than in peripheral regions because larger areas and cities may be a magnet of employment. The empirical evidence shows that the employment effects of location in central areas observed in most studies are positive (seven), although two studies found a negative effect. The last control variable detected in the Type 1 model is related to market dynamics, used only in one article (Peters et al., 2017). These authors created dummy variables for time in order to capture the dynamic of Gross Domestic Product (GDP) altered by the big crisis of 2008. One of the main goals of this article is to study the effects of innovation during the economic cycles of crisis and recovery. The study estimated a large number of models, offering seven estimations with a positive effect and four with a negative impact.

The studies that belong to the Type 2 group, based on Bogliacino et al. (2012), used the following control variables[40]: added value, wage level, and gross investment. In the case of added value (using sales as a proxy variable), a positive effect on employment is expected. Contrarily, a negative employment effect of wages, the price of labor, is expected. As already mentioned, gross investment, which in principle might embody a potential labor-saving technological change, is supposed to generate a negative employment effect. It is important to mention that such control variables are included basically in the studies carried out with data for developed countries and for only one study that analyzed a developing country (see Table 2.6.).

[40] For the way that such variables can be included, see equation 14.

Table 2.6. Control variables: Type 2 models

Variables	Type 2	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Characteristics of the firm:													
Lag of Employment	**(21,0,0)**	**(8,0,0)**	**(2,0,0)**	**(2,0,0)**	**(4,0,0)**	**(1,0,0)**	**(4,0,0)**	**(20,0,0)**	**(1,0,0)**	**--**	**--**	**(10,0,0)**	**(11,0,0)**
Employment size	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Sales and added value size	**(19,0,0)**	**(6,0,0)**	**(2,0,0)**	**(2,0,0)**	**(4,0,0)**	**(1,0,0)**	**(4,0,0)**	**(19,0,0)**	**(0,0,0)**	**--**	**--**	**(10,0,0)**	**(9,0,0)**
Investment	**(14,3,3)**	**(5,1,1)**	**(2,0,0)**	**(2,0,0)**	**(2,1,1)**	**(1,0,0)**	**(2,1,1)**	**(13,3,3)**	**(1,0,0)**	**--**	**--**	**(10,0,0)**	**(4,3,3)**
Wage level	**(0,3,18)**	**(0,1,7)**	**(0,0,2)**	**(0,0,2)**	**(0,1,3)**	**(0,1,0)**	**(0,0,4)**	**(0,3,17)**	**(0,0,1)**	**--**	**--**	**(0,0,10)**	**(0,3,8)**
Salary growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Foreign ownership	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Located in the central region	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Market and Firm Dynamics													
Export growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Sales growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Productivity growth	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Market dynamics (GDP, expanding/contracting market based on demand)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	--	--	(0,0,0)	(0,0,0)
Dummy variables										--	--		
Technological sector dummies	9	3	1	1	2	0	2	9	0	--	--	5	4
Sectors by productive activities	0	0	0	0	0	0	0	0	0	--	--	0	0
Time	16	7	1	1	3	1	3	15	1	--	--	5	11
Size	0	0	0	0	0	0	0	0	0	--	--	0	0
Country	10	3	1	1	2	1	2	10	0	--	--	5	5

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

The lag of employment does not have a direct theoretical interpretation, but it is necessary in order to fulfill the assumptions of the dynamic equation (independence) in order to capture the dynamic of innovation, as explained in Section 2.1.2. All estimations of the studies that used this variable show a positive effect (21 times). Also, the variable or proxy of the added value (sales), shows a positive relationship with employment for all the models using that indicator (19 times). This variable represents the output of the firms in the structural model. As a result, both indicators showed, for all the models, a positive impact on employment**.**

The effects of wages on employment are negative for the majority of the cases (18). However, some non-significant relationships were detected for seven models, six of which were sub-samples. However, the models that included gross investment as the control variable did not confirm the expected negative relationship. Fourteen of the 20 estimations showed a positive effect, and only three models detected a negative effect.

As mentioned, the studies that belong to the Type 3 models are very heterogeneous, using a variated mix of variables and methodologies. In this section, some aspects can be inferred to be related to variables used for this group of studies (see Table 2.7.). The variable "sales" can be related to several important economic shocks, such as overall growth cycles, access to new export markets, variation in wages and prices, and so on, although the microeconomic effects of the employment of each of these shocks at the firm-level is difficult to identify. Moreover, the firm sales are also used as an indicator to control the effects of innovation by 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 a variety of employment by head count. In fact, size controls for different aspects, the market power of firms, among others. It also considers 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).

Also, the variable "investment in capital" can be correlated with different situations or reasons. Three options can be inferred. A first option could be that firms broaden their capital stock as an answer to increasing demand for their "old products," buying similar machines. The second option is that firms buy new machines to 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[41]. A third option is that firms invest in new machines adapted to the production requirement of the new product innovation.

Another control variable frequently used is the costs of employment or its increase,[42] 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. Therefore, the expected effect of the wage level on employment is negative. 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 GDP growth are also used. It is supposed that the

[41]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.

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

growth of the GDP would imply a growing market, and such increasing demand implies a positive impact on employment. The rest of the control variables included in the models are used less frequently.

The majority of the variables that were discussed in the previous paragraphs follow the same pattern, showing a positive effect of added value (five times) of the level of investment (eight times). As for most other studies, a negative effect is found in the case of wage level (six times). In this case, the models that include an indicator of the firm size in terms of employment showed a confused and often contradictory result. It is expected to have a positive effect as was commented, but the estimations show a negative effect (eight times).

This group of studies also included three alternative control variables not used by other authors: one variable that reflects the dynamic of the market of the firms and its own dynamic, export behavior, and an indicator of productivity growth. These indicators are used in only a few studies, but their effect is positive in the majority of the estimations: once in the case of export growth, four times in the case of sales growth, and four times in the case of productivity growth.

Table 2.7. Control variables: Type 3 models

Variables	Type 3	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Signs	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)	(+/ns/-)
Characteristics of the firm:													
Lag of employment	(7,1,3)	(2,1,3)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)	(3,1,3)	(4,0,0)	(0,0,3)	(0,0,0)	(0,0,0)	(7,1,0)
Employment size	(1,0,8)	(0,0,3)	(0,0,1)	(0,0,3)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,8)	(0,0,0)	(1,0,4)	(0,0,4)	(0,0,0)	(0,0,0)
Sales and added value size	(5,0,0)	(3,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(1,0,0)	(5,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(3,0,0)	(1,0,0)
Investment	(8,3,1)	(2,1,0)	(2,0,1)	(1,0,0)	(2,0,0)	(0,1,0)	(1,1,0)	(7,0,1)	(1,3,0)	(2,0,0)	(0,0,0)	(3,0,0)	(3,3,1)
Wage level	(0,0,13)	(0,0,5)	(0,0,2)	(0,0,1)	(0,0,2)	(0,0,1)	(0,0,2)	(0,0,9)	(0,0,4)	(0,0,2)	(0,0,0)	(0,0,3)	(0,0,8)
Salary growth	(0,1,1)	(0,1,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,1,1)	(0,0,0)	(0,0,1)	(0,0,0)	(0,0,0)	(0,1,0)
Foreign ownership	(0,1,0)	(0,1,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,1,0)	(0,0,0)	(0,1,0)	(0,0,0)	(0,0,0)	(0,0,0)
Located in the central region	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
Market and Firm Dynamics													
Export growth	(1,1,0)	(1,1,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,0)	(0,0,0)	(1,1,0)	(0,0,0)	(0,0,0)	(0,0,0)
Sales growth	(4,0,0)	(1,0,0)	(1,0,0)	(2,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(4,0,0)	(0,0,0)	(0,0,0)	(4,0,0)	(0,0,0)	(0,0,0)
Productivity growth	(4,0,1)	(1,0,1)	(1,0,0)	(2,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(4,0,1)	(0,0,0)	(0,0,1)	(4,0,0)	(0,0,0)	(0,0,0)
Market dynamics (GDP, expanding/contracting market based on demand)	(3,1,2)	(3,1,2)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(3,1,2)	(0,0,0)	(3,0,2)	(0,0,0)	(0,0,0)	(0,1,0)
Dummy Variables													
Technological sector dummies	6	3	0	1	0	0	0	6	0	5	0	0	1
Sectors by productive activities	28	6	10	3	4	1	4	24	4	4	17	0	7
Time	23	7	5	0	5	1	5	19	4	4	9	3	7
Size	15	2	5	2	3	0	3	15	0	2	13	0	0
Country	8	3	2	3	0	0	0	8	0	2	4	0	2

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

2.4.4. The use of the instrumental variables in the relevant empirical studies

As mentioned, the endogeneity problem is the most important obstacle to analyzing the employment effects of innovation adequately. The Type 1 group overcomes this problem based on external instrumental variables (IVs). Therefore, explaining the reliability, correctness, advantages and drawbacks of the IVs used is fundamental for a good understanding of the empirical literature.

The instrumental variables observed in the reviewed studies of Type 1 can be grouped basically into four categories (see Table 2.8.). The first and most used 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 is formed by variables that reflect the 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 55 estimations) is the importance of an increase in the range of goods and services. 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)[43]. The same argument is used for the case of the importance of improved quality (used 29 times) and of increased market share (used 21 times).

[43]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.

Table 2.8. The instrumental variables used: Type 1

Variables	Type 1	Total	Manufacturing	Services	High-Tech	Medium-Tech	Low-Tech	Developed Countries	Developing Countries	OLS	2SLS	FE	GMM
Motives and sources													
Motives: Increased range (goods and services)	55	8	16	13	2	--	2	42	13	--	55	--	0
Motives: Improved quality	29	1	10	8	1	--	1	19	10	--	29	--	0
Motives: Increased market share	21	1	10	10	0	--	0	21	0	--	21	--	0
Sources: New inputs utilization as an origin of the innovative idea. [a]	1	1	0	0	0	--	0	0	1	--	1	--	0
Sources: Scientific and technological opportunities [b]	3	0	2	1	0	--	0	3	0	--	2	--	1
Sources: Clients as a source of information	21	0	11	10	0	--	0	20	1	--	21	--	0
Sources: Cooperation	16	4	0	2	1	--	1	16	0	--	16	--	0
Effort													
Innovation intensity (R&D expenditure or Innovation/Sales)	41	10	13	10	0	--	0	41	0	--	40	--	1
Lag of innovation intensity	20	4	8	8	0	--	0	20	0	--	20	--	0
R&D expenditure	4	4	0	0	0	--	0	4	0	--	4	--	0
Continuous R & D engagement [c]	21	0	10	11	0	--	0	21	0	--	20	--	1
Results													
Innovation new to the market [d]	2	0	1	1	0	--	0	2	0	--	0	--	2
Patents	4	0	2	2	0	--	0	4	0	--	2	--	2
Others													
Firm knowledge of public support for innovation activities [e]	19	0	2	0	1	--	1	0	19	--	19	--	0
Increase in productive capacity[f]	4	0	1	0	0	--	0	0	4	--	4	--	0
Product life cycle dummies[g]	10	0	0	0	1	--	1	0	10	--	10	--	0
Obstacles to innovation averaged across firms in the same region	5	1	1	0	1	--	1	0	5	--	5	--	0
New markets[h]	7	1	1	0	1	--	1	0	7	--	7	--	0

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 whether 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 was 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.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 t 1 if the firm has cooperated in innovation projects with other agents like suppliers, research institutions and competitor.

The authors justify the use of the other instrumental variables based on the motives and sources of innovation[26] assuming the same hypothesis as the importance of increase of the range of goods and services. As mentioned in section 2.2, the validity test used by the models with instrumental variables can only be applied if the model includes at least two different instrumental variables (because of the fact that there is a single endogenous regressor). Therefore, additional instruments were used in combination with the first one – the importance of an increase of the range of goods and services– in order to apply the validity test.

The IVs based on the intensity of R&D efforts (R&D or innovation expenditures/sales) are the most utilized (41 times, 20 of which in terms of a lagged value). The authors of group Type 1 that use this variable 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). Also, the Continuous R&D engagement[44] variable (used in 21 estimations) 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).

Some additional instrumental variables were used in only a few studies –for models based on data about Latin American countries– and include the firm's knowledge of public support for innovation activities (19),[45] increase in productive capacity (4), dummies for the life cycle of the product (10), importance of obstacles to innovation averaged across firms in the same region (5) and the use of new inputs as an origin of the innovative idea (7). Other IVs were applied in some studies for developed countries: cooperation (16), scientific

[44]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).
[45] Number of firms that use each aforementioned instrumental variable is in parentheses.

and technological opportunities as a source of innovation (3), innovation new to the market (2) and patents (4).

2.5.- Conclusions

In this section, we offer the facts and the limitations of the empirical evidence, highlighting the most important aspects and empirical findings in order to understand the methodologies used and to explain the limitations and advantages which are relevant for the design of the two empirical analyses presented in the following two chapters of this Ph.D. thesis. Taking into account that the empirical analysis of this Ph.D. thesis is based on the Type 1 model of Harrison et al. (2014), some extra attention will be given to the methodological implications and bottlenecks of this model, as already discussed in the chapter.

2.5.1. A synthesis of the facts and limitations of the empirical evidence

In this chapter, an empirical review has been made for all the articles that analyzed the effects of innovation on employment at the firm level (44). The majority of the studies that were reviewed apply one of the two main methodologies, the HJMP models (Type 1) and the BVP model (Type 2). The first one uses output variables of the innovation process – sales growth due to new products and only process innovation– while the second one uses an input variable, R&D expenditure as a proxy of product innovation. The rest of the articles used a heterogeneous mix of variables and methodologies and have been classified in a third kind of hotchpot group (Type 3 models).

The main concern the empirical models that analyze employment effects of innovation face is the well-known endogeneity problem. In the case of the group Type 1, HJMP model specific instrumental variables (IV) are used as a solution to the problem. The challenge is to find a specific variable that fulfills the assumptions from a theoretical point of view (the theoretical arguments justifies its use) and simultaneously passes the econometric tests for the exclusion and inclusion requirement. As can be seen in Section 2.4.4, the instrumental variable used most in the HJMP model is the importance of the increased range goods and products as a motive for innovation, while the other IVs of this type of model are included in order to permit the econometrics help test the reliability of the IV method used. The Type 2 model uses the lagged values of the endogenous explanatory variable as instruments for the equation in differences, following the Arellano-Bond approach, or a System-GMM, following the Blundell-Bond approach.

In relation to the empirical evidence or the results observed in the 44 studies reviewed, it can be stated that, in general, a positive impact of product innovation and of R&D expenditures on employment was found. The Type 1 models showed a strong and positive effect of sales growth due to new products, and this relationship is proved to be very robust and also confirmed for different sub-samples and different types of countries. The results of input-based models of group Type 2 also show a positive effect of R&D expenditures on employment.

The empirical studies do not reflect a consensus about the effects of process innovation on employment. The HJMP models used the variable "only" process innovation, and the empirical evidence of its effects on employment is rather inconclusive. The number of estimations that show a positive or negative effect is very similar (35 versus 32 models), and another 20 studies showed a non-significant effect of process innovation on employment. These results could be related to the specific types of countries, time span, product cycle, or sectors that were analyzed. If the most successful firms are the ones that invest most in process innovation, there might be a positive impact on employment. However, if the process innovation is based on a defensive strategy to maintain market shares and is embedded in a cost reduction, process negative employment effects can be expected. For a better understanding of such differences, a meta-analysis would be required. However, such a model is out of the scope of this study.

Finally, as is mentioned in 2.3, several advantages of the HJMP model in detriment of the BVP models can be mentioned. Maybe one of the most important advantages of the HJMP model is its output orientation, which allows us to disentangle the effect of product innovation from the effect of process innovation. The percentage of sales related to new products used in this model measure the real importance of the innovations obtained for the firm's sales. In other words, the commercialization of new products is directly related to demand of employment, which measures the relationship that does not require lagged data because both phenomena happen in the same time span. A second advantage of the use of the HJMP model is its direct interpretation in terms of theoretical concepts, as highlighted by Dachs & Peters (2014) and Peters et al. (2017). As mentioned, some elements of the equation of the model can be interpreted directly in terms of the compensation mechanisms (at least the direct effects of product and process innovation).

Finally, access to innovation surveys (in the case of the PITEC) which capture the main innovation concepts and their direct relation to employment trends is easy. The main disadvantage of the Type 2 input model is that it cannot measure any compensation mechanisms. It can only estimate correlation, which is the net outcome of the complex interaction of different forces on employment, as stated by Calvino & Virgillito (2018).

2.5.2. New research lines and final remarks

Based on the review of the literature and the advantages and drawbacks of both models that will be applied in this Ph.D. thesis, we present some novel extension of the basic HJMP models which will be explained in this subsection.

The first limitation is that only a few studies analyzed the impact of innovation for different types of workers, skilled and unskilled workers. Only some developing countries have studied this relationship. Four studies[46] offer an estimation of the differences of the effect of innovation on skilled and unskilled workers, they all cover countries from Latin America, and their results offer a confusing panorama and some quite different and even contradictory differences.[47] These problems should be considered for future studies. For example, nowadays, there are data available to prove the effect of innovation on labor composition in developed countries. A second important limitation is the analysis of innovation effects on employment in the economic downturn cycle; only one study carried out such an analysis, Peters et al., 2017. This type of analysis could be interesting in order to identify whether the relation between innovation and employment changes if the economy faces periods of growth or recession. For instance, it could be possible that during a crisis period, the negative employment effect of innovation on unskilled workers is amplified while skilled workers maintains their jobs. Therefore, the main novelty is the combination of the two topics in one estimation, that is, the combination of the down cycle employment effects by type of worker. Chapter 3 offers an analysis of the specific effects

[46] Elejalde et al. (2015), Aboal et al. (2015), Alvarez et al. (2011) and Crespi and Tacsir (2012).

[47] For a more in-depth review of concepts and results of the studies mentioned in this paragraph, see Chapter 3.

on employment by level of skills in a specific time of the economic cycle –a period of crisis – in order to shed some light on these aspects in the case of a developed country.

On the other hand, 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 limited in the sense that they only pay attention to the direct micro effects within each of the innovative firms and do not consider the possible effects on other firms or on the global macroeconomic international labor market. In other words, the models reflect 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 than non-innovative firms. 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 that the creation of innovation-led new employment in a certain firm may implicate job destruction in others, because it could be obtained at the expense of direct or indirect competitors, providers or customers. Therefore, as mentioned by Greenan & Guellec (2000), the positive effects of a firm may disappear if these effects are taken into account. Anyhow, it seems that at this moment, no reliable data and/or econometric instruments exist in order to do such an overall macroeconomic analysis.

The study of this Ph.D. thesis tries to shed some light on this subject. In Chapter 4, the micro-level analysis will be extended to take into account the upstream, downstream, and same intra-industry employment effects of product innovation. The analysis will use the inter-sectoral flows of goods and services (based on the national input-output (IO) matrix) adjusted by the level of sales of new products in each industry. We believe that such an approach is an important step forward in terms of addressing the limitations of previous empirical analyses.

Annexes

Table 2.1.a Name of the authors that were analyzed for the empirical review

TYPE	Authors
1	(Aboal et al., 2015)
1	(Alvarez et al., 2011)
1	(Benavente & Lauterbach, 2008)
1	(Crespi & Tacsir, 2012)
1	(Peters et al., 2014)
1	(Dachs et al., 2016)
1	(Damijan et al., 2014)
1	(de Elejalde et al., 2015)
1	(Fioravante & Maldonado, 2008)
1	(Hall et al., 2008)
1	(Harrison et al., 2008)
1	(Harrison et al., 2014)
1	(Jaumandreu, 2003)
1	(Leitner et al., 2011)
1	(Peters, 2005)
1	(Peters et al., 2017)
1	(Rojas Pizarro, 2013)
2	(Bogliacino & Vivarelli, 2012)
2	(Bogliacino et al., 2012)
2	(Bogliacino et al., 2014)
2	(Pellegrino et al., 2017)
2	(Piva & Vivarelli, 2005)
2	(Piva & Vivarelli, 2018)
2	(Van Reenen, 1997)
2	(Yu et al., 2015)
3	(Alonso-Borrego & Collado, 2002)
3	(Blanchflower & Burgess, 1998)
3	(Bogliacino & Pianta, 2010)
3	(Brouwer et al., 1993)
3	(Evangelista & Savona, 2003)
3	(Evangelista & Vezzani, 2012)
3	(Falk & Hagsten, 2018)
3	(Garcia et al., 2004)
3	(Greenan & Guellec, 2000)
3	(Greenhalgh et al., 1999)
3	(Heijs et al., 2016)
3	(Klette & Førre, 1998)
3	(Lachenmaier & Rottmann, 2011)
3	(Mairesse et al. 2014)
3	(Matuzeviciute et al., 2017)
3	(Meriküll, 2010)
3	(Lucchese & Pianta, 2012)
3	(Smolny, 1998)
3	(Vivarelli et al., 1996)

Chapter 3. The Effect of Innovation on Skilled and Unskilled Workers during Bad Times

Introduction[48]

Based on the literature review in Chapter 2, an empirical analysis for the Spanish situation during bad economic times is developed. The analysis focuses on the impact of product and process innovation on different types of workers –high- and low-skilled employment – using the oriented model by Harrison et al. (2014). The motive for this approach is to shed some light on the answer to two of the three research questions of this Ph.D. thesis:

1. Does innovation have differential labor effects on workers with a low- or high-skill level?
2. Do differential labor effects of innovation exist during periods of turmoil?

Recent employment dynamics have clearly been influenced by the economic crisis, which destroyed more than 30 million jobs globally, while in Spain around 4.5 million jobs were lost between 2007 and 2013 (ILO, 2015). It seems that the crisis more intensely affected unskilled employment, taking into account that, at least in Spain, the total number of employees with a university degree remained more or less stable during this period. The main goal of this chapter is to analyze the effect of product and process innovation on high-skilled and low-skilled workers during bad times in order to explain the differentiated effect of product and process innovation on this relationship.

This chapter is embedded in three main approaches reflected in the theoretical and empirical literature. First, the general relationship between innovation and employment has

[48] This chapter has been published in a journal titled "Structural Change and Economic Dynamics" https://doi.org/10.1016/j.strueco.2019.09.012

already been discussed by classical authors like Ricardo and Marx, because the various labor-saving and labor-creating effects of product and process innovation have always been problematic from a social or economic point of view. The best-known early example of social turmoil related to this aspect is the Luddite movement of the early 19th century, when English textile artisans protested the mechanization of textile production by destroying some machines (Autor, 2015). Another important aspect is the effect of innovation on labor composition, which has been discussed since the 1960s, leading to the formulation of the skill-biased technological change (SBTC) and routine-biased technological change (RTBC) hypotheses that expect a shift of the demand of total employment toward more highly skilled workers and less routine tasks. Finally, we focus on a period of economic turmoil, and the relationship between innovation and the economic cycle has been controversial. While Schumpeter (1939) considered innovation activities to be countercyclical because of the lower opportunity cost of investments, recent empirical evidence usually shows a procyclical pattern (van Ophem et al., 2019).

The main contributions of our manuscript are the following. First, we analyze the specific effect of each type of innovation (product and process) on different types of workers (high-skilled and low-skilled). While product innovation has usually been found to have a positive effect on employment and the results for process innovation are mixed, no stylized knowledge has been built regarding their specific effect on different type of workers. Second, we focus on a period of economic turmoil where employment is being destroyed, while previous studies usually cover expansion periods characterized by employment creation. Third, we analyze whether the effects of product and process innovation on high-and low- skilled workers are pervasive across industries or whether there are some features specific to high- or low- tech industries.

To accomplish these goals, we use Spanish data from the "Panel de Innovación Tecnológica" (PITEC) on over 27,800 observations for manufacturing firms from 2006 to 2014 and make use of the structural model of Harrison et al. (2014), who analyze the differentiated effects of product and process innovation on employment.

The structure of this Chapter is as follows. In Section 3.1, we offer a very short overview of some of the compensation mechanisms that reduce the loss of employment because of the introduction of innovations and also discuss the causes of the growing demand of the different types of employment (see also Chapter 1). In Section 3.2, we show contextual evidence of the Spanish situation during this period and review previous empirical evidence on the relationship between innovation and employment in this context. In Section 3.3, we present a summary of the theoretical model of Harrison et al. (2008, 2014), its limitations and the specification of this empirical model. In Section 3.4 we review the main empirical works using this model. In Section 3.5 we offer details of the specification of the model and the database and present the basic statistics of the variables used. In Section 3.6 the estimations for the Spanish case are shown, offering the results for total employment, high-skilled employment and low-skilled employment. In the last section, it is presented some conclusions, the limitations of this work and some final remarks.

3.1.- Some basic notions of the effect of innovation on employment and the skill composition

One of the main theoretical debates of the effect of innovation on employment in quantitative terms is related to compensation mechanisms. Although process innovation has a direct negative effect on employment, there are some specific direct and indirect mechanisms that compensate the initial loss of employment. We offer only some short discussion about these mechanisms, highlighting relevant aspects for this paper.[49] The discussion of the compensation mechanisms clearly distinguishes between product innovation and process innovation. Table 3.1. relates the employment effects of each compensation mechanism with the two types of innovation. Theoretically, the direct effect of process innovations is an increase in innovators' production efficiency (*productivity effect of process innovation*) (Peters et al., 2017). It means that production requires less input to produce an item and, hence, process innovation is likely to reduce labor demand. However, the increased efficiency of production reduces costs and, consequently, a *price effect* that could stimulate overall demand of goods. The corresponding higher level of production could compensate the loss of employment with the creation of new jobs (Say's law)[50](Vivarelli, 2014).

For their part, product innovations may affect employment via three channels (Peters et al., 2017). The first is introducing new products in the market, which generates a new demand and therefore increases labor demand (*direct demand effect of product innovation*). Second, if new products are produced more (less) efficiently than old products, they will require less (more) input for a given output. This dampens (strengthens) the positive demand effect,

[49]For a broader discussion, see Calvino & Virgillito, 2018; Peters et al., 2017; and Vivarelli, 1995, 2014 .

[50] There are more compensation mechanisms related to process innovations, like the potential effects of increased benefits and wages, the reduction of general salary level versus labor intensive investments, and the employment effects in the machine and tools sector (see Chapter 1 for more detail).

thus also employment growth (*productivity effect of product innovation*). Third, there is an *indirect demand effect of product innovation*: if products are substitutive, new product demand may replace the demand for the innovators' old products to some degree (product cannibalization[51]). However, if new products are complementary to the old ones, the new product demand stimulates the old product demand.

Table 3.1. Effects of product and process innovation on employment at the firm level.

	Product Innovation	Process Innovation
Employment-reducing effects (displacement effects)	Indirect demand effect: Decrease in demand if the firm substitutes old products by new ones (cannibalization of old products) (−)	Productivity effect of process innovation: Less labor input for a given output (−)
Employment-ambiguous effects	Productivity effect of product innovation: New products require less (or more) labor input (−,+)	
Employment-creating effects (compensation effects)	Direct demand effect: New products increase overall demand (+) Indirect demand effect: Increase in demand of existing complementary products (+)	Price effect: Cost reduction passed on to the price expands demand (+)

Source: Own elaboration based on Dachs & Peters (2014) and Harrison et al. (2014)

Besides the overall effect of innovation on employment, this part tries to assess the quantitative and qualitative impact of innovation on skilled versus unskilled jobs. Therefore, it is important to discuss the reasons that could explain the increasing demand of skilled (or higher educated) labor in absolute terms.

Welch (1970) mentions three basic causes, firstly, the structural change in the composition of the production sector towards high-tech industries observed in the most advanced countries (see also section 1.3 of Chapter 1). Secondly, the increasing use of non-labor

[51] The reduction of the labor demand related to the old products.

input factors can generate –*ceteris paribus*– a positive bias towards the demand of skilled labor. Thirdly, technical change is not neutral between skill classes.[52] *"It may be that increments in technology result in increments in the relative productivity of labor that is positively related to skill level"*(Welch, 1970: P. 38).

In the case of analyzing the effect of innovation on employment in qualitative terms, an important notion is the skill-biased technological change (SBTC) hypothesis because the introduction of new technologies requires workers with new suitable capabilities and skills. However, there is no robust evidence yet on the differential effect of product and process innovation on the different types of workers. The following work aims to contribute in this regard.

Finally, this Chapter deals with a period of economic turmoil. There is some consensus that innovation efforts are procyclical (Archibugi et al., 2013; van Ophem et al., 2019) mainly because of low demand expectations during turmoil (Cohen, 2010) and internal and external financial constraints (Aghion et al., 2012; Himmelberg & Petersen, 1994). Regarding the type of innovation output, Lucchese & Pianta (2012) show that, during downswing periods, firms introduce more process innovation and less product innovation. Also, Peters et al. (2014) argue that the positive effect of product innovation on employment would be higher in upswing periods because of higher potential for demand expansion and extra-normal profits, while process innovation would destroy more employment during downswings, because in shrinking markets, firms would fully use the potential of new process technologies to cut labor costs. Regarding the relationship between skills and the economic cycle, Jaimovich & Siu (2018) highlight that in the last 30 years in

[52] However, even a strict neutral technological change would increase skilled labor demand more (Vivarelli, 2014; Welch, 1970).

the US labor market, almost all the contraction in aggregate employment during recessions can be attributed to job losses in middle-skilled, routine occupations followed by jobless recoveries (Groshen & Potter, 2003). In this same line, Foote & Ryan (2015) highlight the relationship between labor market polarization and non-participation, as middle-skilled workers find it hard to increase education to become high-skilled and would face large salary cuts if competing against low-skilled workers.

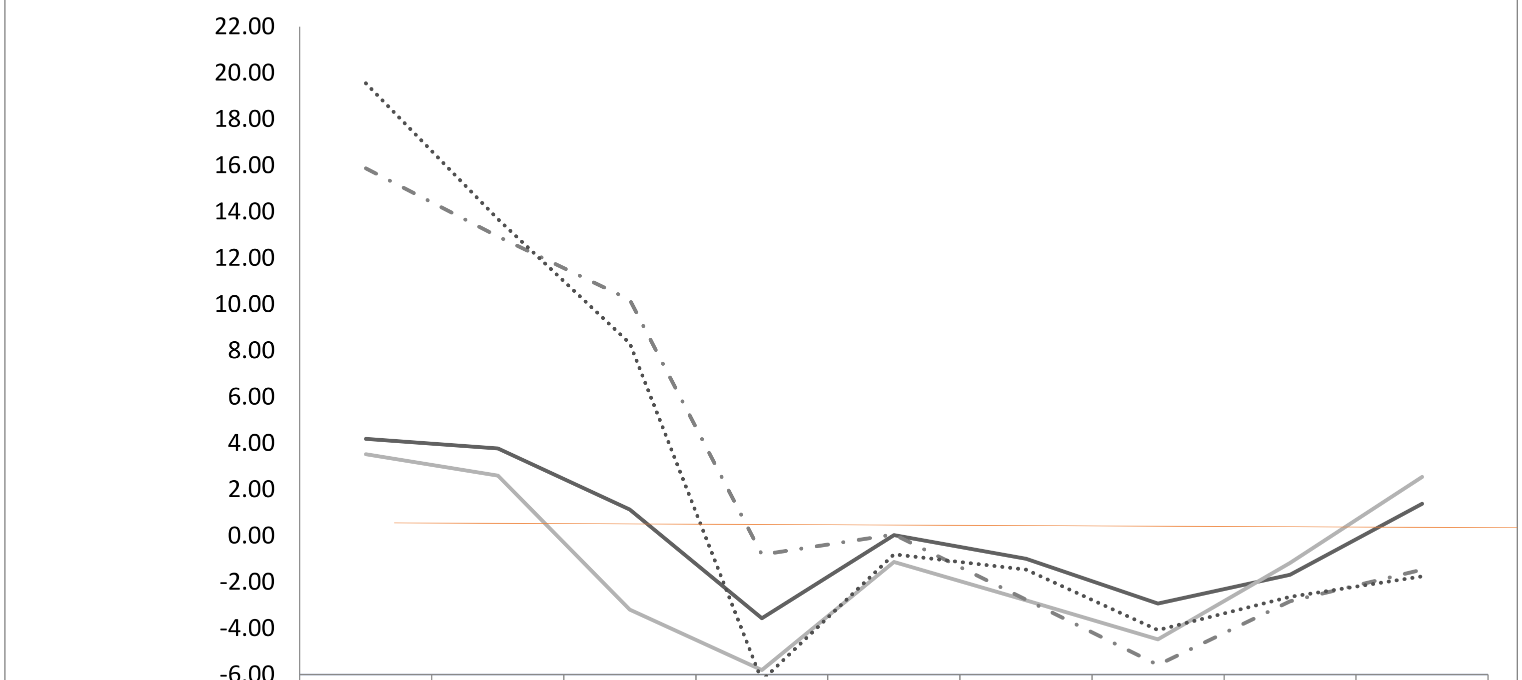
3.2.- The Spanish Case

Figure 3.1. shows the evolution of GDP, employment, GERD and BERD in Spain from 2006 to 2014. While in 2006 and 2007 all indicators grew considerably, employment started to decline in 2008 and did not recover positive rates of growth until 2014. The rest of the indicators started their negative growth in 2009, and GERD and BERD still showed negative growth rates in 2014.[53]The period covered by our analysis is characterized by a hard economic crisis.

The analysis of the relationship between innovation and employment in Spain has received some attention in recent years. Triguero et al. (2014) analyze data from the Spanish Survey of Business Strategies (ESEE) for the period 1990-2008 and conclude that process innovation shows a larger positive employment effect than product innovation, especially for SMEs. Bianchini & Pellegrino (2019) use the same database for a longer period (1991-2012) and find a positive effect of product innovation on employment but no evidence of an effect of process innovation. Harrison et al. (2014) use data from four European countries.

[53] In 2010, there was practically zero growth rate in GDP and GERD.

Figure 3.1. Growth rates of some selected indicators of the Spanish economic and innovative evolution



	2006	2007	2008	2009	2010	2011	2012	2013	2014
GDP	4.17	3.77	1.13	-3.57	0.02	-1.00	-2.93	-1.70	1.38
EMPLOYMENT	3.52	2.59	-3.20	-5.81	-1.14	-2.79	-4.48	-1.18	2.53
GERD	15.87	12.93	10.19	-0.81	0.05	-2.77	-5.59	-2.84	-1.47
BERD	19.55	13.67	8.31	-6.27	-0.81	-1.47	-4.08	-2.65	-1.77

Source: Own elaboration based on data from INE[54] and EUROSTAT

[54] National Statistics Institute (INE for its name in Spanish)

Data for Spain come from the Community Innovation Survey for the period 1998-2000. The results show a positive effect of product innovation and no effect of process innovation. Rojas (2013) uses data from the Spanish Panel of Technological Innovation for the period 2004-2010. He finds a positive and similar effect of both new-to-the- market and new-to-the-firm products and a negative effect of process innovation. Finally, Calvino (2019) uses data from the Spanish Panel of Technological Innovation (PITEC) for the period 2004-2012. He focuses not only on the average but on the entire distribution of employment growth. He concludes that product innovation shows a positive effect on employment, especially for fast- growing and shrinking firms. The results for process innovation are, however, mixed.

None of the previous studies distinguish the effect of innovation on bad times, nor do they distinguish between types of workers. Shedding light on these issues would be the main goal of this Chapter.

3.3. - The output-oriented model of innovation and employment

As was mentioned at the beginning of this section of the thesis, the methodology adopted in this part is the well-known Harrison et al. (2014) model developed in Chapter 2, using equation 2.8 (Section 2.1.1).

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \quad (3.1)$$

The parameter α_0 represents (minus) the average efficiency growth in production of the old product. The binary variable d picks up the additional effect of process innovations 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). Finally, the parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2014). Equation (3.1) is the function to estimate. It is expected that the efficiency of new processes increases more for innovative firms because of spillovers and other factors. In other words, according to Harrison et al. (2008, 2014) the ratio $(\Theta_{21}/\Theta_{22})$ determines the impact of product innovation on employment growth or relative efficiency in producing old and new products. The ratio is less than the unity if the new products are produced more efficiently than old products.

3.4.- Previous results based on this model

This section offers a short synthesis of the results obtained by studies that follow the model of Harrison et al. (2008, 2014). The results of the studies on developed and developing countries differ in a certain way and therefore they are presented in two different tables (Table 3.2. and Table 3.3.).[55]

Table 3.2. Empirical evidence related to micro level studies: The Effect of Innovation on Manufacturing Employment (European countries)

Study	Sample	Period	Country	Process Innovation Only	Sales growth due to new products	Const
Harrison et al., 2014;	Complete sample	1998-2000	France	-1.31	**0.98***	**-3.52***
		1998-2000	Germany	**-6.19***	**1.01***	**-6.95***
		1998-2000	Spain	2.46	**1.02***	**-6.11***
		1998-2000	United Kingdom	**-3.51***	**0.99***	**-6.30***
Rojas, 2013;		2004-2010	Spain	**-3.73***	**0.90***	**-5.44***
Hall et al., 2008;		1995-2003	Italy	**-1.22***	**0.95***	**-2.80***
Dachs et al., 2016;	High-tech	1998-2010	EU	-1.026	**0.99***	**-22.33***
Dachs et al., 2016;	Low-tech	1998-2010	EU	**-1.179***	**0.98***	**-21.03***

* means significant

The studies for European countries (Table 3.2.) usually show a negative effect of process innovation on employment,[56] a positive effect of product innovation with the coefficient around one (meaning that the production of new products is as efficient as the production of

[55] It is important to mention that the results which are captured in Tables 2 and 3 include for each study only one model, selecting the "best model" for the estimations with instrumental variables. For more detail about the rest of the studies, see Appendix Table3.1a. and the literature review of Chapter 1.

[56] The coefficient was negative for five of the eight models: in the other three models, the coefficient was not significant.

old products) and a negative constant, which means that the efficiency in the production of old products increases, thus leading to employment destruction without innovation.

The studies for Latin American countries (Table 3.3.) show very heterogeneous results. For example, the coefficients of process innovation vary broadly with values from -2.7 in Uruguay to 18.4 in Costa Rica (Crespi & Tacsir, 2012). Regarding product innovation, the effect is always positive, but the coefficient varies from 0.549 in Benavente & Lauterbach (2008) to 1.75 in Crespi & Tacsir (2012).[57] This huge heterogeneity might be due to the fact that there are other crucial forces behind employment dynamics in these countries, such as trade, or the location of multinationals.[58]

In the case of Europe, only one study (Dachs et al., 2016) offers additional analysis based on two subsamples of firms: those belonging to either low- or high-tech sectors. This study showed that process innovation has only a significant and negative impact on employment for low-tech sectors. The sales growth due to new products is significant and close to one and the constant is negative (significant) for both sectors.

[57]We eliminate the "constant" column because the majority of the studies on Latin America countries applied dummy variables to control for time and/or sectors. If a control dummy is introduced in the model, the interpretation of the constant changes completely. To assure the same interpretation of the constant, the dummy variables should have been introduced in a specific way so that their sum is zero.

[58] We thank one referee for highlighting this point.

Table 3.3. Empirical evidence related to micro level studies: The Effect of Innovation on Manufacturing Employment (Latin American countries)

Study	Sample	Period	Country	Process Innovation Only	Sales growth due to new products
Crespi & Tacsir, 2012;	All sample	1998-2001	Argentina	1.398	**1.17***
Crespi & Tacsir, 2012;		1995-2007	Chile	0.333	**1.751***
Crespi & Tacsir, 2012;		2006-2007	Costa Rica	**18.413***	**1.015***
Crespi & Tacsir, 2012;		1998-2009	Uruguay	**-2.716***	**0.961***
de Elejalde et al., 2015;		1998-2001	Argentina	1.252	**1.151***
Aboal et al., 2015;		1998-2009	Uruguay	**-2.610***	**0.964***
Alvarez et al., 2011;		1995-2007	Chile	0.297	**1.74***
Benavente & Lauterbach, 2008;		1998-2001	Chile	0.132	**0.549***
Fioravante & Maldonado, 2008;		2001-2003	Brazil	0.0012	**0.933***
de Elejalde et al., 2015;	High-tech	1998-2001	Argentina	3.767	**1.143***
Aboal et al., 2015;		1998-2009	Uruguay	**-2.721***	**0.962***
Alvarez et al., 2011;		1995-2007	Chile	0.028	**1.734***
de Elejalde et al., 2015;	Low-tech	1998-2001	Argentina	0.323	**1.145***
Aboal et al., 2015;		1998-2009	Uruguay	-2.498	**0.877***
Alvarez et al., 2011;		1995-2007	Chile	-0.551	**1.356***
Crespi & Tacsir, 2012;	All sample_skilled	1998-2001	Argentina	3.048	**1.308***
Crespi & Tacsir, 2012;		2006-2007	Costa Rica	2.448	**1.126***
Crespi & Tacsir, 2012;		1998-2009	Uruguay	10.465	**1.01***
de Elejalde et al., 2015;		1998-2001	Argentina	-1.125	**0.963***
Aboal et al., 2015;		1998-2009	Uruguay	2.379	**1.087***
Alvarez et al., 2011;		1995-2007	Chile	2.296	**1.81***
Crespi & Tacsir, 2012;	All sample_unskilled	1998-2001	Argentina	**26.26***	**1.02***
Crespi & Tacsir, 2012;		2006-2007	Costa Rica	2.379	**1.087***
Crespi & Tacsir, 2012;;		1998-2009	Uruguay	**-3.373***	**0.929***
de Elejalde et al., 2015;		1998-2001	Argentina	0.755	**0.952***
Aboal et al., 2015;		1998-2009	Uruguay	**-3.373***	**0.929***
Alvarez et al., 2011;;		1995-2007	Chile	-1.792	1.299
de Elejalde et al., 2015;	High-tech_skilled	1998-2001	Argentina	7.88	**1.327***
Aboal et al., 2015;;		1998-2009	Uruguay	13.813	**1.245***
Alvarez et al., 2011;		1995-2007	Chile	3.983	1.906
de Elejalde et al., 2015;	High-tech_unskilled	1998-2001	Argentina	8.171	**1.246***
Aboal et al., 2015;		1998-2009	Uruguay	-4.271	**0.898***
Alvarez et al., 2011;		1995-2007	Chile	-5.288	0.696
de Elejalde et al., 2015;	Low-tech_skilled	1998-2001	Argentina	1.564	**1.266***
Aboal et al., 2015;		1998-2009	Uruguay	-8.642	**0.892***
Alvarez et al., 2011;		1995-2007	Chile	-1.776	1.581
de Elejalde et al., 2015;	Low-tech_unskilled	1998-2001	Argentina	0.523	**1.143***
Aboal et al., 2015;		1998-2009	Uruguay	-6.127	**0.968***
Alvarez et al., 2011;		1995-2007	Chile	2.635	1.686

* means significant

Four studies offer some estimation of the differences of the effect of innovation on skilled and unskilled workers in Latin America. However, no clear picture emerges. In the case of process innovation, the estimations are rather imprecise.[59] In the case of sales growth due to new products, the coefficients, except for one, are positive and statistically significant. The results might somehow reflect a bias to high-skilled workers because the values of the coefficients are greater for high-skilled workers.

All in all, these few studies do not allow us to establish stylized facts regarding the differential effect of technological change in different industries or in labor composition. Again, other crucial forces might be behind high- and low-skilled employment dynamics, such as specialization trends within the globalizing economy, where a large number of low-skilled, routinized jobs are relocated to low-income countries like those in Latin America.

3.4.1 Meta-regression analysis

This section analyzes the coefficient's heterogeneity among the studies that have applied the Harrison et al. model. Using a meta-regression analysis, it is possible to capture the heterogeneity of the Harrison et al. model's principal coefficients: sales growth due to new products and only process innovation. To achieve this section's goal, we adapted the methodology proposed by Stanley & Doucouliagos (2012)[60]. A meta-regression involves analyzing the distribution of estimated coefficients and identifying elements that drive heterogeneity (Stanley, 2005; Stanley & Doucouliagos, 2012).

[59]Despite having positive and large coefficients for high-skilled workers, these coefficients are non-significant. On the other hand, the coefficient for unskilled workers is positive and very significant for Argentina, but negative and significant for Uruguay

[60] For more details about the methodology, see Stanley & Doucouliagos (2012). This section only presents the results of the estimations that captured the heterogeneity.

Table 3.4. shows the descriptive statistics of the variables that are used for the meta-regression. First, the average results of estimations of sales growth due to new products among the studies is 1.00. The minimum and maximum values of the variable are between 0.33 and 2.14, respectively. The standard deviation associated with the estimated coefficients has a mean of 0.13. These results suggest that all the studies that have applied the Harrison et al. model obtained a positive and significant effect of this variable. These results go in line with the discussion in Section 2.4.2 and with the theoretical approach explained in the previous section.

In the case of only process innovation, the average of this variable is negative (-0.37). However, there is a big dispersion with a standard deviation of 4.24. The minimum and maximum values are -7.32 and 26.26. These results suggest that the relationship between only process innovation and employment does not follow a clear pattern. Table 3.4. also shows the descriptive statistics of the possible variables that explain the heterogeneity of the relevant variables. The majority of them are dichotomic for which the table presents a short description.

Table 3.5. contains the results of meta-regression analysis estimates. The table has the following structure. The results of sales growth due to new products are from columns 1 to 4, while the results of only process innovation are from columns 4 to 8. Columns 1 and 6 only have the standard deviation associated with the estimated coefficients and sales growth due to new products and only process innovation only for each one. Columns 2 and 6 add variables that capture the characteristics of the studies: type of country (developing), data (panel), time (pre-crisis), and size of the sample. The characteristics of the samples are included in Columns 3 and 6.

In sales growth due to new products, the results suggest that only the coefficients of only process innovation affect sales growth due to new products on employment. A one-point increase in the coefficient of only process innovation is associated to an increase in the value of the coefficient of sales growth due to new products in 0.0070. In other words, in those settings where process innovation shows a larger (positive) effect on employment, the effect of product innovation on employment is also larger.

For only process innovation, the estimations' results suggest that the effect of process innovation is greater for developing than for developed countries. Then, the effect of process innovation is lower for manufacturing sectors than for service sectors, and also for small firms rather than for medium-sized and large firms. Finally, if the sample is bigger, the effect of only process innovation on employment tends to be higher.

The rest of the variables included in the model are not significant. It means that no other factors affect the results of the estimates of “only” process innovation on employment. However, there is no consensus about the effect of this variable empirically.

To sum up, the meta-regression analysis results suggest that there is not a variable that explains heterogeneity in sales growth due to new products. On the other hand, in the case of only process innovation, the heterogeneity behind the studies' results is explained by the type of country, the size of sample, the type of sector, and the sample.

Table 3.4. Description of the variables in meta-regression analysis

Variable	Obs	Mean	Std. Dev.	Min	Max	Description
Sales growth due to new products (g2)	179	1.00	0.25	0.33	2.14	The coefficients that capture the effect of sales growth due to new products on employment growth
Standard error of g2	179	0.13	0.19	0.02	1.21	The standard errors associated with the coefficients of g2
Only process innovation (d)	179	-0.37	4.24	-7.32	26.26	The coefficients that capture the effect of only process innovation on employment growth
Standard error of (d)	179	2.46	2.08	0.02	12.66	The standard errors associated with the coefficients of d
Developing countries	179	0.45	0.50	0	1	A dummy variable that takes value 1 if the study is for developing countries, 0 otherwise.
Cross Section	179	0.58	0.49	0	1	A dummy variable that takes value 1 if the study uses cross-section data, 0 otherwise.
Panel	179	0.42	0.49	0	1	A dummy variable that takes value 1 if the study uses panel data, 0 otherwise.
Pre-crisis	179	0.43	0.50	0	1	A dummy variable that takes value 1 if the study period is before 2008, 0 otherwise.
Log of size of sample	179	7.94	1.52	4.69	11.92	Logarithm of the number of observations
Manufacturing sector only	179	0.81	0.39	0	1	A dummy variable that takes value 1 if the study sample is the manufacturing sector, 0 otherwise.
High-tech sector only	179	0.10	0.30	0	1	A dummy variable that takes value 1 if the study sample is for the high-tech sector, 0 otherwise.
Low-tech sector only	179	0.10	0.30	0	1	A dummy variable that takes value 1 if the study sample is for the low-tech sector, 0 otherwise.
Large firm sample only	179	0.07	0.26	0	1	A dummy variable that takes value 1 if the study sample is for large firms, 0 otherwise.
Small firm sample only	179	0.15	0.36	0	1	A dummy variable that takes value 1 if the study sample is for small firms, 0 otherwise.

Table 3.5. Meta-regression for sales growth due to new products and only process innovation

Dependent variable	Sales growth due to new products			Only process innovation		
VARIABLES	1	2	3	4	5	6
Standard error of sales growth due to new products	0.9227***	0.8481***	0.8562***	--	--	--
	[0.039]	[0.098]	[0.108]	--	--	--
Standard error of only process innovation	--	--	--	0.1228***	0.1371***	0.1386***
	--	--	--	[0.013]	[0.011]	[0.010]
Only process Innovation	0.0085**	0.0087*	0.0089*	--	--	--
	[0.004]	[0.004]	[0.004]	--	--	--
Sales growth due to new products	--	--	--	0.7951	1.2238	1.5438
	--	--	--	[1.295]	[0.934]	[0.977]
Developing countries	--	-0.0549	-0.0539	--	2.3580**	2.8106**
	--	[0.066]	[0.064]	--	[1.104]	[1.018]
Panel	--	0.0997	0.1018	--	-1.0657	-1.0084
	--	[0.071]	[0.076]	--	[0.741]	[0.731]
Pre-crisis	--	0.0338	0.0395	--	1.2028	0.9856
	--	[0.074]	[0.077]	--	[0.949]	[0.912]
Log of size of the sample	--	-0.0276	-0.0250	--	0.9818***	0.9624***
	--	[0.020]	[0.020]	--	[0.324]	[0.296]
Manufacturing sector only	--	--	0.0270	--	--	-1.0782*
	--	--	[0.023]	--	--	[0.601]
High-tech sector only	--	--	0.0296	--	--	0.6387
	--	--	[0.044]	--	--	[0.898]
Low-tech sector only	--	--	-0.0566	--	--	-0.4372
	--	--	[0.061]	--	--	[0.461]
Large firm sample only	--	--	0.0624	--	--	-0.4454
	--	--	[0.064]	--	--	[1.640]
Small firm sample only	--	--	-0.0097	--	--	-1.6488*
	--	--	[0.046]	--	--	[0.800]
Constant	0.9503***	1.1786***	1.1572***	-2.4292	-10.9611***	-11.1349***
	[0.027]	[0.152]	[0.150]	[1.491]	[2.922]	[2.507]
Observations	179	179	179	179	179	179
R-squared	0.528	0.560	0.573	0.501	0.562	0.596

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1.
Standard errors clustered at the study level

3.5. - Methodological Framework of the application of the model for Spain

3.5.1.- Data base and specification of the model

In this section, we present the model of Harrison et al. (2008, 2014). The firm-level panel data set is based on the Spanish Innovation Survey –available online[61]– conducted by the Spanish Foundation of Science and Technology and the National Statistics Institute. We use the data of the so-called "Panel of Technological Innovation" (PITEC) for the time span of 2006 to 2014.

Similar to the model of Harrison et al. (2008), we classify the firms into five categories: non-innovators, only process innovators, product innovators, only product innovators, and a category that includes both (product and process innovators). Additionally, the PITEC data allows us to obtain the sales growth related to new and old products. Finally, the PITEC provides information on the percentage of workers with a university degree, which allows us to analyze the differential effect of innovation on workers with and without a degree (high-skilled vs low-skilled).

In order to interpret the results correctly, it should be highlighted that PITEC takes account of product and process innovations developed during the three previous years. For this reason, growth rates are estimated for a three-year period (t-3). Another important aspect is that, in order to have a more homogeneous data set, the analysis is only applied to manufacturing firms. We exclude service sector firms because the characteristics of innovation[62] are very different in this sector (Cainelli et al., 2005). The original model of

[61] https://icono.fecyt.es/pitec

[62] For example, in such sectors, it is often difficult to distinguish clearly between process and product innovation.

Harrison et al. uses cross-section data, while in our case, we work with panel data as other authors[63] did with other countries.

Table 3.2.a (in the appendix) describes the information of the sample (all the statistics come from the PITEC). The number of innovative firms represents more than 50 percent in the whole sample. It is clear from the data that we are dealing with a period characterized by an economic crisis: employment growth has been negative through all the three-year windows. This decrease is more remarkable in non-innovators than in innovating firms.

In terms of sales, the average growth taking into account the whole sample is -2.85 per cent. In the first three periods (2006-2009, 2007-2010 and 2008-2011), sales have a negative growth rate. Afterwards, the sales growth rate becomes positive. The sales growth rate due to old products (on average) has decreased 19.64 percent while the sales growth rate due to new products (on average) has increased 24.62 percent. An important aspect is that the sales growth rates due to old products are always negative and they are smaller than sales growth rates due to new products.

To summarize, Table 3.1a shows that employment growth is negative, but it is higher for innovative firms than for non-innovative firms. Even so, this effect is more intense in firms with product innovations than in firms with process innovations. Another important aspect is related to the sales of innovative firms. In the case of the demand for old products, they always decrease. However, the demand for new products increases.

[63]Aboal et al., 2015; Alvarez et al., 2011; Crespi & Tacsir, 2012; de Elejalde et al., 2015; Hall et al., 2008.

3.5.2.- Specification of the model: Instrumental variables

As we stated before, this Chapter is based on the Harrison et al. model. It is important to mention that the original work uses cross section data. In our case, we are going to work with panel data (thanks to the PITEC) as other authors did with other countries (Aboal et al., 2015; Alvarez et al., 2011; Crespi & Tacsir, 2012; de Elejalde et al., 2015; Hall et al., 2008). However, our model has to face specification problems, as does Harrison's.

Firstly, we do not directly have either y_1 or y_2. In the latter, we observe only the increase of sales. This variable may include the effect of different prices for both new and old products. In the former, we only have the nominal growth of old products. As we can see, both problems are related to unavailability of firm prices. To solve this problem, we will use the prices at the industrial level (π) to deflate the growth of sales due to old products (substitute g_1 for y_1). Furthermore, we will substitute g_2 for y_2 because we observe sales growth due to new products (Harrison et al., 2014). Taking into account these changes, we obtain equation (3.2):

$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i$(3.2)

Equation (3.2) still has several issues to be addressed. In the first place, β is biased because there is a problem of measure (error in variables) in g_2. This variable also included unanticipated shocks. Both problems mentioned earlier would create an endogeneity problem. To avoid this, we will seek instruments correlated with y_2, but not correlated with ε_i when we substitute g_2 for y_2.

Moreover, there is another problem related to g_1. If there is a divergence between the prices of the firm and the industry, it would cause an identification problem. In other words, we would underestimate the displacement effect of process innovation. We follow Harrison et al. (2014) assuming that in the absence of firm-level price information, we can only identify an effect of process innovation on employment net of (direct) compensating firm-level price variation.[64]

The solution to the problem is to apply the methodology of instrumental variables.[65]Harrison et al. (2014) recommend some variables to be used as instruments. Their preferred instrument is increased range of products, although they check robustness by trying other instruments, such as an increased market share, improved quality of products, clients as a source of information and others.[66]

There are two main theoretical reasons to support the use of increased range of products as an instrument. First, the degree by which product innovation is aimed to increase the range of products is likely to be correlated with planning (R&D, design, and marketing exploration) and the expectations of sales. Second, enlarging the range of products does not imply any particular direction of the changes in prices (increased market share is likely to be correlated with lower prices and improved quality with possibly higher prices). It also seems unlikely that the range of products is correlated with unanticipated productivity shocks (Harrison et al., 2014).

Also, the instruments must satisfy the inclusion and exclusion restrictions. The first refers to the relation between the endogenous variable and the instrument, which has to be significant ($cov(z_{i,}g_2) \neq 0$). The second postulate is associated with the relation of the instrument and the residual of the structural equation, which has to be zero ($cov(z_{i,}\varepsilon_i) =$

[64] For more information about these problems, see Harrison et al.(2008, 2014).
[65] This issue was discussed in Chapter 1, Section 2.1.
[66] To see more details, see the table of instrumental variables in the empirical studies (Chapter 2, section 2.5).

0). This means that there is no information in the instrument that would explain the structural equation.

3.6.- The empirical results for Spain

In this section, we present the results for the Spanish case, applying the following different methodologies in order to obtain robust estimations: ordinary least squares with panel data (OLS), OLS with instrumental variables (OLSIV), panel data models of fixed effects (FE) and random effects (RE),[67] and RE with instrumental variables (REIV). The instruments that are applied in our model are the importance of the increased range of goods and services as an objective and the importance of clients as a source of information. The first of these instruments was used by all the studies that applied the model of Harrison et al., (2008, 2014), while the second one was used less frequently.[68]

We will carry out three different analyses. First, we are going to replicate the original work of Harrison et al. (2014) but using panel data for Spain in a period affected by the crisis (2006 to 2014). Second, we will estimate the effect of innovation on different types of workers (separating high- and low-skilled employment). Using the variable that reflects the "percentage of paid staff with higher education," we calculate the number of high- and low-skilled workers for each firm. They are used as dependent variables to estimate the effect of innovation on the employment dynamics of each type of worker. Third, we estimate the

[67] The regression with fixed effects with instrumental variables looks too demanding for the data at hand, especially when estimating the effect of only process innovation (standard errors more than doubled compared with fixed effects estimation or IV estimation). This situation happens in all the estimations when fixed effects are used. For this reason, we are going to omit the results of fixed effects with instrumental variables for the next estimations.

[68] Like Dachs & Peters(2014); Harrison et al. (2008, 2014); and Peters et al.(2017). Moreover, for this paper, some other instruments were tested, like quality of goods and services as an objective and innovation effort (research and development expenditure over sales), but they did not satisfy the assumptions (exclusion and inclusion restrictions), especially the Sargan Test.

models earlier mentioned by sectors based on the R&D intensity of their firms.[69] We estimated additional models for four subsamples: high-tech, medium high-tech, medium low-tech, and low-tech, following the classification of the OECD.

3.6.1.- Global effect of innovation on employment

The results of the estimations of Equation 3.2 are presented in Table 3.6. The endogenous variable is the employment growth rate (l) minus the sales growth rate due to old products (g_1) and inflation (π) ($l - g_1 - \pi$). The independent variables are only process innovation (d) and sales growth rate due to new products (g_2). All the estimations include time and industry dummies. As in Harrison et al. (2014), the coefficients of time and sector dummies were restricted to add up to zero to maintain the interpretation of the constant term.

We present the estimations of OLS, FE and RE, although they suffer from measurement errors and include unanticipated shocks which might likely result in biased results. For this reason, we focus our discussion on the results of the estimations that include instrumental variables.[70] The results of the IV estimations[71] (iv^a and $reiv^a$) are in columns 2 and 6.

A first result is that the parameter of "only process innovation" (d) for both models (iv^a and $reiv^a$) has a negative sign (-0.0540 and -0.0440 respectively). This means an additional increase in productivity of old products, which generates an additional reduction on employment, in line with the results of previous studies.

[69]As did Aboal et al. (2015); Alvarez et al. (2011); Dachs et al. (2016); and de Elejalde et al. (2015).
[70]There is a difference between their instrument and ours. We took only the extreme values of the variable. To do it more clearly, we constructed a variable which takes only two values (1 or 4). If the value of the variable is 1, it is put in the new variable 1, but if the instrument is 4, the new variable is 0.
[71] In the case of IV estimations, the test of endogeneity is shown for all of them whose null hypothesis is exogeneity of the variable. In the case of our models, the null hypothesis is rejected, so it is possible to say that sales growth due to new products is an endogenous variable, as we assumed theoretically.

In our estimation (iv[a] and reiv[a]), the sign of g_2 –which measures the employment effect of product innovation– is positive in both models and offers very similar significant values smaller than one. As in Harrison Harrison et al. (2014), the magnitude of this coefficient is higher with IV estimations than with OLS or RE estimations. This is consistent with the expected correction of the downward bias related to the error-in-variable problem and includes an adjustment for unanticipated shocks.

In the structural model, the coefficient of g_2 reflects the ratio between the efficiency of the production of old and new products. If this coefficient –the sales growth rate due to new products– is less than one, it means that the efficiency of the production of new products is greater than the old ones. Our general model shows values below one (for iv[a]0.888, and for reiv[a] 0.895). In fact, when we apply an F-test for both models, the null hypothesis is rejected.[72] Therefore, there is evidence to state that new products are produced more efficiently than old ones.

Third, the constant term for both models (iv[a] and reiv[a]) is positive and has similar statistically significant values. This implies, within the theoretical and conceptual framework of the model, that the model detects a loss of efficiency of the production of old products. This decrease of productivity means that –*ceteris paribus*– the production process is more labor-intensive, requiring more employees. Most studies obtained, as expected by the theory, a negative coefficient for the constant term, indicating continuous productivity growth. The results obtained in this study seem to be specific to recession periods (Peters et al., 2017).

[72]The coefficient is less than one because the null hypothesis of the F-test is rejected, saying that g2 is equal to one.

Those authors explained this unexpected result by the existence of so-called ‘labor hoarding’. This concept means that in recession periods firms might reduce their staff by less than the number required by the reduction of demand (Bhaumik, 2011) with the aim of retaining workers for the following expansion period, because this may be a better choice than firing, hiring and training new workers after the recession has subsided (Biddle, 2014). In other words, labor hoarding is understood as the holding of workers that are not necessary for production during the recession period (Horning, 1994).

In order to provide some additional statistical evidence for the consistency and robustness of our results, we add a second instrument to our estimations: importance of clients as a source of information.[73] The estimations are in Table 3.6., in columns 3 and 7 (iv^b and $reiv^b$). The results are practically the same as those described previously with only one instrument (increased range). Regarding the exclusion restriction, the Sargan test reflects the validity of the instruments, and the inclusion restriction satisfies the requirements of the specifications.

To summarize, the effect of process innovation on employment is negative and the effect of sales growth due to new products is positive, with the magnitude of these two effects much in line with previous studies for Europe. The constant terms suggest the existence of labor hoarding during the period analyzed.

[73] The way to calculate this instrument is the same as increased range (taking only extreme values).

Table 3.6. The effects of innovation on employment of manufacturing (t-3)[74]

Dependent variable: l-g1-π							
Variables	ols(1)	iv[a](2)	iv[b](3)	fe(4)	re(5)	reiv[a](6)	reiv[a](7)
d	-0.0742***	-0.0540***	-0.0556***	-0.0552***	-0.0668***	-0.0440***	-0.0441***
	[0.00662]	[0.00956]	[0.00900]	[0.0105]	[0.00836]	[0.0124]	[0.0115]
g2	0.803***	0.888***	0.881***	0.780***	0.793***	0.895***	0.895***
	[0.00817]	[0.0285]	[0.0255]	[0.0139]	[0.0109]	[0.0391]	[0.0335]
cons	0.0847***	0.0686***	0.0673***	0.0824***	0.0872***	0.0639***	0.0599***
	[0.00295]	[0.00723]	[0.00655]	[0.00365]	[0.00396]	[0.00961]	[0.00849]
Tests of endogeneity		9.20	10.18			-3.090	-3.47
P-value		0.002	0.001			0.002	0.001
Test of Sargan		0.020	0.999			0.276	0.641
P-value		0.888	0.802			0.599	0.887
First-Stage		615.0	418.2			402.84	589.87
P-value		0.000	0.000			0.000	0.000
H0: g2=1	580.7	15.50	21.86	251.2	360.1	7.263	9.919
P-value	0.0000	0.0001	0.0000	0.0000	0.0000	0.00704	0.00164
N	27805	27805	27805	27805	27805	27805	27805
R-sq	0.412	0.409	0.409	0.341			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
a Instrument used is increased range
b Instruments used are increased range and clients as a source of information

[74] We have performed a robustness check, analyzing only firms that stay in the panel for the whole period. The results of the estimations are very similar for all the models (general employment, high- and low-skilled employment).

3.6.2.- Effect of innovation on employment by skill level

In the previous section, we show that the results of the Harrison et al. model using Spanish data agree with those obtained by previous literature. In what follows, we will address the main goal of this work: to analyze the effect of innovation on low-skilled and high-skilled workforces. As we mentioned before, we have at our disposal a variable that allows us to divide the total employment into two categories, high-skilled and low-skilled. We modify Harrison et al. model to obtain equations 3.3 and 3.4.

$$l^{hs} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i^{hs} \quad (3.3)$$

$$l^{ls} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i^{ls} \quad (3.4)$$

where l^{hs} is the high-skilled employment growth rate and l^{ls} is the low-skilled employment growth. That is, we do not analyze the evolution of the ratio of workers that pertain to a specific skill level (which is dependent on the evolution of the specific type of employment but also on the general evolution of employment), but rather the growth rates of the absolute number of high-skilled and low-skilled workers. As with the previous results for general employment, these estimations contain variables that control the difference between sectors and time (using dummy variables for each of these). Also, we estimate the model for high- and low-skilled with diverse methodologies (OLS, OLSIV, FE, RE, REIV).

Table 3.7. and Table 3.8. show the results of the effect of innovation on labor composition (high- and low- skilled workers). We focus the discussion on our preferred specifications from columns 6 and 7, where both random effects and instrumental variables are used. In the case of process innovation, a negative effect is found for low-skilled employment, which means a labor-saving effect for this kind of worker. By contrast, no effect of process

innovation on high-skilled employment is found. That is, the displacement effect of process innovation exists for low-skilled workers only.

The effect of sales growth due to new products is positive and significant for the employment growth for high- and low-skilled workers. It is important to mention that new products are less efficient in high-skilled than in low-skilled workers because the estimated coefficients are lower for low-skilled than for high-skilled employment. It means that there is no evidence found of labor displacement of product innovation for high-skilled workers.

In the case of low-skilled workers, this coefficient is less than one, so the efficiency production of new products is higher than old ones, resulting in less labor demand for low-skilled workers (see the F-test for all the estimations). In other words, new products are relatively more demanding of high-skilled workers and less demanding of low-skilled workers. The constant is significant and positive for both high- and low-skilled workers. However, the effect is greater for high-skilled workers than for low-skilled workers. It means that there is a stronger labor hoarding effect for high-skilled employment than for low-skilled employment during the period analyzed. In fact, Rinne & Zimmermann (2012) highlight that in German labor hoarding, it is especially important for high-skilled workers, as firms are afraid of a future shortage of skilled workers in the industries and regions most affected by the crisis.[75]

[75] In addition, high-skilled workers are usually costlier to fire and require larger investments in specific training.

Table 3.7. The Effects of Innovation on High-skilled Employment of Manufacturing (t-3)

Dependent variable: l-g1-π

Variables	ols(1)	iv[a](2)	iv[b](3)	fe(4)	re(5)	reiv[a](6)	reiv[a](7)
d	-0.0658***	-0.00373	-0.0207	-0.0561*	-0.0617**	0.016	-0.00704
	[0.0172]	[0.0269]	[0.0250]	[0.0256]	[0.0195]	[0.0318]	[0.0291]
g2	0.846***	1.092***	1.024***	0.801***	0.831***	1.151***	1.056***
	[0.0187]	[0.0841]	[0.0740]	[0.0273]	[0.0217]	[0.106]	[0.0909]
cons	0.207***	0.150***	0.164***	0.207***	0.190***	0.117***	0.135***
	[0.00744]	[0.0215]	[0.0192]	[0.00784]	[0.00897]	[0.0268]	[0.0234]
Tests of endogeneity		8.834	6.044			-3.120	3.630
P-value		0.003	0.014			0.002	0.000
Test of Sargan		0.120	3.719			0.141	3.676
P-value		0.728	0.293			0.708	0.299
First-Stage		409.491	276.208			296.730	441.150
P-value		0.000	0.000			0.000	0.000
H0: g2=1	67.79	1.190	0.108	53.12	60.94	2.031	0.384
P-value	0.0000	0.275	0.742	0.0000	0.0000	0.154	0.535
N	23093	23093	23093	23093	23093	23093	23093
R-sq	0.122	0.113	0.117	0.096			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001

d Process innovation only

g2 Sales growth due to new products

a Instrument used is increased range

b Instruments used are increased range and clients as a source of information

Table 3.8. The Effects of Innovation on Low-skilled Employment of Manufacturing (t-3)

Dependent variable: l-g1-π							
Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
d	-0.0729***	-0.0658***	-0.0619***	-0.0597***	-0.0682***	-0.0613***	-0.0532***
	[0.00798]	[0.0116]	[0.0110]	[0.0123]	[0.00981]	[0.0148]	[0.0122]
g2	0.828***	0.858***	0.874***	0.791***	0.813***	0.847***	0.882***
	[0.00998]	[0.0360]	[0.0321]	[0.0165]	[0.0128]	[0.0480]	[0.0386]
cons	0.0815***	0.0759***	0.0683***	0.0819***	0.0850***	0.0741***	0.0614***
	[0.00362]	[0.00897]	[0.00808]	[0.00430]	[0.00471]	[0.0117]	[0.00954]
Tests of endogeneity		0.727	0.929			-3.170	-3.630
P-value		0.394	0.818			0.002	0.000
Test of Sargan		0.009	0.929			0.027	2.310
P-value		0.923	0.818			0.870	0.511
First-Stage		602.473	409.129			396.570	581.560
P-value		0.000	0.000			0.000	0.000
H0: g2=1	296	15.46	15.31	161.4	211.5	10.14	9.293
P-value	0.000	0.000	0.000	0.000	0.000	0.001	0.002
N	27603	27603	27603	27603	27603	27603	27603
R-sq	0.331	0.331	0.33	0.265			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
a Instrument used is increased range
b Instruments used are increased range and clients as a source of information

To sum up, we find that process innovation destroys low-skilled employment but has no effect on high-skilled employment, while product innovation increases both types of employment, but it is relatively more demanding of high-skilled workers. Finally, a labor hoarding effect is found for both types of workers, but this effect is larger for high-skilled workers.

3.6.3.- Analysis by subsamples based on the R&D intensity of the sectors

Once we have assessed the impact of innovation (product and process innovation) on employment (general, high-skilled and low-skilled employment), it is important to know whether there is a differential effect at the sector level, the same as Dachs et al. (2016) (although the classification is different). As we mentioned earlier, the sample was divided into four categories, high-tech, medium high-tech, medium low-tech, and low-tech sectors (it is made based on the OCDE classification)[76].

To save space in Table 3.9., the results are reported only for instrumental variable estimations with random effects (increased range and clients as a source of information as instrumental variables[77]). For process innovation, no effect is found for high-skilled workers in any sector. It suggests that there is no evidence of labor displacement due to process innovation for high-skilled employment even in low-tech sectors. On the other hand, for low-skilled employment, a displacement effect of process innovation is found in all sectors, except in the high-tech sector. Similar results are achieved for the general model with the exception that for medium low-tech a non-significant effect is found.

[76] In this section, we estimated interaction models in order to evaluate the heterogeneity among sectors (see appendix Tables 3.3a, 3.4a, and 3.5a). The results suggest no differences among sectors. Then, we estimated sector by sector to analyze the effect of innovation on employment growth for general, high- and low-skilled workers.

[77] In the appendix, the rest of the estimations are presented (Tables 3.6a, 3.7a, and 3.8a).

Table 3.9. The Effects of Innovation on General, High-, and Low-skilled Employment of Manufacturing (Yt-3) by Sectors

Dependent variable: l-g1-π		Total employment	High-skilled workers	Low-skilled workers
Sector	Variables	reiv^b(1)	reiv^b(2)	reiv^b(3)
High-tech	d	-0.0201	0.18	-0.0795
		[0.0708]	[0.134]	[0.0977]
	g2	0.931***	1.396***	0.786**
		[0.191]	[0.364]	[0.270]
	cons	-0.0222	-0.0971	0.0789
		[0.0654]	[0.128]	[0.0950]
	H0: g2=1	0.130	1.187	0.631
	P-value	0.718	0.276	0.427
HighM-tech	d	-0.038	0.029	-0.0698*
		[0.0224]	[0.0535]	[0.0278]
	g2	0.907***	1.092***	0.870***
		[0.0540]	[0.139]	[0.0691]
	cons	0.0599***	0.140***	0.0698***
		[0.0160]	[0.0411]	[0.0200]
	H0: g2=1	2.979	0.437	3.532
	P-value	0.0843	0.509	0.0602
LowM-tech	d	-0.0527**	-0.0181	-0.0409
		[0.0197]	[0.0544]	[0.0224]
	g2	0.881***	1.149***	0.929***
		[0.0597]	[0.197]	[0.0700]
	cons	0.0701***	0.149***	0.0564***
		[0.0143]	[0.0435]	[0.0162]
	H0: g2=1	3.940	0.572	1.023
	P-value	0.0471	0.450	0.312
Low-tech	d	-0.0448*	-0.0523	-0.0452*
		[0.0184]	[0.0485]	[0.0214]
	g2	0.892***	0.906***	0.878***
		[0.0584]	[0.160]	[0.0701]
	cons	0.0594***	0.144***	0.0589***
		[0.0136]	[0.0394]	[0.0161]
	H0: g2=1	3.447	0.341	3.033
	P-value	0.0633	0.559	0.0816

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
b Instruments used are increased range and clients as a source of information

A positive and significant effect is found for sales growth due to new products for all sectors. The coefficient is bigger for high-skilled than for low-skilled in every industry, with the difference much higher in high-tech industries. Also, its value is more than one for high-skilled employment, meaning that new products do increase demand for high-skilled workers. In the general case, the value of sales growth due to new products is one (see F-test). There is no evidence that new products are produced more efficiently than the old ones at the sector level.

In the case of the constant, a positive (significant sign) is usually found, with values higher for high-skilled than for low-skilled workers. The only exception is for the high-tech industry, where both coefficients are not statistically different from zero. To sum up, these results show that the general relationships between innovation and different types of workers hold across industries. The differential effect of product innovation between high- and low-skilled workers is remarkably larger in high-tech industries.

3.6.4.- Employment Growth Decomposition

Estimating equation (3.2), it is possible to decompose employment growth into several components (Harrison et al., 2014) using Equation 3.4:

$$l = \sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji} + \hat{\alpha}_1 d + [1 - 1(g_2 > 0)](g_1 - \pi) + 1(g_2 > 0)(g_1 - \pi + \hat{\beta} g_2) + \hat{\varepsilon}_i \quad (3.4)$$

The first element computes the change of employment due to (industry specific) productivity trends in the production of old products $\sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji}$ [78]. The second element $\hat{\alpha}_1 d$ estimates the gross effect of process innovation on the growth of employment in the production of old products for firms innovating only in process). The third element $[1 - 1(g_2 > 0)](g_1 - \pi)$captures the employment changes related to sales growth due to old products if a firm has not introduced any product innovation (non-innovator or process innovator only). The fourth element $1(g_2 > 0)(g_1 - \pi + \hat{\beta} g_2) + \hat{\varepsilon}_i$ gives information about the employment growth associated with the net sales of new products (if a firm has introduced a new one). $\hat{\varepsilon}_i$is a zero-mean residual. Taking into account Equation (3.4), it is possible to

[78] For Dachs et al.(2016), $\hat{\alpha}_0$ may capture efficiency gains due to improvements in management practices, sales of unprofitable business units, training, improvements in human capital endowment or industrial relations, or productivity effects from spillovers.

discuss how the different effects contribute to the average employment growth in Equation (3.5):

$l = t + \hat{\alpha}_1 P_{PO} + P_{NI} g_{NI} + P_I g_I$(3.5)

The average employment growth is l. The weight average of the indsustrial specific trends is t. The sample proportions are $P_{PO}$of process innovator only,$P_{NI}$of non-product innovator and$P_I$of product innovator. $g_{NI}$is the average of rate of non-product innovator[79]and g_I is the average of rate of product innovator.[80]

In Table 3.10., the statistics related to equation 3.5 are presented. In this case, it is calculated for general, high- and low-skilled samples. Firstly, it is possible to see that the productivity trend has improved a little for all the samples (the impact is small; it is not bigger than 0.15). These results mean that during the period-analyzed, there has not been a big improvement in efficiency because productivity growth has been low in Spain. The gross effect of process innovation in old products has an additional negative impact on employment (-0.04), mainly for low-skilled workers (-0.05) and almost null for high-skilled workers. Negative sales growth of old products for non-product innovators due to less demand during the crises results in additional employment losses.

---

[79] $g_{NI} = \frac{1}{N_{NI}} \sum_{i \in NI} g_{1i}$

[80] $g_I = \frac{1}{N_I} \sum_{i \in I} (g_{1i} + \hat{\beta} g_{2i})$

Table 3.10. Unweighted Averages

	All sample	High-skilled	Low-skilled
Firm's employment growth	-6.03	8.09	-6.28
Productivity trend in production of old products	0.06	0.14	0.06
Gross effect of process innovation on old products	-0.04	-0.01	-0.05
Sales growth in old products for non- product innovators	-12.62	-12.62	-12.62
Non-innovators	-16.07	-16.07	-16.07
Process innovators only	-4.86	-4.86	-4.86
Net sales growth of product innovators (new prods.-subs.)	-10.75	-7.39	-11.02
Sales growth due to old products	-29.42	-29.42	-29.42
Sales growth due to new products	18.67	22.03	18.40

[a]Based on descriptives of Table 7 and regression IV (only with increased range as instrument)
[a]The period of all-sample is from 2007 to 2014. For high- and low-skilled, it is from 2009 to 2014

Another important aspect that can be checked is price-compensation. The condition is that the sales growth of non-innovators is smaller than the sales growth of process innovation only. In this case, although the sales growth is negative for non-product innovators (for all the samples), there is a price compensation mechanism because the sales increase of process innovators only (still negative in high- and low-skilled) is higher than the sales increase of non-innovators. Finally, product innovators also suffered from negative sales growth but to a lesser extent because of the increase of sales due to new products.

Table 3.11. Contribution to average growth of employment

	All-sample	High-skilled	Low-skilled
Firms' employment growth	-6.03	8.09	-6.28
Due to productivity trend in production of old products trend	5.59	17.93	5.48
Due to gross effect of process innovation on old products	-0.0065	-0.0010	-0.0078
Due to sales growth in old products for non-product innovators	-5.95	-5.95	-5.95
Due to non-innovators	-5.23	-5.23	-5.23
Due to process innovators only	-0.72	-0.72	-0.72
Due to net sales growth of product innovators (new prods-subs.)	-5.67	-3.90	-5.81
Due to sales growth due to old products	-15.51	-15.51	-15.51
Due to sales growth due to new products	9.84	11.61	9.70

[a]Based on descriptive of Table 7 and regression IV (only with increased range as instrument)
[a]The period of all-sample is from 2007 to 2014. For high- and low-skilled, it is from 2009 to 2014

Table 3.11. shows the components in terms of contribution to average growth of employment. The productivity trend in the production of old products has a positive effect, especially for high-skilled workers. As we commented in the interpretation of the constant, labor hoarding is detected when a recession period is presented, and this labor hoarding is especially important for high-skilled workers. These results differ from Harrison et al.

(2014), but they are similar to the findings of Dachs et al., (2016) when the authors analyzed the recession. Individual process innovations account for only a small displacement effect (because there are few process-only innovators), in line with previous studies. The (negative) sales growth of old products contributes to employment destruction while the effect of the sales growth of new products is quite similar to those found in expansion periods by previous studies, although it is not able to compensate the employment losses caused by the decrease of old product sales.

All in all, there is a difference of 14.37 points in employment growth between high- and low-skilled workers. 12.45 points are explained by the different productivity trend, which is greater in high-skilled than in low-skilled workers, and 1.91 points are explained by the different effect of new product sales on employment. These results suggest that innovation explains approximately 13.3 percent of the different evolution between high- and low-skilled employment for manufacturing firms in Spain during the period of economic turmoil. We do not know whether this result could be different in an expansion period as we do not have data to analyze it.[81]

3.7.- Conclusions

This Chapter sheds light on the effect of innovation on the Spanish manufacturing case from 2006 to 2014. The models fit in the empirical literature based on the model of Harrison et al., (2008, 2014), but this study introduces some novelties in relation to other studies for developed counties. First, the analysis covers a period with huge employment losses. Second, the existing studies for developed countries do not distinguish between

[81]Unfortunately, we are not able to perform such an analysis for 2004-2006. The reason is that the data for high- and low-skilled workers start in 2006.

different types of workers. It is addressed this limitation by calculating individual models for the labor demand for high- and low-skilled workers.

The descriptive data of the sample shows that the negative growth of employment during the crisis seemed to be less accentuated in innovative firms than in non-innovative ones, and that this positive effect of innovation is remarkably larger for high-skilled than for low-skilled workers. It seems that the crisis affected unskilled employment more intensely, taking into account that, at least in Spain, the total number of employees with a university degree remained more or less stable during this period.[82] The main results of the estimations confirm the conclusions of earlier studies, suggesting a positive general effect of innovation on the total employment of firms, even in a period of economic crisis. In addition, a labor hoarding effect is found for both types of workers, but this effect is larger for high-skilled workers, an atypical effect that seems to appear at the time of the crisis, as mentioned by Peters et al. (2017). Moreover, the models for the sector-based subsamples reflect that this result holds across different industries and the impact of product and process innovation is exacerbated in high-tech industries.

Process innovation seems to have a small effect on overall and high- and low-skilled employment. For the correct interpretation of the results, it should be stated, as discussed in section two, that introduction of process innovation can have different contradictory effects on mechanisms of compensation. On the one hand, it can generate a loss of employment

[82]Anyhow, the debate on this subject that could limit the generalization of our study is the increasing percentage of people –and therefore workers– that have university studies. This fact might imply an increase of the percentage of workers with a university degree independent of the kind of job they carry out. In fact, some firms require a bachelor's degree for jobs that in earlier times were done by workers with less education, especially if one compares the cohort of persons that are at the age of retirement with young people entering the labor market.

due to higher productivity but, at the same time, if such lower costs result in lower prices, total demand might increase, implying that the loss of employment would be eased.

Regarding the relationship between innovation and type of employment, the empirical data show that the product innovation is largely responsible of the skill-biased effect of innovation. Although product innovation positively affected both types of employment, the effect is much larger for high-skilled workers. It is estimated that product innovations account for around 13% of the different evolution between high-skilled and low-skilled employment during the crisis, while the role of process innovation was very limited. It is not possible to know whether this result is specific to a period of economic turmoil.

Observing the additional models for subsamples by sectors, it can be stated that the effect of product innovation on high-skilled employment is larger in high-tech industries and lower in low-tech industries (see also Peters et al., 2017). This would confirm the role of structural change in explaining the skill bias in labor demand, as mentioned by Welch, (1970).

Annexes

Box 3.1.a. Definitions and creations of the variables

Nominal increased rates for all the products:

$$\hat{g} \equiv \frac{(current\ sales\ old + current\ sales\ new) - past\ sales\ old}{past\ sales\ old}$$

Proportion of sales of new products:

$$s \equiv \frac{current\ sales\ new}{current\ sales\ old + current\ sales\ new}$$

Sales growth due to new products:

$$g_2 \equiv \frac{current\ sales\ new}{past\ sales\ old} = s(1 + \hat{g})$$

Nominal sales growth due to old products:

$$\widehat{g_1} \equiv \frac{current\ sales\ old - past\ sales\ old}{past\ sales\ old} = \hat{g} - g_2$$

Real sales growth for all products: $g \equiv \hat{g} - \pi$

Real sales growth due to old products: $g_1 \equiv \widehat{g_1} - \pi$

Table 3.1.a. Empirical evidence related to level studies: The Effect of Innovation on Employment (European countries)

Study	Sample	Country	Const	Process Innovation Only	Sales growth due to new products
Harrison et al., 2014;	MSa	France	-3.520	-1.310	0.980
	MSb	Germany	-6.950	-6.190	1.010
	MSc	Spain	-6.110	2.460	1.020
	MSd	United Kingdom	-6.300	-3.510	0.990
Peters et al., 2017;	Ta	EU	-64.522	-2.283	0.966
	Tb	EU	3.931	-0.698	0.96
	Tc	EU	-21.702	-2.08	0.98
	Td	EU	2.973	-0.359	0.98
Dachs et al., 2016;	MSa	EU	-22.334	-1.026	0.999
	MSb	EU	-21.032	-1.179	0.977
	MSaa	EU	-53.55	-2.813	0.995
	MSab	EU	-9.65	1.522	0.964
	MSac	EU	-20.328	-1.408	1.021
	MSad	EU	-0.632	0.568	0.993
	MSba	EU	-69.29	-1.613	0.972
	MSbb	EU	-39.935	-0.573	0.97
	MSbc	EU	-14.044	-1.921	0.997
	MSbd	EU	3.554	-0.634	0.955
Dachs et al., 2016;	MSa	EU	-14.062	-1.970	1.011
	MSb	EU	-14.020	-1.970	1.011
	MSc	EU	-14.015	-1.973	1.011
Rojas F., 2013;	MSa	Spain	-0.660	-3,57	0.900
	MSb	Spain	-4.280	-6.570	0.920
	MSc	Spain	9.210	-2.610	0.950
	MSd	Spain	11.610	-0.640	0.900
	MSe	Spain	-5.440	-3.730	0.900
Leitner et al., 2011;	MS	EU		2.397	0.621
Hall et al., 2008;	MSa	Italy	-2.8	-1.22	0.95
	MSb	Italy	-2.98	-1.84	0.96
	MSc	Italy	-5.84	0.18	0.94
	Msd	Italy	1.91	-1.15	1.07

Notes: MS=Manufacturing Sector, SS=Services Sector.
Harrison et al., 2014, a= France, b=Germany, c=Spain, and d= United Kingdom; Peters et al., 2017, a=Upturn, b= Boom, c=Downturn, and d= Recession; Dachs et al., 2016, a=high-tech manufacturing, b= low-tech manufacturing. The second letter means a=Upturn, b=Boom, c= Downturn, and c=Recession; Dachs& Peters, 2014, a= Domestically owned group firms (DGF) and Foreign-owned firms (FOF), b= Foreign-owned EU firm (FOFEU) and Foreign-owned NON-EU firm (FOFNONEU), and c= Foreign-owned US firm (FOFUS) and Foreign-owned Rest of the World firm (FOFROW); Rojas, 2013, a=2004-2007, b=2005-2008 c=2006-2009, d=2007-2010, e=Total; Hall et al., 2008; a=All years, b=1995–1997, c=1998–2000, d=2001–2003
* means significant

Table 3.2.a. Descriptive statistics in percentage (triennial): product and process innovators, growth of employment and sales. Manufacturing firms (2004-2014)

	2006-2009	2007-2010	2008-2011	2009-2012	2010-2013	2011-2014	TOTAL
No. of firms	5427	5189	5000	4777	4569	3559	28521
Non-innovators (%)	21.60	20.99	36.18	41.80	43.34	31.33	32.12
Process innovators only (%)	15.79	15.42	14.94	14.19	13.35	14.84	14.80
Product innovators (%)	62.61	63.60	48.88	44.00	43.31	53.84	53.08
Product innovators only (%)	14.94	14.47	16.00	15.64	16.57	21.33	16.22
[Of which are product & process innovators]	47.67	49.12	32.88	28.37	26.75	32.51	36.86
Employment growth (%)							
All firms	-5.92	-9.69	-9.27	-5.30	-4.82	-1.14	-6.03
Non-innovators (%)	-11.90	-14.59	-14.45	-10.85	-10.69	-6.64	-11.52
Process innovators only (%)	-7.46	-11.16	-8.13	-2.26	-0.40	2.20	-4.54
Product innovators (%)	-3.49	-7.75	-5.81	-1.03	-0.36	1.07	-2.89
Product innovators only (%)	-8.19	-11.50	-8.42	-3.82	-2.80	-1.78	-6.09
[Of which are product & process innovators]	-2.01	-6.64	-4.54	0.52	1.15	2.94	-1.43
Sales growth (%)							
All firms	-7.85	-13.23	-8.72	7.16	1.66	3.90	-2.85
Non-innovators (%)	-14.27	-20.70	-15.33	-1.77	-6.33	-1.93	-10.06
Process innovators only (%)	-6.63	-13.18	-6.79	13.96	9.61	9.51	1.08
Product innovators (%)	-5.95	-10.81	-4.46	13.41	7.16	5.69	0.84
Old products	-31.89	-36.45	-28.61	-13.27	-17.30	-20.21	-24.62
New products	22.85	22.44	19.10	19.25	18.17	23.36	20.86
Prices growth (%)							
All firms	6.8	4.8	4.2	6.7	4.9	1.4	4.8
Non-innovators (%)	7.4	5.2	4.3	6.8	5.3	2.0	5.2
Process innovators only (%)	7.3	5.2	4.5	6.8	5.2	1.4	5.1
Product innovators (%)	6.6	4.8	4.4	7.3	5.1	1.3	4.9
Product innovators only (%)	6.7	4.5	4.1	6.2	4.6	1.1	4.5
[Of which are product & process innovators]	6.6	4.9	4.6	7.9	5.4	1.5	5.1

Table 3.3.a. The total effect of innovation on employment of manufacturing by sectors

Dependent variable: l-g1-π							
Variables	ols	iv[a]	iv[b]	fe	re	reiv[a]	reiv[b]
d	-0.135***	-0.0352	-0.00684	-0.137**	-0.142***	-0.0497	-0.00505
	[0.0273]	[0.0615]	[0.0494]	[0.0432]	[0.0347]	[0.0810]	[0.0652]
g2	0.587***	0.844***	0.917***	0.459***	0.521***	0.790***	0.912***
	[0.0333]	[0.142]	[0.107]	[0.0554]	[0.0470]	[0.213]	[0.162]
islowtech	0.0223	0.111	0.138**		-0.00243	0.0856	0.129*
	[0.0138]	[0.0574]	[0.0433]		[0.0210]	[0.0836]	[0.0639]
ismlowtech	0.0412**	0.094	0.127**		0.0236	0.0613	0.116
	[0.0140]	[0.0582]	[0.0439]		[0.0211]	[0.0847]	[0.0649]
ismhightech	0.0406**	0.0853	0.118**		0.0238	0.0624	0.113
	[0.0138]	[0.0580]	[0.0443]		[0.0210]	[0.0842]	[0.0650]
d*islowtech	0.0515	-0.0366	-0.0634	0.0823	0.0718	-0.00885	-0.05
	[0.0292]	[0.0633]	[0.0512]	[0.0461]	[0.0373]	[0.0834]	[0.0674]
d*ismlowtech	0.0617*	0.00948	-0.0236	0.0688	0.0714	0.0428	-0.0101
	[0.0295]	[0.0641]	[0.0520]	[0.0468]	[0.0376]	[0.0847]	[0.0688]
d*ismhightech	0.0257	-0.019	-0.0522	0.0397	0.0373	0.00486	-0.0437
	[0.0302]	[0.0643]	[0.0526]	[0.0482]	[0.0389]	[0.0847]	[0.0693]
g2*islowtech	0.226***	0.0135	-0.0533	0.361***	0.294***	0.084	-0.0238
	[0.0367]	[0.149]	[0.114]	[0.0605]	[0.0512]	[0.221]	[0.169]
g2*ismlowtech	0.159***	0.0939	0.00151	0.269***	0.214***	0.208	0.0508
	[0.0378]	[0.153]	[0.117]	[0.0613]	[0.0528]	[0.228]	[0.174]
g*2ismhightech	0.152***	0.0713	-0.0172	0.226***	0.186***	0.126	-0.00924
	[0.0360]	[0.149]	[0.115]	[0.0593]	[0.0503]	[0.221]	[0.170]
cons	0.0424**	-0.0654	-0.0890*	0.0827***	0.0656***	-0.054	-0.0912
	[0.0130]	[0.0571]	[0.0427]	[0.00396]	[0.0199]	[0.0804]	[0.0620]
Tests of endogeneity		8.620	11.043				
P-value		0.000	0.000				
Test of Sargan		6.904	18.405			6.735	14.357
P-value		0.141	0.104			0.151	0.278
First-Stage		0.020	0.035			430.95	612.33
P-value		0.019	0.034			0.000	0.000
N	37871	37871	37871	37871	37871	37871	37871
R-sq	0.368	0.35	0.349	0.291			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001.
d Process innovation only, g2 Sales growth due to new products, a Instrument used is increased range, b Instruments used are increased range and clients as a source of information.

Table 3.4.a. The effects of innovation on high-skilled employment of manufacturing by sectors

Dependent variable: l-g1-π							
Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
d	-0.0325	0.197	0.194	0.0198	-0.0292	0.222	0.197
	[0.0659]	[0.156]	[0.116]	[0.0980]	[0.0705]	[0.185]	[0.141]
g2	0.762***	1.424***	1.415***	0.603***	0.715***	1.482**	1.399***
	[0.0557]	[0.400]	[0.292]	[0.0914]	[0.0686]	[0.512]	[0.380]
islowtech	0.0517	0.273	0.279**		0.0298	0.281	0.265
	[0.0274]	[0.145]	[0.107]		[0.0336]	[0.183]	[0.137]
ismlowtech	0.115***	0.246	0.279**		0.103**	0.247	0.26
	[0.0283]	[0.146]	[0.108]		[0.0347]	[0.184]	[0.138]
ismhightech	0.0973***	0.262	0.270*		0.0879**	0.268	0.247
	[0.0267]	[0.144]	[0.107]		[0.0329]	[0.183]	[0.138]
d*islowtech	-0.0335	-0.254	-0.260*	-0.0698	-0.0311	-0.269	-0.257
	[0.0712]	[0.162]	[0.122]	[0.105]	[0.0768]	[0.192]	[0.148]
d*ismlowtech	-0.0585	-0.189	-0.222	-0.107	-0.059	-0.192	-0.207
	[0.0731]	[0.163]	[0.124]	[0.110]	[0.0793]	[0.194]	[0.150]
d*ismhightech	-0.0112	-0.177	-0.184	-0.0559	-0.00851	-0.182	-0.163
	[0.0745]	[0.163]	[0.125]	[0.111]	[0.0811]	[0.194]	[0.151]
g2*islowtech	0.116	-0.512	-0.541	0.320**	0.169*	-0.541	-0.515
	[0.0655]	[0.425]	[0.317]	[0.103]	[0.0791]	[0.541]	[0.408]
g2*ismlowtech	0.0634	-0.139	-0.299	0.175	0.0906	-0.115	-0.227
	[0.0690]	[0.439]	[0.331]	[0.106]	[0.0811]	[0.557]	[0.425]
g*2ismhightech	0.101	-0.333	-0.362	0.191	0.128	-0.344	-0.29
	[0.0633]	[0.418]	[0.313]	[0.102]	[0.0776]	[0.533]	[0.404]
cons	0.125***	-0.0918	-0.0917	0.207***	0.122***	-0.119	-0.0972
	[0.0237]	[0.139]	[0.101]	[0.00783]	[0.0295]	[0.177]	[0.131]
Tests of endogeneity		3.249	2.976				
P-value		0.011	0.018				
Test of Sargan		6.326	14.632			4.048	10.232
P-value		0.176	0.262			0.400	0.596
First-Stage		0.013	0.022			305.260	453.430
P-value		0.012	0.020			0.000	0.000
N	23093	23093	23093	23093	23093	23093	23093
R-sq	0.122	0.105	0.11	0.097			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only, g2 Sales growth due to new products, a Instrument used is increased range, b Instruments used are increased range and clients as a source of information.

Table 3.5.a. The effects of innovation on low-skilled employment of manufacturing by sectors

Dependent variable: l-g1-π							
Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
d	-0.0807*	-0.0754	-0.0435	-0.111	-0.0945*	-0.119	-0.0862
	[0.0388]	[0.0940]	[0.0775]	[0.0604]	[0.0481]	[0.115]	[0.0970]
g2	0.795***	0.811**	0.906***	0.681***	0.751***	0.678*	0.778**
	[0.0373]	[0.256]	[0.207]	[0.0589]	[0.0452]	[0.330]	[0.266]
islowtech	0.0219	0.0415	0.0662		0.0042	-0.000676	0.0185
	[0.0185]	[0.0884]	[0.0713]		[0.0235]	[0.112]	[0.0905]
ismlowtech	0.0400*	0.0296	0.0601		0.0259	-0.024	0.00479
	[0.0186]	[0.0886]	[0.0714]		[0.0236]	[0.112]	[0.0906]
ismhightech	0.0484**	0.032	0.0632		0.0423	-0.00145	0.0283
	[0.0186]	[0.0889]	[0.0721]		[0.0237]	[0.112]	[0.0914]
d*islowtech	0.0198	0.0000932	-0.0245	0.0829	0.0453	0.0481	0.03
	[0.0408]	[0.0956]	[0.0791]	[0.0633]	[0.0505]	[0.117]	[0.0991]
d*ismlowtech	0.0107	0.021	-0.00948	0.0643	0.0335	0.0819	0.0543
	[0.0413]	[0.0959]	[0.0795]	[0.0639]	[0.0509]	[0.117]	[0.0995]
d*ismhightech	-0.00804	0.00833	-0.0228	0.0158	0.00359	0.0459	0.0168
	[0.0419]	[0.0965]	[0.0803]	[0.0662]	[0.0525]	[0.119]	[0.101]
g2*islowtech	0.0776	-0.00443	-0.0661	0.215***	0.129**	0.112	0.0771
	[0.0409]	[0.262]	[0.213]	[0.0648]	[0.0498]	[0.339]	[0.274]
g2*ismlowtech	0.0134	0.0733	-0.0149	0.123	0.0542	0.254	0.175
	[0.0418]	[0.264]	[0.214]	[0.0667]	[0.0516]	[0.341]	[0.275]
g*2ismhightech	0.02	0.0832	-0.00894	0.0561	0.034	0.179	0.0916
	[0.0410]	[0.262]	[0.214]	[0.0657]	[0.0505]	[0.338]	[0.275]
cons	0.0459**	0.0697	0.0286	0.0820***	0.0610**	0.118	0.0661
	[0.0177]	[0.0883]	[0.0711]	[0.00429]	[0.0222]	[0.111]	[0.0898]
Tests of endogeneity		1.199	1.396				
P-value		0.309	0.232				
Test of Sargan		5.040	9.074			2.971	6.491
P-value		0.283	0.697			0.563	0.889
Partial R-sq.		0.015	0.024			403.610	591.220
Adj. Partial R-sq.		0.014	0.023			0.000	0.000
N	27603	27603	27603	27603	27603	27603	27603
R-sq	0.332	0.33	0.329	0.267			

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001

d Process innovation only, g2 Sales growth due to new products, a Instrument used is increased range, b Instruments used are increased range and clients as a source of information.

Table 3.6.a. The effects of innovation on employment of manufacturing by sectors (Yt-3)

Dependent variable: l-g1-π

Sector	Variables	ols	vi[a]	vi[b]	Fe	re	reiv[a]	reiv[b]
High-tech	d	-0.135***	-0.0507	-0.0189	-0.140**	-0.143***	-0.0697	-0.0207
		[0.0271]	[0.0585]	[0.0483]	[0.0432]	[0.0344]	[0.0777]	[0.0638]
	g2	0.593***	0.813***	0.895***	0.469***	0.531***	0.744***	0.883***
		[0.0326]	[0.134]	[0.104]	[0.0550]	[0.0461]	[0.208]	[0.160]
	cons	0.0424**	-0.0654	-0.0890*	0.0884***	0.0654**	-0.052	-0.091
		[0.0130]	[0.0571]	[0.0427]	[0.0214]	[0.0199]	[0.0849]	[0.0617]
HighM-tech	d	-0.108***	-0.0539**	-0.0583**	-0.0960***	-0.103***	-0.0449	-0.0489*
		[0.0130]	[0.0186]	[0.0181]	[0.0212]	[0.0177]	[0.0244]	[0.0234]
	g2	0.742***	0.915***	0.901***	0.688***	0.710***	0.916***	0.904***
		[0.0137]	[0.0436]	[0.0412]	[0.0212]	[0.0179]	[0.0578]	[0.0528]
	cons	0.0841***	0.022	0.0262	0.0996***	0.0914***	0.0176	0.0214
		[0.00500]	[0.0144]	[0.0137]	[0.00678]	[0.00667]	[0.0186]	[0.0171]
LowM-tech	d	-0.0771***	-0.0289	-0.0356*	-0.0750***	-0.0759***	-0.0163	-0.0244
		[0.0111]	[0.0181]	[0.0164]	[0.0178]	[0.0142]	[0.0243]	[0.0223]
	g2	0.742***	0.936***	0.909***	0.722***	0.732***	0.976***	0.942***
		[0.0177]	[0.0561]	[0.0461]	[0.0261]	[0.0234]	[0.0758]	[0.0636]
	cons	0.0853***	0.0306*	0.0360**	0.0893***	0.0902***	0.0211	0.0276
		[0.00549]	[0.0153]	[0.0127]	[0.00686]	[0.00694]	[0.0200]	[0.0170]
Low-tech	d	-0.0825***	-0.0708***	-0.0693***	-0.0518**	-0.0672***	-0.0536*	-0.0498**
		[0.0104]	[0.0153]	[0.0139]	[0.0160]	[0.0138]	[0.0213]	[0.0188]
	g2	0.813***	0.859***	0.865***	0.822***	0.817***	0.883***	0.899***
		[0.0155]	[0.0442]	[0.0382]	[0.0244]	[0.0204]	[0.0660]	[0.0537]
	cons	0.0638***	0.0491***	0.0484***	0.0575***	0.0621***	0.0406*	0.0388**
		[0.00492]	[0.0117]	[0.0102]	[0.00625]	[0.00667]	[0.0167]	[0.0137]

Standard errors in brackets * $p<0.05$, ** $p<0.01$, *** $p<0.001$

d Process innovation only

g2 Sales growth due to new products

a Instrument used is increased range

b Instruments used are increased range and clients as a source of information

Table 3.7.a. The effects of innovation on high-skilled employment of manufacturing by sectors

Dependent variable: l-g1-π								
Sector	Variables	ols	vi[a]	vi[b]	Fe	re	reiv[a]	reiv[b]
High-tech	d	-0.0392	0.176	0.177	0.00531	-0.0392	0.176	0.18
		[0.0655]	[0.152]	[0.114]	[0.0979]	[0.0675]	[0.162]	[0.134]
	g2	0.769***	1.395***	1.398***	0.625***	0.747***	1.395**	1.396***
		[0.0555]	[0.391]	[0.291]	[0.0900]	[0.0648]	[0.430]	[0.364]
	cons	0.125***	-0.0918	-0.0917	0.159***	0.124***	-0.0918	-0.0971
		[0.0238]	[0.139]	[0.101]	[0.0329]	[0.0283]	[0.154]	[0.128]
HighM-tech	d	-0.0426	0.0209	0.0104	-0.0352	-0.0377	0.0402	0.029
		[0.0347]	[0.0483]	[0.0464]	[0.0529]	[0.0393]	[0.0567]	[0.0535]
	g2	0.863***	1.087***	1.050***	0.792***	0.847***	1.133***	1.092***
		[0.0302]	[0.126]	[0.116]	[0.0449]	[0.0358]	[0.156]	[0.139]
	cons	0.225***	0.159***	0.168***	0.238***	0.215***	0.130**	0.140***
		[0.0122]	[0.0368]	[0.0342]	[0.0137]	[0.0145]	[0.0456]	[0.0411]
LowM-tech	d	-0.0937**	0.00297	-0.0342	-0.0934	-0.0918*	0.0236	-0.0181
		[0.0320]	[0.0501]	[0.0467]	[0.0493]	[0.0371]	[0.0587]	[0.0544]
	g2	0.823***	1.270***	1.098***	0.772***	0.799***	1.349***	1.149***
		[0.0409]	[0.185]	[0.160]	[0.0539]	[0.0436]	[0.229]	[0.197]
	cons	0.254***	0.143***	0.178***	0.243***	0.226***	0.117*	0.149***
		[0.0161]	[0.0415]	[0.0362]	[0.0144]	[0.0186]	[0.0497]	[0.0435]
Low-tech	d	-0.0623*	-0.0528	-0.0608	-0.0436	-0.0546	-0.0363	-0.0523
		[0.0271]	[0.0452]	[0.0408]	[0.0376]	[0.0305]	[0.0551]	[0.0485]
	g2	0.884***	0.923***	0.890***	0.934***	0.895***	0.974***	0.906***
		[0.0345]	[0.149]	[0.127]	[0.0489]	[0.0396]	[0.194]	[0.160]
	cons	0.177***	0.169***	0.176***	0.154***	0.145***	0.129**	0.144***
		[0.0136]	[0.0370]	[0.0319]	[0.0129]	[0.0163]	[0.0472]	[0.0394]

Standard errors in brackets * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
a Instrument used is increased range
b Instruments used are increased range and clients as a source of information

Table 3.8.a. The effects of innovation on low-skilled employment of manufacturing by sectors

Dependent variable: l-g1-π

Sector	Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
High-tech	d	-0.0781*	-0.0645	-0.0345	-0.106	-0.0945	-0.106	-0.0795
		[0.0392]	[0.0929]	[0.0772]	[0.0610]	[0.0499]	[0.113]	[0.0977]
	g2	0.795***	0.836***	0.925***	0.671***	0.735***	0.704*	0.786**
		[0.0371]	[0.252]	[0.206]	[0.0584]	[0.0460]	[0.326]	[0.270]
	cons	0.0459**	0.0697	0.0286	0.0784***	0.0654**	0.109	0.0789
		[0.0177]	[0.0883]	[0.0711]	[0.0212]	[0.0229]	[0.108]	[0.0950]
HighM-tech	d	-0.0890***	-0.0677**	-0.0671**	-0.0953***	-0.0909***	-0.0731*	-0.0698*
		[0.0157]	[0.0222]	[0.0216]	[0.0270]	[0.0208]	[0.0288]	[0.0278]
	g2	0.815***	0.892***	0.895***	0.736***	0.790***	0.858***	0.870***
		[0.0171]	[0.0588]	[0.0560]	[0.0289]	[0.0221]	[0.0748]	[0.0691]
	cons	0.0965***	0.0718***	0.0680***	0.113***	0.104***	0.0774***	0.0698***
		[0.00642]	[0.0171]	[0.0164]	[0.00818]	[0.00835]	[0.0215]	[0.0200]
LowM-tech	d	-0.0725***	-0.0572**	-0.0568**	-0.0517*	-0.0657***	-0.0431	-0.0409
		[0.0142]	[0.0198]	[0.0184]	[0.0206]	[0.0161]	[0.0239]	[0.0224]
	g2	0.808***	0.881***	0.884***	0.799***	0.804***	0.919***	0.929***
		[0.0191]	[0.0660]	[0.0547]	[0.0311]	[0.0247]	[0.0846]	[0.0700]
	cons	0.0992***	0.0718***	0.0669***	0.0804***	0.0893***	0.0633***	0.0564***
		[0.00670]	[0.0153]	[0.0131]	[0.00704]	[0.00817]	[0.0189]	[0.0162]
Low-tech	d	-0.0573***	-0.0720***	-0.0638***	-0.0179	-0.0416**	-0.0633**	-0.0452*
		[0.0125]	[0.0180]	[0.0167]	[0.0184]	[0.0150]	[0.0238]	[0.0214]
	g2	0.877***	0.810***	0.848***	0.910***	0.889***	0.796***	0.878***
		[0.0168]	[0.0575]	[0.0504]	[0.0269]	[0.0210]	[0.0852]	[0.0701]
	cons	0.0678***	0.0814***	0.0708***	0.0506***	0.0642***	0.0790***	0.0589***
		[0.00598]	[0.0136]	[0.0120]	[0.00652]	[0.00788]	[0.0192]	[0.0161]

Standard errors in brackets * $p<0.05$, ** $p<0.01$, *** $p<0.001$

d Process innovation only

g2 Sales growth due to new products

a Instrument used is increased range

b Instruments used are increased range and clients as a source of information

Chapter 4.- The Effects of Product Innovation across the Value Chain on Different Types of Employment: An Empirical Analysis of Spanish Manufacturing Firms

4.1.- Introduction and research question

As discussed in the first chapters of this study, disentangling the impact of innovation on employment is not an easy task when the focus is on the quantity of the employment and when looking at the nature of the jobs created and destroyed. The employment effects of innovation vary depending on whether it represents a new product or production process. The former type of innovation is considered to have a positive effect on employment via a higher demand. While process innovation is generally considered, at least from a theoretical point of view, to be detrimental to employment because of its labor-saving nature, the review of the empirical literature presented in Chapter 2 showed inclusive results.

From a micro-level perspective, the literature has focused on the employment effect of product and process innovation introduced by the focal firm. Also, in the previous chapter of this Ph.D. thesis, a pure firm-level approach was applied. However, focal firm's employment may depend not only on the innovation introduced by the focal firm itself but also on the innovation introduced by related firms. The goal of this chapter is to delve into this issue by analyzing the employment effects of the product innovations introduced by firms in upstream and downstream industries as well as by firms in the same industry to which the focal firm belongs[83].

[83]In this chapter, we focus on product innovation rather than process innovation for two reasons. First, product innovation by its own nature extends its influence on other firms (as products are sold in a market) while process innovation likely shows an impact which is to a large extent confined to the focal firm. Second, the data available for product innovation is much richer (continuous indicator for sales from new products) than the data available for process innovation (just a dummy variable).

The linkages within the value chain are measured with sectoral data obtained from the national input-output tables. The upstream indicator includes basically the “weighted” purchases (input) obtained by the sector focal firms belong to from all the other sectors and the downstream. For its part, downstream indicators reflect all the sales (output) of the firms vended to the other sectors. It should be highlighted that such average sector data are used because the data do not permit us to identify the specific providers, customers and competitors for each firm. This means that in this analysis all firms in the same industry will receive exactly the same amount of upstream/downstream innovation or are affected equally by firms of their own sector. Our upstream indicator will include providers, our downstream indicator will include customers and our same industry indicator will include all the firms (providers, customers and competitors) that belong to the same sector as the focal firm.[84]

Despite these limitations, which we share with the studies focused on spillovers from multinational firms (from which we import the methodology), we believe that the indicators used are a good novel “proxy” for the overall situation and will shed some new light on the employment effects of innovations beyond the focal firm. They reflect the externality effects in term of employment caused by the product innovations by firms in related industries.

The product innovations introduced by firms in upstream sectors reflect the embodied technological change included in the investment and intermediate goods that they supply to the market, and this would be a “technological input” for the focal firm that may affect its

[84] In addition to the impossibility of identifying the specific providers, customers and competitors for each firm, the average sector data is used; the available industry classification is the two-digit NACE. This way of analyzing inter- and intra-sectoral linkages includes information about firms without any formal or informal relationship with the focal firm.

employment because of an increase of sales or variations in productivity. Such goods embed all the R&D endeavors that had gone into their development and benefit downstream firms through knowledge circulation (Meyer-Krahmer, 1992). Actually, product-embodied knowledge accounted for a notable share of knowledge used by firms (Hauknes & Knell, 2009). On the other hand, innovation in downstream sectors can be challenging for firms located upstream, as they can suggest or require improvements to the catalogue of products they are currently selling to the market (Montresor & Marzetti, 2008; von Hippel, 1976). Finally, innovation by firms in the same industry may generate a business stealing effect, destroying employment in the focal firm (Aghion & Howitt, 1998). The business stealing effect is caused if new products by competitors substitute the old products (creative destruction) of the focal firm. In other words, the competitors might, because of innovations, increase their market share, so they displace the focal firm from the market. It might cause fewer sales by the focal firm and a loss of employment.

That is, there are reasons to believe that the employment effect of innovation in each "focal" firm is not influenced only by its own innovation results, but also more directly by innovation of the firms in the upstream and downstream sectors and those introduced by enterprises of the same industry. In order to correctly explain or interpret the results obtained, it must be kept in mind that the impact of other firms in the value chain is measured by keeping the innovation of the focal firm constant in terms of product and process innovation. That is, the total effect of upstream and downstream innovation on firms' employment will likely be higher if positive knowledge spillovers exist (meaning that focal firm product innovation increases when there is more upstream/downstream innovation). However, this channel of the effect is not the focus of our study and, as just said, the model controls for such indirect relationship.

This chapter analyzes the employment effects caused by innovations within the value chain of the focal firm. In addition, as highlighted in Chapters 2 and 3, it has been shown that the employment effect of innovation varies depending on the type of worker, so this should be taken into account in our analysis. Accordingly, the goal of this Chapter 4 is to answer the following two research questions:

Research question 1.- What is the effect of upstream, downstream and same-industry product innovations on the employment of the focal firm?

Research question 2.- What is the skill composition of these employment effects of upstream, downstream and same-industry product innovation?

The remainder of the paper is structured as follows. In Section 4.2., we review the streams of the literature related to our analysis. In Section 4.3., the main specification of the extension based on the empirical model of Harrison et al. (2014) will be presented. In Section 4.4., we briefly present the data set used and offer some descriptive information on the level of product innovations by the different sectors. Section 4.5. presents the results of the estimations and the last section discusses conclusions.

4.2. Embeddedness of our methodology within the previous literature

The approach used in this chapter is related to two strands of empirical studies that analyzed the role of upstream, downstream and same-industry technology flows. A first strand of contributions that can shed light on the existence of upstream, downstream and intra-industry effects of innovation is the literature on inter-sectoral knowledge flows that flourished in the 20th century. Several theoretical and empirical studies underpin the impact of external agents on the total factor productivity (in terms of inter- and intra-industry linkages), which has been a topic of analysis since the late 1950s. In this respect, input-output relations between upstream and downstream sectors have received a great deal of attention, with a focus on backward and forward linkages that relate to the derived demand and supply, respectively (see Hirschman, 1967). In this context, the role of knowledge spillovers was already mentioned by Schmookler (1966) and analyzed by authors like Scherer (1982); Sveikauskas (1981); Terleckyj (1974). Also, the role of intra-industry effects was already an important topic in the empirical studies of the second half of the 20th century (see, among others, Blomström, Kokko, and Zejan, 1994; Caves, 1974). Finally, Griliches (1979) introduced another important concept, differentiating from knowledge spillover. He called it rent spillover, which captures pecuniary benefits obtained by firms that purchase new innovative products whose value is higher than the price they paid for it.

Recent works have focused on the mechanisms related to industrial upstream and downstream linkages, observing customer sector employment. These effects are induced by patents shocks, which are conceived to represent fiercer international competition in addition to technological changes on the frontier (Acemoglu et al., 2017). Autor & Salomons (2018) find that labor-displacing productivity growth in upstream sectors has a beneficial offsetting impact on customers' industries, which are benefiting from a price decline.

A second relevant strand of studies directly connected with our approach is the studies on the role of Foreign Direct Investments (FDI) in national production sectors (Javorcik, 2004). This literature broadly analyzes the general impact through forward and backward linkages, and the importance of technological spillovers is also deeply rooted in this strand.

The first empirical studies were at the industry level, basically showing a positive effect of the presence of multinational enterprises on the productivity of local firms (Blomström & Persson, 1983; Caves, 1974; Globerman, 1979, among others), although these studies analyzed global spillover effects and did not differentiate for horizontal and vertical linkages. Since the beginning of the 1990s, a broad number of firm-level studies have analyzed the vertical and horizontal knowledge spillovers of multinational firms (for a survey, see Blomström et al., 1994; Fan, 2003; Heijs, 2006; Hvranek & Irsova, 2011), including a large number which analyzed the Spanish case (Barrios, 2000; Heijs, 2006; Jabbour & Mucchielli, 2007; Mancebón Torrubia & Lozano Chavarría, 2001; Merino de Lucas & Salas Fumás, 1995). This literature shows broad evidence of a higher-level productivity generated by the presence of multinationals in upstream, downstream and the same industries[85].

More recently, some studies proxy the importance of linkages derived from multinationals in upstream, downstream and the same industry for sales of national firms (Javorcik, 2004), thus differentiating between ”output-based spillovers” and “technological spillovers.” This novel literature shows that this distinction is important. It shows that forward ”output-based” spillovers are negative, but forward technological spillovers are positive, while the volume of backward technological spillovers is much lower (approximately 44%) than the

[85]The usual interpretation of these results has been made according to technological spillovers from multinational firms to local firms, although the majority of studies do not employ any technological indicator to measure the presence of multinational firms. This interpretation has been controversial as it has been purely speculative.

level of output-based backward spillovers (Barge-Gil et al., 2020)[86]. The design of our empirical analysis, combining firm-level data with sector-level information from the input-output table, is taken from the analytical framework for FDI defined by Javorcik (2004).

Another important strand of literature related to the analysis of this chapter is its embeddedness in the literature on skill-biased technological change. As done in Chapter 3, this analysis again distinguishes between the effect of innovation on employment, considering the types of jobs that are created or destroyed by upstream, downstream and same-industry innovation. In doing so, we connect to the economic literature that considered the heterogeneity and non-neutrality of the employment effect of innovation (Autor et al., 2003). In particular, we draw from the consideration, as proved by our analysis in the former chapter, that the impact of innovation on employment is biased in favor of high-skilled workers and against low-skilled ones. The canonical Skill-Biased Technical Change (SBTC) framework states that innovations complement the work of high-skilled workers, increasing their demand. This approach has been recently complemented by the routine- biased technical change (RBTC) approach, which contends that technical change, especially related to ICTs, complements workers who perform non-routinized tasks and substitutes workers who perform cognitive and manual activities that follow explicit routines (Acemoglu & Autor, 2011; Autor et al., 2003)[87]. As in almost all studies of this type, the skill-level will be introduced by a proxy based on the level of education (see Section 4.3).

[86] Horizontal spillovers are similar, using both indicators.
[87] Because of data constraints, we will not be able to provide evidence exactly in line with the RBTC.

4.3.- Specifications of the extended HJMP model

4.3.1. The extended HJMP model

In order to measure the effects of product innovation from upstream, downstream and the same industry the firms belong to , an extended Harrison et al. (2014) model[88] is proposed. The basic HJMP model, explained in detail in Chapter 2, estimates the employment effects of innovation for three aspects. The first one is the impact of the product innovation, measured by the variable "sales growth due to new products." The coefficient for this variable (g_2) shows two types of effects. It reveals the direct employment effects of product innovation and simultaneously analyzes the possible loss of employment in the case that new products are produced more efficiently than old products. Another type of employment effect would be generated by process innovations. Therefore, the model includes a dummy variable (*d*) for firms that carried out "only process innovation" not associated with product innovation. Finally, in this specific model, the constant term (α_0) expresses the average efficiency growth in the production of old products (Harrison et al., 2014). However, in this section, we only offer a synthetic description of the model that explains each of its main components.[89] equation (4.1) shows the empirical equation of the Harrison et al. model.

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \qquad (4.1)$$

where l is employment growth, g_1 and g_2 are the sales growth due to old (1) and new products (2) respectively, π is the price or inflation correction at the industrial level as a

[88] In this paper, we refer to the model as the HJMP model as an abbreviation of the names of the authors: Harrison, Jaumandreu, Mairesse and Peters.

[89] For more detail of the standard model, see the literature review presented in chapter two and see also Harrison et al. (2014); Peters et al. (2017); Dachs & Peters (2014)

proxy of firm prices, and d is a binary variable that picks up the additional effect of process innovations 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 product innovation (only process innovation). If a firm introduces a new process, the efficient production of old products improves, so it reduces the employment of the firm. The parameter α_0 represents (minus)[90] the average efficiency growth in production of the old products (in other words, the growth of employment in the case of the absence of innovation). The parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2014). If the coefficient is less than unity, it means that the new products are produced more efficiently than old products. In other words, the new products require less labor input than the old ones. ε_i is an error term.

Taking into account equation (4.1), it is possible to extend the original HJMP model –see equation (4.2) – adding the new variables that contain the product innovation effects through the value chain of intra-industrial flows ($intra$), downstream ($down$), and upstream (up) linkages. ε_i is an uncorrelated zero mean error term. We build these variables following the literature that has analyzed spillovers from Foreign Direct Investment (FDI) (see Javorcik, 2004).

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \gamma_1 intra_{prod_{jt}} + \gamma_2 down_{prod_{jt}} + \gamma_3 up_{prod_{jt}} + \varepsilon_i \quad (4.2)$$

[90] Minus means that a negative coefficient is expected, such negative effects is based not based on process innovation though a kind of learning effects or scale effect in the case that the firm amplifies its total production of old product.

4.3.2. The intra-sectoral indicator for product innovation

The level of innovation of the same sector (intra-sectoral flows) from a focal firm is defined as the share of the total output[91] (sales as a proxy variable) of an industry that introduces a product innovation "s" weighted by each firm's share in sectorial sales. It subtracts the effect of the focal firm for the industrial indexes $(s_{it} * sales_{it})$ and $(sales_{it})$. Sub-index "prod" refers to product innovation and this new variable varies by industry (j) and time (t)[92].

$$Intra_{\ prod_{jt}} = \frac{\left[\sum_{i \forall i \in j}(s_{it} * sales_{it})\right] - [s_{it} * sales_{it}]}{\left[\sum_{i \forall i \in j} sales_{it}\right] - [sales_{it}]} \quad \text{(4.3) Intra-sectoral product innovation}$$

where s_{it}[93] captures the percentage of the sales of new products which represent a novelty to the market (see Box 4.1).

Box 4.1. A numerical example of the creation variable "Intra"

The expression (4.3) can be represented with numerical examples, assuming only four firms for the same industry for the same period of time.

$$s = \begin{pmatrix} 0.10 \\ 0.30 \\ 0.60 \\ 0.90 \end{pmatrix} sales = \begin{pmatrix} 22046996 \\ 24656080 \\ 23038443 \\ 18603994 \end{pmatrix}$$

$$\sum_{i \forall i \in j} (s_{it} * sales_{it}) = (0.10 * 22046996) + (0.30 * 24656080) + (0.60 * 23038443) + (0.90 * 18603994)$$

$$= (2204699.6) + (7396824) + (13823065.8) + (16743594.6) = 40168184$$

$$\sum_{i \forall i \in j} sales_{it} = (22046996) + (24656080) + (23038443) + (18603994) = 88345513$$

$$\left[\sum_{i \forall i \in j} (s_{it} * sales_{it})\right] - [s_{it} * sales_{it}] = \begin{pmatrix} 40168184 \\ 40168184 \\ 40168184 \\ 40168184 \end{pmatrix} - \begin{pmatrix} 2204699.6 \\ 7396824 \\ 13823065.8 \\ 16743594.6 \end{pmatrix} = \begin{pmatrix} 37963484.4 \\ 32771360 \\ 26345118.2 \\ 23424589.4 \end{pmatrix}$$

[91]In this case, the total amount of sales of each sector is used as a proxy variable, because there is no information of a more correct indicator of output in the data set like added value.

[92] A robustness check was made to test the validity of the model. In order to do that, we use alternative variables to measure product innovation in terms of growth rate (t-3) (for more information, see Box 4.2.a in the appendix).

[93] For easier interpretation, it will be called "product innovation."

$$\left[\sum_{i\forall i\in j} sales_{it}\right] - [sales_{it}] = \begin{pmatrix}88345513\\88345513\\88345513\\88345513\end{pmatrix} - \begin{pmatrix}22046996\\24656080\\23038443\\18603994\end{pmatrix} = \begin{pmatrix}66298517\\63689433\\65307070\\69741519\end{pmatrix}$$

$$Intra_{\ prod} = \begin{pmatrix}37963484.4/66298517\\32771360/63689433\\26345118.2/65307070\\23424589.4/69741519\end{pmatrix} = \begin{pmatrix}0.57261\\0.51455\\0.40340\\0.33588\end{pmatrix}$$

The average value of the industry, in this case, is **0.457**

4.3.3. The downstream indicator for product innovation

$down_{prod_{jt}} = \sum_{k\ if\ k\neq j} \propto_{jk} * Intra_{\ prod_{jt}}$ (4.4) Downstream product innovation

To build the indicator for downstream innovation, we combine the information of the share of industry j's production that is sold to industry k, obtained from the input-output tables, indicated as $\propto_{jk.}$ with an adjustment in terms of new products of each sector based on expression 4.3. In fact, in the case of the forward linkages for each sector, they multiply the size of the new product of the focal firm ($Intra_{\ prod_{jt}}$) with the share of its output absorbed by the receiving sector ($\propto_{jk}$). Afterwards, the values of all the sectors are summed up in order to get the weighted average value for $down_{prod_{jt}}$ (see Box 4.2.).

Box 4.2. A numerical example of the creation variable "downstream" sector

The expression (4.4) can be represented with numerical examples, assuming four industries. One of these industries is calculated in Box 4.1.

$Intra_{\ prod} = \begin{pmatrix}0.600\\0.557\\\mathbf{0.457}\\0.100\end{pmatrix}$ We can call this expression vector "h",

using the following hypothetical input-output matrix($\propto_{jk}$) for four sectors. It is important to mention that the matrix $\propto_{jk}$ is the share of industry j's production that is sold to industry k, obtained from the input−output tables

$$\propto_{jk} = \begin{bmatrix}0.000 & 0.328 & 0.468 & 0.093\\0.204 & 0.000 & 0.468 & 0.075\\0.153 & 0.494 & 0.000 & 0.084\\0.198 & 0.255 & 0.546 & 0.000\end{bmatrix}$$

Operating the vector "h" with the matrix "$\propto_{jk}$" and following the expression (4.4):

$$down_{prod_{jt}} = \propto_{jk} * h = \begin{bmatrix} 0.000 & 0.328 & 0.468 & 0.093 \\ 0.204 & 0.000 & 0.468 & 0.075 \\ 0.153 & 0.494 & 0.000 & 0.084 \\ 0.198 & 0.255 & 0.546 & 0.000 \end{bmatrix} \begin{pmatrix} 0.600 \\ 0.557 \\ 0.457 \\ 0.100 \end{pmatrix} = \begin{pmatrix} 0.4059 \\ 0.3435 \\ 0.3760 \\ 0.5108 \end{pmatrix}$$

The downstream value for the first sector is 0.4059, for the second sector 0.3435, for the third sector 0.3760, and for the fourth sector 0.5108.

4.3.4. The indicator for upstream product innovation

$$up_{prod_{jt}} = \sum_{m \; if \; m \neq j} \sigma_{jm} * \frac{\left[\sum_{i \forall i \in m}(s_{it} * (sales_{it} - x_{it}))\right] - \left[s_{it} * (sales_{it} - x_{it})\right]}{\left[\sum_{i \forall i \in m}(sales_{it} - x_{it})\right] - \left[sales_{it} - x_{it}\right]} \quad (4.5) \text{ Upstream product innovation}$$

Although a similar approach is applied in the case of upstream industries, in this case an adjustment is included for exports. Following the method developed by Javorcik (2004), the exports x_{it} are extracted in order to consider only the products sold in the domestic market. This is important because the analysis is focused on the forward effects of the firms located in Spain. The factor $up_{prod_{jt}}$ is based on the weighted average of new products of each sector adjusted by its multiplication with the weight of the sector as their upstream. This weight (σ_{jm}) is the share of industry j's inputs that is purchased from the national industry m taken from the input-output tables; this is also used from 2010. The same as the downstream variable, the own effect of the focal firm is extracted from the industries indexes $(s_{it} * (sales_{it} - x_{it}))$ and $[sales_{it} - x_{it}]$.

Box 4.3. A numerical example of the creation variable "upstream" sector

Expression (4.5) can be represented with numerical examples, assuming only four firms for the same industry for the same period of time.

$$s = \begin{pmatrix} 0.10 \\ 0.30 \\ 0.60 \\ 0.90 \end{pmatrix} sales = \begin{pmatrix} 22046996 \\ 24656080 \\ 23038443 \\ 18603994 \end{pmatrix} x_{it} = \begin{pmatrix} 6614098.8 \\ 14793648 \\ 2303844.3 \\ 8371797.3 \end{pmatrix}$$

$$\begin{aligned} \sum_{i \forall i \in j} (\mathrm{s_{it}} * (\mathrm{sales_{it}} - x_{it})) \\ &= \big(0.10 * (22046996 - 6614098.8)\big) + \big(0.30 * (24656080 - 14793648)\big) \\ &+ \big(0.60 * (23038443 - 2303844.3)\big) + \big(0.90 * (18603994 - 8371797.3)\big) \\ &= (0.10 * 15432897.2) + (0.30 * 9862432) + (0.60 * 20734598.7) + (0.90 * 10232196.7) \\ &= (1543289.72) + (2958729.6) + (12440759.22) + (9208977.03) = 26151755.57 \end{aligned}$$

$$\sum_{i\forall i\in j}(sales_{it}-x_{it}) == (22046996-6614098.8)+(24656080-14793648)+(23038443-2303844.3)$$

$$+(18603994-8371797.3)=(15432897.2)+(9862432)+(20734598.7)+(10232196.7)$$
$$=56262124.6$$

$$\left[\sum_{i\forall i\in j}(s_{it}*(sales_{it}-x_{it}))\right]-[s_{it}*(sales_{it}-x_{it}]=\begin{pmatrix}26151755.57\\26151755.57\\26151755.57\\26151755.57\end{pmatrix}-\begin{pmatrix}1543289.72\\2958729.6\\12440759.22\\9208977.03\end{pmatrix}=\begin{pmatrix}24608465.85\\23193025.97\\13710996.35\\16942778.54\end{pmatrix}$$

$$\left[\sum_{i\forall i\in j}sales_{it}-x_{it}\right]-[sales_{it}-x_{it}]=\begin{pmatrix}56262124.6\\56262124.6\\56262124.6\\56262124.6\end{pmatrix}-\begin{pmatrix}15432897.2\\9862432\\20734598.7\\10232196.7\end{pmatrix}=\begin{pmatrix}40829227.4\\46399692.6\\35527525.9\\46029927.9\end{pmatrix}$$

$$\frac{[\sum_{i\forall i\in m}(s_{it}*(sales_{it}-x_{it})]-[s_{it}*(sales_{it}-x_{it})]}{[\sum_{i\forall i\in m}(sales_{it}-x_{it})]-[sales_{it}-x_{it}]}=\begin{pmatrix}24608465.85/40829227.4\\23193025.97/46399692.6\\13710996.35/35527525.9\\16942778.54/46029927.9\end{pmatrix}=\begin{pmatrix}0.60272\\0.49985\\0.38593\\0.36808\end{pmatrix}$$

The average value of the industry, in this case, is **0.464.**

Taking into account the average calculated average and assuming three more industries, we have the following expression:

$$\frac{[\sum_{i\forall i\in m}(s_{it}*(sales_{it}-x_{it})]-[s_{it}*(sales_{it}-x_{it})]}{[\sum_{i\forall i\in m}(sales_{it}-x_{it})]-[sales_{it}-x_{it}]}=\begin{pmatrix}0.602\\0.550\\\mathbf{0.464}\\0.100\end{pmatrix}$$ We can call this expression vector "h",

using the following hypothetical input-output matrix (σ_{jm}) for four sectors. It is important to mention that the matrix (σ_{jm}) is the share of industry j's inputs that is purchased from the national industry m taken from the input-output tables. This is also used from 2010.

$$\sigma_{jm}=\begin{bmatrix}0.000&0.305&0.325&0.083\\0.186&0.000&0.325&0.067\\0.186&0.611&0.000&0.100\\0.186&0.244&0.390&0.000\end{bmatrix}$$

Operating the vector "h" with the matrix "σ_{jm}" and following the expression (4.5):

$$down_{prod_{jt}}=\propto_{jk}*Intra_{\ prod}=\begin{bmatrix}0.000&0.305&0.325&0.083\\0.186&0.000&0.325&0.067\\0.186&0.611&0.000&0.100\\0.186&0.244&0.390&0.000\end{bmatrix}\begin{pmatrix}0.602\\0.550\\0.464\\0.100\end{pmatrix}=\begin{pmatrix}0.3272\\0.2697\\0.4584\\0.4277\end{pmatrix}$$

The downstream value for the first sector is 0.3272, for the second sector 0.2697, for the third sector 0.4584, and for the fourth sector 0.4277.

4.3.5 Conceptual issues

In order to assure a correct interpretation of the results, some explicit decisions and implicit implications should be mentioned. First, the indicator of the volume of innovative products is restricted to those products which are new-to-the-market, or, in other words, the incremental and radical innovations. That is, the sales of products "new" to the firm are not taken into account, and this is important because the sales of the “imitation”-driven innovations are excluded from the model. We do not deny that imitation may have an effect on employment. However, the focus of this work is on analyzing the effect of innovation (rather than imitation) on employment.

Second, the upstream and downstream indicators should not be interpreted in terms of providers and customers of the focal firm. The reason is that we do not know which firms are the providers and customer of each focal firm. Accordingly, our indicator is more general and, using the standard labels from the international economics literature, captures upstream and downstream innovation. In the same line, the intra-industry indicator should not be interpreted as competitors. We do not know which firms are the specific competitors of each focal firm, which is too broad, so it likely contains most firms that actually do not compete against the focal firm.

Third, the coefficients from upstream industries reflect downstream effects while the coefficients from downstream industries should be interpreted as upstream effects. For example, a positive coefficient for upstream industries would mean that product innovation introduced by firms in upstream industries shows a positive effect on the focal firm’s employment (which is located downstream in the value chain). The same idea applies to the coefficient for downstream industries.

4.3.6 Estimation issues

Once the indicators of the forward and backward linkages of the equation (4.2) are created, some methodological problems have to be solved in the estimation process. Harrison et al. (2014) mentioned that an incorrect measure of prices at the firm-level and the unanticipated shocks generate the so-called “endogeneity problem” in the variable “sales growth due to new products”(g_2). This problem would imply a biased estimator of the parameters. As a solution to this problem, the instrumental variable methodology is applied. HJMP suggests different instruments, but one of them is preferable: the importance of the increase of the range of products as a motive for innovation. According to the authors, there are two main theoretical reasons to justify the use of the importance of this motive as an instrument. First, the degree by which product innovation is aimed to increase the range of products is likely to be correlated with planning (R&D, design, and marketing exploration) and the expectations of sales. Second, enlarging the range of products does not imply any particular direction of the changes in prices (while an increased market share is likely to be correlated with lower prices and improved quality with possibly higher prices). It also seems unlikely that the range of products is correlated with unanticipated productivity shocks.[94] Other instrumental variables are used in order to prove the robustness of the model, such as the importance of the clients as a source of information.[95]

4.4.- Data and descriptive statistics of the focal firms and the upstream, downstream and same industry

The firm-level panel data set is based on the Spanish Innovation Survey –available online– conducted by the Spanish Foundation of Science and Technology and the National Statistics Institute. We use the “Panel of Technological Innovation” (PITEC) for the time span of 2006 to 2012[96], which contains information about sales, employment, investment, and variables related to input and output of innovation. Table 4.1. shows descriptive statistics of the sample applied to analyze the effect of the product through the value chain

[94] Furthermore, it is important that the estimations with instrumental variables satisfy the inclusion and exclusion restrictions.
[95] For a critical review of these variables, see Chapter 2.
[96] In fact, our model covers the period 2009-2012; the data for 2006-2008 are used to create some variables.

on employment. First, the number of innovative firms represents more than fifty percent in the whole sample (a pattern that remains over time).

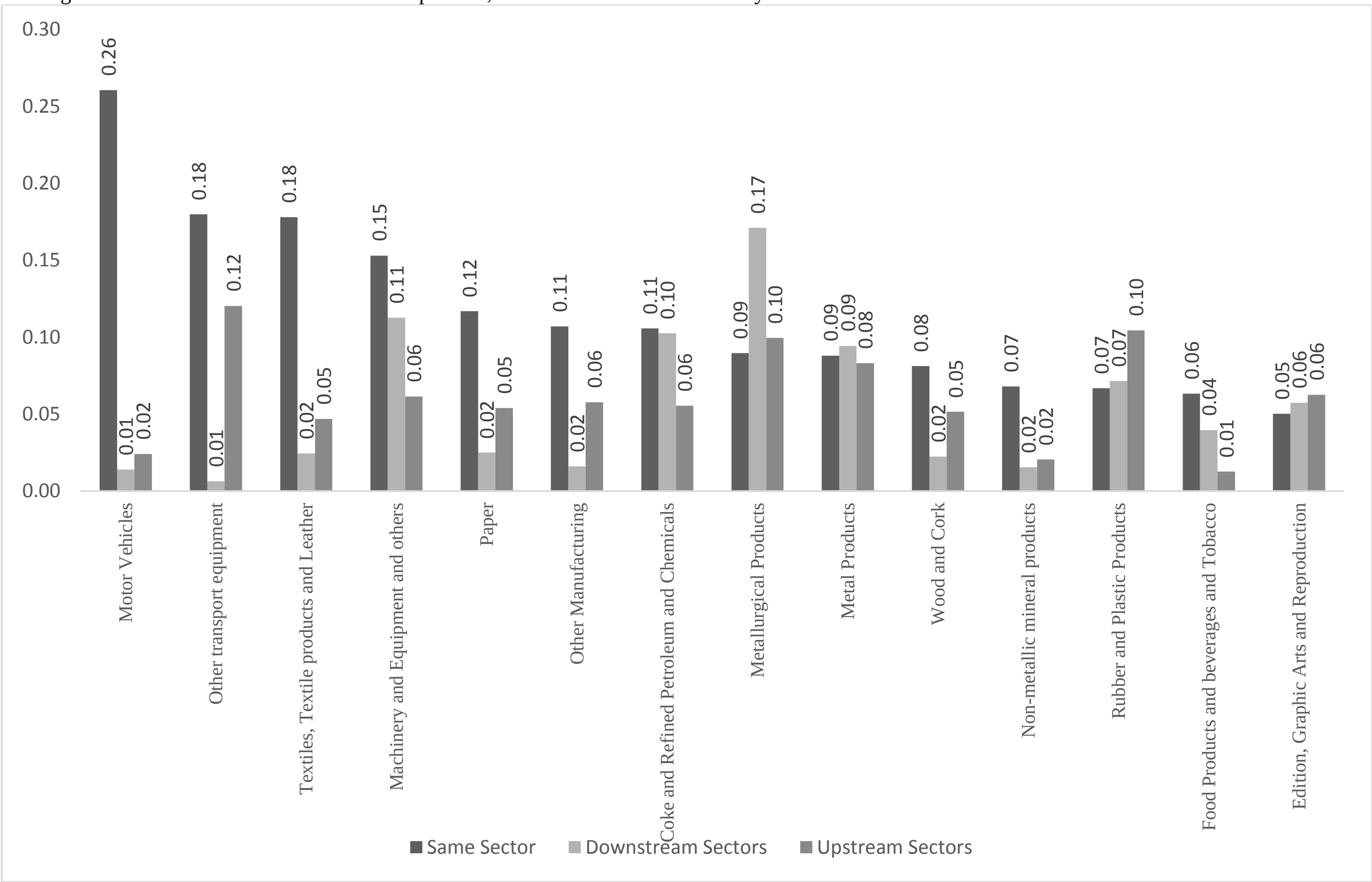
This high percentage is inherent to the PITEC data base. The sample should be representative of innovative firms in Spain[97] for the population while the non-innovative firms in the sample were added to improve the potential use of PITEC for research activities. Second, employment growth is negative for each year. The average of the employment growth for the whole sample is -5.99%. These results imply that we are dealing with a period of crisis. This effect is more remarkable in non-innovator (-10.36%) firms than in innovator firms.

[97] The Spanish Innovation Survey is sent to all firms that carry out innovative activities frequently and that received support for R&D and innovation form national, regional or European sources.

Table 4.1. Descriptive Statistics in percentages (triennial). Manufacturing firms (2009-2012)

	2009	2010	2011	2012	TOTAL
No. of firms	4294	4294	4294	4294	17176
Non-innovators (%)	19.56	19.19	33.72	40.27	28.18
Process innovators only (%)	16.14	15.84	15.58	14.32	15.47
Product innovators (%)	64.3	64.97	50.7	45.41	56.35
Product innovators only (%)	14.95	14.63	16.33	15.93	15.46
[Of which product & process innovators]	49.35	50.35	34.37	29.48	40.89
Employment growth (%)					
All firms	-3.82	-7.90	-8.01	-4.23	-5.99
Non-innovators (%)	-8.24	-12.32	-11.96	-8.93	-10.36
Process innovators only (%)	-4.83	-9.07	-6.26	-0.69	-5.21
Product innovators (%)	-2.22	-6.30	-5.93	-1.19	-3.91
Product innovators only (%)	-5.89	-9.73	-8.22	-3.87	-6.93
[Of which product & process innovators]	-1.11	-5.31	-4.84	0.26	-2.75
Sales growth (%)					
All firms	-9.39	-13.74	-10.01	2.27	-7.72
Non-innovators (%)	-16.04	-20.27	-15.14	-5.11	-14.14
Process innovators only (%)	-9.22	-15.17	-8.53	10.72	-5.55
Product innovators (%)	-7.42	-11.47	-7.04	6.15	-4.95
Old products	-33.41	-37.05	-29.90	-17.48	-29.46
New products	22.94	22.58	19.19	18.75	20.87
Prices growth (%)					
All firms	5.08	4.22	4.34	6.84	5.12
Non-innovators (%)	5.71	4.03	4.03	6.63	5.10
Process innovators only (%)	5.45	4.23	4.49	6.58	5.19
Product innovators (%)	4.79	4.27	4.50	7.11	5.17
Product innovators only (%)	4.79	3.82	4.16	6.05	4.71
[Of which product & process innovators]	4.80	4.40	4.65	7.68	5.38
Same firms (%)					
All firms	13.37	12.81	10.61	9.92	11.68
Non-innovators (%)	12.96	12.10	10.11	9.78	11.24
Process innovators only (%)	12.07	11.42	10.38	9.64	10.88
Product innovators (%)	13.82	13.35	11.02	10.14	12.08
Product innovators only (%)	14.66	14.71	11.52	10.64	12.88
[Of which product & process innovators]	13.56	12.96	10.78	9.87	11.79
Downstream (%)					
All firms	6.37	6.18	5.82	4.86	5.81
Non-innovators (%)	6.29	6.09	5.75	4.81	5.73
Process innovators only (%)	6.18	5.93	5.72	4.75	5.65
Product innovators (%)	6.44	6.26	5.90	4.95	5.89
Product innovators only (%)	6.55	6.44	6.13	5.02	6.04
[Of which product & process innovators]	6.41	6.21	5.79	4.91	5.83
Upstream (%)					
All firms	8.05	8.20	7.70	6.48	7.61
Non-innovators (%)	7.26	7.48	7.17	6.10	7.00
Process innovators only (%)	7.41	7.26	7.13	6.12	6.98
Product innovators (%)	8.46	8.64	8.23	6.94	8.06
Product innovators only (%)	9.08	9.43	8.71	7.34	8.64
[Of which product & process innovators]	8.27	8.41	7.99	6.72	7.85

Figure 4.1. Average of the share of Product Innovation in upstream, downstream and same industry



Source: Own elaboration with data of PITEC and input-output matrix (2010).

Also, in the case of sales, the data present a basically negative growth. The average of the whole period is -7.72. The negative effect is also stronger in non-innovative than innovative firms. However, sales growth due to new products is positive for the whole period. Finally, the information on the variables upstream, downstream and same industry, presented in Table 4.1., shows that the average sectoral share of new product on the market on the level of competitors is greater for those innovative firms (product) than those non-innovative firms at the sector level. Similar results are found for the case of upstream and downstream industries.

Figure 4.1. shows the unweighted average of product innovation in upstream, downstream and the same industry. As can be observed in the case of own industry the focal firm belongs to, the sectors with the higher effect of product innovation are motor vehicle (0.26), then other transport equipment (0.18) and finally textiles, textile products and leather (0.18).

For downstream industries, in the case of product innovation, the most outstanding sectors are other transport equipment (0.12), rubber and plastic products (0.10), and metallurgical products (0.10). Finally, for upstream industries, the most notable sectors that introduce product innovation are metallurgical products (0.17), machinery and equipment and others (0.11), coke and refined petroleum and chemicals (0.10).

4.5.- Results of the estimations

The estimations of the model take into account the period of time from 2006 to 2012. It is important to mention that the results of the estimations that are shown in the following sections are based on the random effects models that include two instrumental variables.

The first one is the importance of “increased product range as a motive”, suggested by Harrison et al. (2014), and of “customers as a source of information”, tested by Harrison et al. (2014) and Peters et al. (2017). Another important aspect is that a balanced data panel was used in order to respect the merge between the input-output matrix and innovation survey (PITEC).

4.5.1.- The extended HJMP model: effects on the overall employment growth

Column 1, in Table 4.2., shows the results of the original Harrison et al. (2014) model for our sample. They are in line with the findings of previous studies for Spain using the Harrison et al. (2014) model[98]: the effect of product innovation (g2) is close to 1, suggesting that the production of the new products is as efficient as the production of old ones. The coefficient for “only” process innovation (d) is negative, suggesting that process innovation of old products reduces employment in the focal firm. Finally, the constant term is positive and significant, which possibly reflects a labor hoarding effect[99] that can appear during a period of crisis (Peters et al., 2017).

The effects observed between innovation in the same industry and innovation in downstream industries or in upstream industries is significant. Several models were estimated to handle the strong positive correlation observed between innovation in downstream and upstream industries. For this reason, we also use a parsimonious approach to introduce the different variables in the subsequent columns of Table 4.2.

[98] Including our own result obtained in Chapter 3.

[99] This concept refers to the fact that in recession periods firms might maintain unnecessary (taking into account the decreasing demand) some part of their staff because the expected labor costs of those workers during the crisis are higher than the costs of firing, hiring and training new workers after the recession has subsided (Bhaumik, 2011; Biddle, 2014; Peters et al., 2017).

Table 4.2. The (inter)sectoral effects of product innovation on Employment of focal firm

	1	2	3	4	5	6	7
Employment	Basic Model	Only Same Sectors	Only downstream	Only Upstream	Same-downstream	Same-upstream	Jointly
d	-0.0293**	-0.0294**	-0.0291**	-0.0300**	-0.0292**	-0.0302**	-0.0298**
	[0.014]	[0.014]	[0.014]	[0.015]	[0.014]	[0.014]	[0.014]
g2	0.9092***	0.9123***	0.9077***	0.9005***	0.9109***	0.9036***	0.9059***
	[0.045]	[0.045]	[0.045]	[0.045]	[0.045]	[0.046]	[0.046]
Same sector	--	-0.1147**	--	--	-0.1159**	-0.1131**	-0.1146**
	--	[0.053]	--	--	[0.053]	[0.053]	[0.053]
Downstream Sector	--	--	0.3732***	--	0.3748***	--	0.2459
	--	--	[0.123]	--	[0.123]	--	[0.167]
Upstream Sector	--	--	--	0.2517***	--	0.2509***	0.1566
	--	--	--	[0.083]	--	[0.083]	[0.113]
Constant	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Sargan Test	1.233	1.328	1.165	1.206	1.248	1.277	1.246
P-value	0.745	0.723	0.761	0.752	0.741	0.735	0.742
Observations	17,176	17,176	17,176	17,176	17,176	17,176	17,176

Notes: Every specification includes the year dummies.
All industry variables are demeaned so that the constant term keeps its original interpretation.
Clustered standard errors are shown between brackets. * $p<0.05$, ** $p<0.01$, *** $p<0.001$
d Process innovation only
g2 Sales growth due to new products
* The two instrumental variables used are increased range and clients as a source of information.

Columns 2, 3 and 4 introduce each industry variable individually. Column 2 shows that, holding focal firms´ innovation constant, being located in a more product-innovative industry shows a negative influence on firms' employment. More precisely, a 1 percentage point (pp) increase in sales from new products in their same industry causes a 0.11 decrease of employment growth of the focal firm.

The intuition is that, ceteris paribus, the focal firm is in a better competitive situation, which subsequently implies a positive effect on its employment if its competitors are less product-innovative than if its competitors are more product-innovative. This result follows the logic of the business-stealing effect already mentioned.

Column 3 shows that, in the same innovative conditions, in downstream industries a higher level of product-innovation is related to a positive effect on firms' employment. More precisely, a 1 pp increase in sales from new products in downstream industries implies a 0.37 increase of employment growth for the focal firm.

The intuition is that, ceteris paribus, the focal firm that sells to more product-dynamic industries is in a better competitive situation than firms that sell to more stagnant industries. That is, product innovation from downstream industries shows a carry-over effect on upstream industries. Innovation in downstream industries can be challenging for firms located upstream, as they can suggest or require improvements on the catalogue of products they are currently selling to the market (Montresor & Marzetti, 2008; von Hippel, 1976). These means that firms located upstream should develop process of change dynamics that will likely be labor-intensive, or at least more labor-intensive than the contrafactual (downstream industries not being innovative, or not very innovative). Under this counterfactual, the focal firm operates in a stable environment in which, more or less informally, it tries to gain efficiency in doing the same thing that it was already doing at a lower cost, which usually implies cutting jobs.

Column 4 reflects that upstream industries that are more product-innovative have a positive effect on firms' employment. More precisely, a 1 pp increase in sales from new products in upstream industries is related to a 0.25 increase of employment growth of the focal firm. The intuition is that, ceteris paribus, the focal firm that buys from more product-dynamic industries is in a better situation than firms that buy from more stagnant industries. That is product innovation from upstream industries spillsover downstream. The product innovations introduced by firms in upstream sectors reflect the embodied technological change included in the investment and intermediate goods that they supply to the market, and this would be a "technological input" for the focal firm that may affect its employment because of an increase of sales or variations in productivity. In addition, as with innovation from downstream industries, it is likely that upstream innovations might generate dynamic processes of adaptation in downstream industries. The new inputs open the window to doing different things or doing things in a different way. Again, these dynamic processes of change may be labor-intensive or at least more labor-intensive than the contrafactual: upstream industries are not innovative, or not very innovative, so the focal firm operates in a stable environment in which, more or less informally, it tries to gain efficiency in doing the same thing that it was already doing at a lower cost.

Column 5 shows the result of the models that include both same industry and downstream at the same time, while column 6 simultaneously includes the indicator of the same industry and upstream sector. We can observe that the coefficients are very similar to those obtained in columns 2-4. Finally, column 7 shows the results including the three industry variables at the same time. On the one hand, the coefficient for same industries remains very stable. On the other hand, we observe that the size of the coefficients for downstream and upstream are approximately 63% of the ones from previous specifications. This fact, together with the increase in standard errors caused by the collinearity between both indicators, makes them not individually significant.[100] The issue here is that the high degree of correlation between them does not allow the model to estimate the partial effect of each of them (holding the other constant) with much precision.

To sum up, the results show that product innovation in the same industry affects the focal firm's employment negatively while product innovation across the value chain (upstream and downstream) affects the employment of the focal firm positively. The effect of downstream innovation is around 50% higher than the effect from upstream innovation. Several reasons of this differentiated impact could be imagined. Among others, it could be supposed that the impact of innovations is partially shrunken because all firms that compete with the focal firms could potentially have access to (or buy) the same product innovations from upstream industries, making the effects more diffuse. The large correlation between innovation by downstream and by upstream industries suggests that firms correctly embedded in the 'innovative value chains' show a positive impact on their employment growth.

[100]However, the coefficients are still positive and of relevant magnitude. In other words, the results are robust, so it seems that the collinearity problem does not generate an important bias of the value or signs of the parameters.

Table 4.3. The (inter)sectoral effects of product innovation (Lag) on employment of focal firm

	1	2	3	4	5	6	7
Employment	Basic Model	Only Same Sectors	Only downstream	Only Upstream	Same-downstream	Same-upstream	Jointly
solinnproc	-0.0293**	-0.0288**	-0.0292**	-0.0299**	-0.0288**	-0.0294**	-0.0291**
	[0.014]	[0.014]	[0.014]	[0.015]	[0.014]	[0.015]	[0.015]
wg2e	0.9092***	0.9163***	0.9078***	0.9032***	0.9149***	0.9103***	0.9125***
	[0.045]	[0.045]	[0.045]	[0.045]	[0.045]	[0.046]	[0.046]
Lag Same Sector	--	-0.2435***	--	--	-0.2445***	-0.2418***	-0.2435***
	--	[0.052]	--	--	[0.052]	[0.052]	[0.052]
Lag Downstream Sector	--		0.2865**	--	0.2899**	--	0.2287
	--		[0.121]	--	[0.120]	--	[0.162]
Lag Upstream Sector	--		--	0.1656**	--	0.1616**	0.0738
	--		--	[0.081]	--	[0.081]	[0.110]
Constant	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Sargan Test	1.233	1.438	1.166	1.204	1.346	1.374	1.338
P-value	0.745	0.697	0.761	0.752	0.718	0.712	0.720
Observations	17,176	17,176	17,176	17,176	17,176	17,176	17,176

Notes: Every specification includes the year dummies.
All industry variables are demeaned so that the constant term keeps its original interpretation.
Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
* The two instrumental variables used are increased range and clients as a source of information

Table 4.4. The (inter)sectoral effects of product innovation on employment of focal firm using sales growth

	1	2	3	4	5	6	7
Employment	Basic Model	Only Same Sectors	Only downstream	Only Upstream	Same-downstream	Same-upstream	Jointly
D	-0.0293**	-0.0295**	-0.0291**	-0.0302**	-0.0293**	-0.0305**	-0.0303**
	[0.014]	[0.014]	[0.014]	[0.015]	[0.014]	[0.014]	[0.014]
g2	0.9092***	0.9154***	0.9074***	0.8984***	0.9140***	0.9045***	0.9059***
	[0.045]	[0.045]	[0.045]	[0.045]	[0.045]	[0.046]	[0.046]
Same Sector	--	-0.1621***	--	--	-0.1751***	-0.1795***	-0.1813***
	--	[0.051]	--	--	[0.050]	[0.051]	[0.050]
Downstream Sector	--	--	0.3372***	--	0.3670***	--	0.1389
	--	--	[0.111]	--	[0.109]	--	[0.155]
Upstream Sector	--	--	--	0.2833***	--	0.3067***	0.2527**
	--	--	--	[0.071]	--	[0.070]	[0.100]
Constant	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***	0.0893***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Sargan Test	1.233	1.411	1.161	1.199	1.315	1.324	1.307
P-value	0.745	0.703	0.762	0.753	0.726	0.723	0.728
Observations	17176	17,176	17,176	17,176	17,176	17,176	17,176

Notes: Every specification includes the year dummies.
All industry variables are demeaned so that the constant term keeps its original interpretation.
Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
* The two instrumental variables used are increased range and clients as a source of information

The models are tested in order to show their reliability and robustness. A first aspect that can be highlighted is that the introduction of the industry indicators does not change the coefficients substantially for the main variables of the basic HJMP model, as reflected in column 1 of Table 4.2. In fact, in all the models, the coefficients for process (d), product innovation (g2) and the constant are very stable across specifications. Moreover, the robustness check presented in Table 4.2. assumes a contemporaneous relationship between the introduction of product innovation in the different industries and employment variations in the focal firm.

As discussed in the introduction of this chapter, the use of percentage of sales of new products by total sales would imply that at the firm-level this relationship has a contemporaneous character. Anyhow, the innovation carried out by different firms and industries could have a delayed influence on the focal firm, so some models based on a lagged sector variable were estimated. In the lagged model, the coefficient for the employment effects of product innovation in same industry (see Table 4.3.) is more than the double the coefficient observed in Table 4.2., suggesting that most of the negative effects of same industry innovation take some time. On the other hand, the coefficients for downstream and upstream industries are closer to the contemporaneous ones, although a bit lower (78% for downstream and 66% for upstream).

In Table 4.4., we check the robustness of the results, taking into consideration a different indicator of industry product innovation. Instead of using the sales from new products, we use an indicator of the growth of sales from new products (for more details about the constructions of this variable, see the appendix in Box 4.2.a).

For this alternative indicator, we observe the same relationships as in the main model reflected in Table 4.2. Product innovation in the same industry negatively affects firms' employment growth, while product innovation in downstream and upstream industries positively affects firms' employment growth. As in the main model, the magnitude of the effect is the lowest for same industry but, contrary to previous findings, the coefficient for the upstream is now around 30% larger than the coefficient for the downstream and retains more of the effect when the two of them are jointly introduced into the model.

4.5.2.- Effect on High- and Low-Skilled employment

To delve more into the employment effects through the value chain, we also analyze the effects of product innovation of downstream, upstream and same industry for high- versus low-skilled employment, using the level of education as an indicator for the level of skills (Díaz et al., 2020). We modify the HJMP model to obtain equations and sum up the new variable's c (see equations 4.1 and 4.2).

$$l^{ls} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \gamma_1 Comp_{prod_{jt}} + \gamma_2 clients_{prod_{jt}} + \gamma_3 prov_{prod_{jt}} + \varepsilon_i^{ls} \quad (4.9)$$

$$l^{hs} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \gamma_1 Comp_{prod_{jt}} + \gamma_2 clients_{prod_{jt}} + \gamma_3 prov_{prod_{jt}} + \varepsilon_i^{hs} \quad (4.10)$$

where l^{ls} is low-skilled employment and l^{hs} is high-skilled employment.[101] The rest of the variables are the same as the general model (see equation 2). Table 4.5. and Table 4.6. show the results for low- and high- skilled employment, respectively. The structure of these tables is similar to that of Table 4.2.

The results for low-skilled workers are similar to the general results in Table 4.2. The coefficient for same industry innovation is of a similar size, the coefficient for downstream

[101] It is calculated as a percentage of paid staff with higher education for high-skilled workers.

is slightly lower and the coefficient for upstream is around 40% larger than the coefficient in Table 4.2. In addition, when upstream and downstream are included together, the coefficient for upstream remains very stable, and the coefficient for the downstream is the one going close to zero. On the other hand, the results for high-skilled workers show no significant relationship between any of the industry variables and the high-skilled employment of firms.

To sum up, it suggests that the effect of innovation through the value chain on firms' employment is almost entirely due to low-skilled workers while we do not find evidence that the employment of high-skilled workers is affected by innovation outside the firm.

Table 4.5. The effects of product innovation on low-skilled employment

	1	2	3	4	5	6	7
Employment	Basic Model	Only Same Sectors	Only downstream	Only Upstream	Same-downstream	Same-upstream	Jointly
d	-0.0315*	-0.0317*	-0.0314*	-0.0327*	-0.0316*	-0.0329*	-0.0328*
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]
g2	0.8965***	0.8995***	0.8950***	0.8835***	0.8981***	0.8865***	0.8870***
	[0.054]	[0.055]	[0.054]	[0.055]	[0.055]	[0.055]	[0.055]
Same Sector	--	-0.1135*	--	--	-0.1147*	-0.1108*	-0.1112*
	--	[0.062]	--	--	[0.062]	[0.062]	[0.062]
Downstream Sector	--	--	0.3260**	--	0.3276**	--	0.0514
	--	--	[0.144]	--	[0.144]	--	[0.195]
Upstream Sector	--	--	--	0.3558***	--	0.3548***	0.3351**
	--	--	--	[0.097]	--	[0.097]	[0.132]
Constant	0.0923***	0.0923***	0.0923***	0.0923***	0.0923***	0.0923***	0.0923***
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
Sargan Test	2.208	2.337	2.099	2.076	2.221	2.178	2.170
P-value	0.530	0.505	0.552	0.557	0.528	0.536	0.538
H0:g2=1	3.622	3.378	3.713	4.459	3.465	4.190	4.157
Prob>F	0.0570	0.0661	0.0540	0.0347	0.0627	0.0407	0.0415
Observations	17,069	17,069	17,069	17,069	17,069	17,069	17,069

Notes: Every specification includes the year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001
d Process innovation only
g2 Sales growth due to new products
b Instruments used are increased range and clients as a source of information

Table 4.6. The effects of product innovation on high-skilled employment

	1	2	3	4	5	6	7
Employment	Basic Model	Only Same Sectors	Only downstream	Only Upstream	Same-downstream	Same-upstream	Jointly
d	-0.0271	-0.0269	-0.0272	-0.0273	-0.0269	-0.0271	-0.0268
	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]
g2	1.0712***	1.0682***	1.0705***	1.0715***	1.0675***	1.0685***	1.0705***
	[0.134]	[0.135]	[0.134]	[0.135]	[0.135]	[0.136]	[0.136]
Same Sector	--	0.1050	--	--	0.1048	0.1048	0.1037
	--	[0.168]	--	--	[0.168]	[0.168]	[0.168]
Downstream Sector	--	--	0.1078	--	0.1072	--	0.2123
	--	--	[0.361]	--	[0.361]	--	[0.434]
Upstream Sector	--	--	--	-0.0489	--	-0.0473	-0.1274
	--	--	--	[0.243]	--	[0.243]	[0.292]
Constant	0.1784***	0.1784***	0.1784***	0.1784***	0.1784***	0.1784***	0.1784***
	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]
Sargan Test	2.267	2.268	2.258	2.315	2.259	2.314	2.338
P-value	0.519	0.519	0.521	0.510	0.520	0.510	0.505
H0:g2=1	0.284	0.257	0.277	0.280	0.251	0.253	0.269
Prob>F	0.594	0.612	0.598	0.596	0.616	0.615	0.604
Observations	14,321	14,321	14,321	14,321	14,321	14,321	14,321

Notes: Every specification includes the year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001

d Process innovation only

g2 Sales growth due to new products

b Instruments used are increased range and clients as a source of information

4.6.- Conclusions

In this chapter, an extended HJMP model is developed, based on the firm's employment equation from the basic model of Harrison et al. (2014) that is applied to firm-level data. A new data panel set was created, combining the micro data of the Spanish Innovation Survey with sector-level data on product innovation. The sector data comes from the national input-output tables published by the Spanish National Office of Statistics and is used to build an indicator of the level of product innovation in related industries. The data used in this article comes from the Panel of Technological Innovation (PITEC) from 2006 to 2012 for the Spanish economy with the input-output matrix from 2010.

The objective is to address a research question seldom analyzed in the literature of economics of innovation by using a methodological approach that has been successfully applied in a related stream of literature, the analysis of the employment effects of product innovations by downstream, upstream and same industry on focal firms. In other words, the overall sector-level product innovations benefit or deteriorate the focal firm's employment situation. To this aim, we extend the Harrison et al. (2014) model to analyze the relationship between firm innovation and firm employment**.** We account for innovation through the value chain based on a panel data set of innovation activities of Spanish firms combined with an indicator of inter-sectoral trade flows. These flows are defined as the inter-sectoral flows of intermediate goods, based on the sector-level input-output data adjusted for its sector level intensity of sales of new products by total sales.

The results show that product innovation in the same industry affects the focal firm's employment negatively while product innovation across the value chain (downstream and upstream) positively affects employment at the firm-level. We also find that these positive and negative effects exist in the case of low-skilled labor, while for high-skilled workers, no statistically significant effects were detected. A result that should be highlighted is that the effect of product innovation by downstream industries is around 50% higher than the effect of product innovation by upstream industries.

To conclude, the results suggest that the introduction of product innovation in the same industry has a labor-saving impact on the focal firm. Contrarily, new products generated by upstream and downstream industries have a positive effect on the total employment of the focal firm. For different types of workers, the results also show a fall in the firm's labor growth for effect on low-skilled employment if the product innovation is introduced by firms in the same industry. Contrarily, positive results on low-skilled employment are found if the product innovation is generated downstream or upstream. We do not find evidence that the employment of high-skilled workers is affected by innovation outside of the firm.

Regarding the limitations of this work, which also constitute opportunities for future research, it can be mentioned that we do not observe the specific clients, providers and customers of each firm. Moreover, we used the statistical classification of economic activities in the European Community (NACE) at a two-digit level. If data on this were available, a more fine-grained analysis could be made and the role of agglomeration effects by geographical close relations and the role of the characteristics of the interactions could be analyzed.

Box 4.1.a Definition of innovation by the OECD

The Oslo Manual defines four types of innovation:

- Product innovation: A good or service that is new or significantly improved. This includes significant improvements in technical specifications, components and materials, software in the product, user friendliness or other functional characteristics.

- Process innovation: A new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software.

Box 4.2.a- The construction of other variables to test robustness of the model.

It is important to mention that new variables are built only taking into account the impact of the innovation on the market (taking away the impact of the firm). The construction of the competitors and providers changes as can be seen in the following equations:

$$Intra_{\ prod_{jt}} = \frac{[\sum_{i \forall i \in j}(s_{it} * sales_{it})] - (s_{it} * sales_{it})}{[\sum_{i \forall i \in j} sales_{it-3}] - (sales_{it-3})} \ (1)$$

$$down_{prod_{jt}} = \sum_{k \ if \ k \neq j} \propto_{jk} * \ (Comp_{\ prod})(2)$$

$$up_{prod_{jt}} = \sum_{m \ if \ m \neq j} \sigma_{jm} * \frac{[\sum_{i \forall i \in m}(s_{it} * (sales_{it} - x_{it}))] - (s_{it} * (sales_{it} - x_{it}))}{\sum_{i \forall i \in m}(sales_{it-3} - x_{it-3}) - (sales_{it-3} - x_{it-3})} \ (3)$$

where s is the percentage of sales of new products which represent a novelty to the market. The final structure is in terms of growth rates.

Chapter 5.- Conclusions, limitations and final remarks

5.1.- Summary of the main aspects treated in this study and the overall empirical results and conclusion

In this section, the main conclusions of the different chapters will be summarized. Throughout this Ph.D. thesis, various aspects of the relationship between innovation and employment are analyzed. This research started with a review of the approaches that have historically driven the theoretical discussion about the employment effects of innovation. It seems that all schools of economic thought agree with the existence of compensation mechanisms that mitigate the initial negative impact of process innovation. Keynesian and Schumpeterian economics also recognize several of the effects of such mechanisms, but they deny some of the assumptions behind them. Moreover, modern theories underpin the importance of the "creative destruction," which not only implies structural changes in the production sector, but also "destroys" the abilities and accumulated experience of workers in "old" sectors, which makes it difficult for such workers to find jobs in the emerging sector.

The second part of the first chapter shows the effects of innovation in qualitative terms, using two complementary theoretical, conceptual frameworks that discuss this phenomenon. The first one is the Skill-Biased Technological Change (SBTC) hypothesis, proposed by Griliches (1969). According to the SBTC, new technology complements skilled workers while new machines might substitute unskilled workers. The hypothesis is enriched by a second concept, the Routine-Biased Technological Change (RBTC) hypothesis, assuming that replacement depends on the routine component of jobs. Skilled workers tend to execute non-routine activities, so it is difficult to substitute them. On the other hand, unskilled workers tend to do routine tasks, which makes it easy to replace them with new technologies.

An important conclusion of Chapter 1 is that the corresponding theoretical studies support the labor-creating effect of product innovation. Another essential aspect that has to be kept in mind is that many empirical studies, especially those carried out in the past century, used a macroeconomic approach, or analyzed the employment effects of innovation at the sector-level. The theoretical discussion presented in the first chapter is a macro-level debate.

Chapter 2 offers a review of empirical studies that have analyzed the effects of innovation at the firm-level. The firm-level studies that examine the impact of innovation on employment can be divided into two main types of approaches. The first one is an output-oriented model defined by Harrison et al. (2014) that represents innovation by the introduction of new products (percentage of total sales coming from new products) and of new processes not related to new products (only process innovation). The second type is an input-oriented model proposed by Bogliacino et al. (2012, 2014), with R&D expenditures proxying for the innovation of firms.

The 44 studies reviewed in Chapter 2 suggest that product innovation has a strong and positive effect on employment for different types of samples developed and developing countries, manufacturing and service sectors and high- and low-tech sectors. However, no definite conclusions were reached about the impact of process innovation on employment. The result is ambiguous as a similar number of studies reflect a negative or positive employment effect derived from process innovation, and most of them show a non-significant effect. On the other hand, the vast majority of the articles that analyze the employment effects generated by R&D expenditures (the input orientation) show a clear, positive impact on employment.

The review of the theoretical debate and the empirical studies revealed, among others, two essential aspects of the employment effects of innovation seldom analyzed at a firm level. First, to the best of our knowledge, only one study examined the possible differential effects of innovation on employment during bad times in comparison with a more stable economic situation. Second, only a few studies, all of them for developing countries of Latin America, analyzed the effects of innovation on employment for different types of workers: skilled versus unskilled. In this thesis, we try to deal with these two limitations at the same time for the Spanish case.

Another relevant aspect is that the firm-level empirical studies focus on the direct micro effects within each focal firm. Such studies do not analyze the possible impact of innovation introduced by other firms. For example, the decrease of employment in the focal firms may be caused by a business stealing effect as a consequence of a product innovation from a competitor. In this Ph.D. thesis, we try to go beyond the direct micro impact of innovations introduced by each focal firm on its employment. We analyze more global effects within the value chain by combining firm-level data with data on product innovations integrated in the intra- and inter-sectoral linkages (based on the input-output tables). The motive is to build indicators of downstream, upstream, and intra-industry product innovation and analyze their effect on the employment of the focal firm. In other words, this work tries to measure the employment effects of innovation along the value chain.

For both empirical models developed for this Ph.D. study, the approach of Harrison et al. (2014) is used. The main advantage of this model is that it allows us to analyze the differentiated impact of product and process innovation on different types of workers. Also, the model is flexible enough to be extended with product innovation throughout the value chain.

In Chapter 3, the main results of the estimations confirm the conclusions of earlier studies, suggesting a positive general effect of innovation on the total employment of firms, even in a period of economic crisis. Also, a labor hoarding effect is found for both types of workers, but this effect is larger for high-skilled workers, an atypical effect that seems to appear at the time of the crisis, as mentioned by Peters et al. (2017). Moreover, the models for the sector-based subsamples reflect that this result holds across different industries and the impact of product and process innovation is exacerbated in high-tech industries. Product innovation has a positive effect on overall, high- and low-skilled jobs, while process innovation seems to have a small effect on overall and high- and low-skilled employment.

Regarding the relationship between innovation and type of employment, the empirical data show that product innovation is mainly responsible for the skill-biased effect of innovation. Although product innovation positively affected both types of employment, the effect is much larger for high-skilled workers. It is estimated that product innovations account for around 13% of the different evolution between high-skilled and low-skilled employment during the crisis

Chapter 4 provides an insight into the employment effects of the focal firm if downstream, upstream, and the same sectors introduce product innovations. We found that innovation in the same industry is related to a reduction in focal firms' employment, which suggests a business stealing effect. The intuition is that, holding focal firm innovation constant, the focal firm is in a better competitive situation that subsequently implies a positive impact on its employment if firms in its same industry are less product-innovative than if they are more product-innovative.

On the other hand, we found that both downstream and upstream sectors positively affect a firm’s employment if they generate new products. We also found that downstream and upstream product innovation are very correlated. The intuition is that, holding focal firm innovation constant, firms embedded in innovative value chains enjoy higher employment growth. We found that low-skilled workers entirely capture these three effects. In contrast, high-skilled workers are insensitive to product innovation in the same and related industries.

5.2.- Policy implications

The evidence emerging from our analysis relates to several policy-relevant aspects. Policymakers must be aware of the effects of innovation on employment to offer an optimal design of public policies. Logically, most innovation policies are focused on goals in terms of firms' product innovation or on improving overall performance (productivity growth based on process innovations) and consider other effects (such as employment) only marginally. Therefore, such innovation policies should be combined or coordinated with other policy fields, especially labor, education, and vocational training.

The study results are not easily convertible directly into new policy measures, although its embeddedness in the overall literature on employment effects of innovation makes it possible to derive different policy implications or, better said, confirms existing studies' notions or mindsets.

This thesis offers four main conclusions. First, product innovation is associated with positive employment effects. Therefore, policy measures fostering the creation and diffusion of new products will have positive employment effects. Most of these policies come from the supply side, promoting the development of product innovation by firms through traditional tools like subsidies or tax credits. Although in the last two decades the demand side based on innovation policies gained importance, like the fostering of specific new products based on public procurement policies and/or the imposition of standard requirements on new technologies with social benefits, such as clean new products. Also, innovation policies need to be coordinated with labor policies to have better results. In other words, the innovation policy must consider that the results obtained might impact on employment. As a result, a system vision is crucial for policymakers.

Second, we have found that product innovation shows a positive effect on employment even during a period of economic crisis, which constitutes an argument for innovation policy not to be pro-cyclical. An important aspect taken into account is that in Spain, the public R&D expenditures did drastically decline during the 2008 crisis and did not recover its level. Between 2006 and 2017, Spain's direct and indirect support (respectively subsidies and tax credits) for R&D and innovation decreased from 0.125% to 0,093% of the GDP, and their support intensity occupies the 27th position of the 37 OECD members (Fundación Cotec, 2020).

Third, in relation to process innovation, especially recent literature on the potential employment impact of "robotization" and automatization as a form of process innovation – often publicly incentivized by specific technology policy programs– will have a negative short-term impact on employment. Replacing workers for the new process innovation like new machines, computers or robots. The analytical framework of this study does not allow such macro-economic analysis, though its microeconomic results confirm the adverse employment effects of process innovation –at least short-term effect–, although such negative employment effects can be compensated with the positive effect of product innovation (which facilitates process innovation in customers).

Fourth, one of the thesis's main novelties was analyzing the differentiated impact of innovation on employment by skill levels. According to our estimates, product innovation is responsible for the skill-biased effect in the focal firm. However, the introduction of product innovation by upstream and downstream sectors might compensate for the skilled bias generated in the focal firm. As Acemoglu & Restrepo (2017) stated, the skill-biased employment effects of innovation are most pronounced in manufacturing, particularly in industries most exposed to innovation; in routine manual, blue-collar, assembly related occupations; and for workers with less than a college education. In their study, they used the "robots" as a proxy of innovation.

Keynes underpinned the role of "technical unemployment" based on the crowding-out effects of jobs due to technical changes. The skills of the expelled workers are partially obsolete. It means that they cannot find a job even in the shortage of workers for specific jobs (but that require new skills not easy to learn) in the same or other sectors. A result of this phenomenon is that many of the losses in factory jobs have been countered by an increase in the service industries with low wages (Autor, 2015). So, their skill level has effectively removed them from the labor force, and such a situation brings "long life learning" in the center of labor and education policies.

Therefore, this study's analysis focused on the skill-biased impact is relevant to identify the policy implications. As mentioned, we found a positive effect of sales growth due to new products for all types of jobs: high-, low-skilled and total employment. On the other hand, in process innovation, we found a negative effect for low-skilled workers and total employment, while no effects exist for high-skilled workers.

Although we do not have enough information to test the labor polarization hypothesis, we shed light on how technology complements high-skilled workers and detriments low-skilled workers. Again, this skill bias might be compensated if upstream and downstream sectors introduce new products. To deal with skill-bias generated by innovation, it is necessary to update training and educational programs in order to reduce the existing gap between high- and low- workers. For example, Vocational Educational training system (VET) links a continuous education scheme between companies' technological processes and educational sectors, promoting not only the insertion of their population as part of an active learning process but allowing pedagogical forms to correlate to the needs of labor markets. It has been used as a public policy to reduce the drop out of young people from schools in European countries (Arenas Díaz et al., 2020). It is also applied in the case of migrants in Germany (Burkert & Seibert, 2007). It might work in the case of those workers that belong to the low-skilled level.

5.3.- Main limitations and future lines of research

As always, each research project addresses problems and limitations that cannot be solved, or their inclusion implies an extreme additional workload. The researcher selects only some of the open research questions and has to leave others unanswered. One crucial drawback that has to be taken into account for the correct interpretation of the results is that the models only include short-term effects, which might be different from the long-term effects.

A second limitation of this study is that the indicator available in the Spanish innovation survey to measure the skills of workers distinguishes only two groups of employees (high- and low-skilled workers) and is based on their educational level. In other words, there is neither information on the real skill-content of the jobs nor data to account for the number of employees of an intermediate skill. This last aspect makes it impossible to analyze the issue of a potential labor polarization effect: a growth of demand for high- and very low-skilled workers accompanied simultaneously by a reduction of the number of required medium-skilled workers (Autor et al., 2006).

A third limitation is that it is observed only in a period of turmoil. Therefore, it is not possible to compare the effect of product and process innovation on high- and low-skilled workers against an expansion period. Another interesting aspect of analysis would be the impact of innovation on relative wages of high- and low- skilled workers. However, the lack of data on wages makes it impossible to analyze this aspect.

A fourth limitation, especially for Chapter 3, is related to the used data. PITEC is representative only for firms with internal and external R&D investments. The results found in Chapter 3 cannot be extrapolated to the whole population of firms[102]. A fifth limitation regarding the analysis made in Chapter 4 is that we do not observe the specific clients, providers and customers of each firm. If such data were available, a more fine-grained analysis could be made. Moreover, it would be interesting to analyze inter-sectoral

[102] We thank one external reviewer for highlighting this point.

flows and the role of traditional spillover effects simultaneously, based on the agglomeration effects by close geographical relations.

One last critical remark is that the analysis focuses on product innovation only. Indeed, technological flows across industries usually take place through products. However, it would be of interest to analyze whether there are employment effects of the downstream, upstream, and the same industry for process innovation on the focal firm's employment.

Finally, the possible effect of process innovation on back shoring is a future line of research. Many of the activities, which took place in low-wage countries, could return to the more advanced countries, making the more developed countries monopolize the increase in productivity generated by technological change (Dachs et al., 2019). For those formerly labor-intensive activities for which the new forms of "robotization" drastically decrease labor costs in the total added value–due to productivity growth– there is no longer any need to locate them in low wage countries. Therefore, it can be shored back to high-income countries. Although there is already literature that conceptually and empirically analyzes the issue of return (Dachs et al., 2019; Fratocchi & Di Stefano, 2020; Kinkel et al., 2020), it is too early to evaluate the long-term consequences of this process. There are clear policy implications because back shoring could be an interesting policy measure for advanced countries like Spain.

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. https://doi.org/10.1080/1540496X.2015.998072

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, *40*(1), 7–72. https://doi.org/10.1257/jel.40.1.7

Acemoglu, D., Akcigit, U., & Kerr, W. (2017). Networks and the macroeconomy: An empirical exploration. In *NBER Macroeconomics Annual* (Vol. 30, Issue 1). https://doi.org/10.1086/685961

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics* (Vol. 4, Issue PART B). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., LeLarge, C., & Restrepo, P. (2020). *COMPETING WITH ROBOTS: FIRM-LEVEL EVIDENCE FROM FRANCE* (Vol. 2011, Issue 26738). http://www.nber.org/papers/w26738

Acemoglu, D., & Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. *NBER WORKING PAPER SERIES*, *23285*. https://doi.org/10.3386/w23285

Acemoglu, D., & Restrepo, P. (2018). Low-skill and high-skill automation. *Journal of Human Capital*, *12*(2), 204–232. https://doi.org/10.1086/697242

Aghion, P., Askenazy, P., Berman, N., Cette, G., & Eymard, L. (2012). Credit constraints and the cyclicality of R&D investment: Evidence from France. *Journal of the European Economic Association*, *10*(5), 1001–1024. https://doi.org/10.1111/j.1542-4774.2012.01093.x

Aghion, P., & Howitt, P. (1998). A schumpeterian perspective on growth and competition. In F. Coricelli, M. di Matteo, & F. Hahn (Eds.), *New Theories in Growth and Development* (pp. 9–49). Palgrave Macmillan. https://doi.org/10.1007/978-1-349-26270-0

Alonso-Borrego, C., & Collado, M. D. (2002). Innovation and job creation and destruction: Evidence from Spain. *Recherches Economiques de Louvain*, *68*(1–2), 149–168. https://doi.org/10.3917/rel.681.0148

Alvarez, R., Benavente, J. M., Campusano, R., & Cuevas, C. (2011). Employment generation, firm size and innovation in Chile. In *IDB - Technical Notes* (IDB-TN-319; Issue October). www.iadb.org

Archibugi, D., Filippetti, A., & Frenz, M. (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy*, *42*(2), 303–314. https://doi.org/10.1016/j.respol.2012.07.002

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Arenas Díaz, G., Guzzeti, G., Irigoyen, S., & Nardi, P. (2020). Capability Approach in VET as a Strategy to Reduce Dropout : The " Job High-School " Case in Italy. In C. Nägale, B. E. Stalder, & N. Kersh (Eds.), *Proceedings of the European Conference on Educational Research (ECER): Vol. III* (pp. 19–29). Vocational Education and Training Network. https://doi.org/https://doi.org/10.5281/10.5281/zenodo.4005697

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, *159*, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Autor, D. (2010). The Polarization of Job Opportunities in the U . S . Labor Market. *Community Investments*, *23*(April), 360–361. http://econ-www.mit.edu/files/5554

Autor, D. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D., & Dorn, D. (2013). *American Economic Association The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*. *103*(5), 1553–1597. http://www.jstor.org/stable/42920623

Autor, D., Katz, L. F., & Kearney, M. S. (2006). The polarization of the U.S. labor market. *American Economic Review*, *96*(2), 189–194. https://doi.org/10.1257/000282806777212620

Autor, D., Katz, L. F., & Kearney, M. S. (2008). Trends in U . S . Wage Inequality : Revising the Revisionists. *The Review of Economics and Statistics*, *90*(2), 300–323. https://doi.org/10.1016/j.mycmed.2014.02.007

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Autor, D., & Salomons, A. (2018). Is automation labor share–displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity*, *2018*(Spring), 1–87. https://doi.org/10.1353/eca.2018.0000

Barge-Gil, A., López, A., & Núñez-Sánchez, R. (2017). Estimation of Foreign MNEs spillovers in Spain. In *Economic Policy* (Issue 77348). https://doi.org/10.1227/01.NEU.0000349921.14519.2A

Barge-Gil, A., López, A., & Núñez-Sánchez, R. (2020). Technological spillovers from multinational presence. *The World Economy*. https://doi.org/10.1177/146499340901000301

Barrios, S. (2000). *Foreign Direct Investment and Productivity Spillovers*. https://www.researchgate.net/publication/5022373

Benavente, J. M., & Lauterbach, R. (2008). Technological innovation and employment: complements or substitutes? *The European Journal of Development Research*, *20*(2), 318–329. https://doi.org/10.1080/09578810802060744

Bhaumik, S. (2011). Productivity and the Economic Cycle. In *BIS Economics Paper No 12* (Issue 12). https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/32108/

11-772-productivity-and-the-economic-cycle.pdf

Bianchini, S., & Pellegrino, G. (2019). Innovation persistence and employment dynamics. *Research Policy*, *48*(5), 1171–1186. https://doi.org/10.1016/j.respol.2018.12.008

Biddle, J. E. (2014). Retrospectives: The cyclical behavior of labor productivity and the emergence of the labor hoarding concept. In *Journal of Economic Perspectives* (Vol. 28, Issue 2, pp. 197–212). American Economic Association. https://doi.org/10.1257/jep.28.2.197

Blanchflower, D. G., & Burgess, S. M. (1998). New technology and jobs: Comparative evidence from a two country study. *Economics of Innovation and New Technology*, *5*(2–4), 109–138. https://doi.org/10.1080/10438599800000002

Blomström, M., Kokko, A., & Zejan, M. (1994). Host country competition, labor skills, and technology transfer by multinationals. *Weltwirtschaftliches Archiv*, *130*(3), 521–533. https://doi.org/10.1007/BF02707611

Blomström, M., & Persson, H. (1983). Foreign investment and spillover efficiency in an underdeveloped economy: Evidence from the Mexican manufacturing industry. *World Development*, *11*(6), 493–501. https://doi.org/10.1016/0305-750X(83)90016-5

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised pavitt classes. *Research Policy*, *39*(6), 799–809. https://doi.org/10.1016/j.respol.2010.02.017

Bogliacino, F., & Pianta, M. (2015). The Pavitt Taxonomy, Revisited. Patterns of Innovation in Manufacturing and Services. In *Documento Escuela de Economía* (No. 57). https://doi.org/10.2139/ssrn.2579642

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. https://doi.org/10.1016/j.econlet.2012.01.010

Bogliacino, F., Piva, M., & Vivarelli, M. (2014). Technology and employment: The job creation effect of business R & D. *Rivista Internazionale Di Scienze Sociali*, *3*, 239–264. https://doi.org/10.1400/228563

Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers*, *51*(2), 96–113. https://doi.org/10.1111/j.1467-8454.2012.00425.x

Boianovsky, M., & Trautwein, H. M. (2010). Schumpeter on unemployment. *Journal of Evolutionary Economics*, *20*(2), 233–263. https://doi.org/10.1007/s00191-009-0154-8

Brouwer, E., Kleinknecht, A., & Reijnen, J. (1993). Employment growth and innovation at the firm level an empircal study. In *Journal of Evolutionary Economics* (Vol. 3, Issue 2, pp. 153–159). https://doi.org/10.1111/j.1435-5957.2011.00394.x

Burkert, C., & Seibert, H. (2007). Labour market outcomes after vocational training in Germany: equal opportunities for migrants and natives? In *IAB Discussion Paper:*

Beiträge zum wissenschaftlichen Dialog aus dem Institut für Arbeitsmarkt- und Berufsforschung: Vol. 31/2007. https://www.ssoar.info/ssoar/handle/document/31990#

Caballero, R., & Hammour, M. (1997). *Jobless Growth: Appropriability, Factor Substitution, and Unemployment* (No. 6221). https://doi.org/10.3386/w6221

Cainelli, G., Evangelista, R., & Savona, M. (2005). Innovation and economic performance in services: A firm-level analysis. *Cambridge Journal of Economics*, *30*(3), 435–458. https://doi.org/10.1093/cje/bei067

Calvino, F. (2019). Technological innovation and the distribution of employment growth: A firm-level analysis. *Industrial and Corporate Change*, *28*(1), 177–202. https://doi.org/10.1093/icc/dty003

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. https://doi.org/10.1111/joes.12190

Caves, R. E. (1974). Multinational Firms, Competition, and Productivity in Host-Country Markets. *Economica*, *41*(162), 176–193. https://doi.org/10.2307/2553765

Crespi, G., & Tacsir, E. (2012). The Economic Effects of Innovation on Employment in Latin America. In *IDB - Technical Notes* (IDB-TN-496; Issue December).

Dachs, B., Hud, M., Koehler, C., & Peters, B. (2016). Innovation, creative destruction and structural change: firm-level evidence from European countries. *Industry and Innovation*, *24*(4), 346–381. https://doi.org/10.1080/13662716.2016.1261695

Dachs, B., Kinkel, S., & Jäger, A. (2019). Bringing it all back home? Backshoring of manufacturing activities and the adoption of Industry 4.0 technologies. *Journal of World Business*, *54*(6). https://doi.org/10.1016/j.jwb.2019.101017

Dachs, B., & Peters, B. (2014). Innovation, employment growth, and foreign ownership of firms: A European perspective. *Research Policy*, *43*(1), 214–232. https://doi.org/10.1016/j.respol.2013.08.001

Damijan, J., Kostevc, Č., & Stare, M. (2014). Impact of innovation on employment and skill upgrading. In *The Journal of the Kyushu Dental Society* (Issue 44). https://doi.org/10.2504/kds.38.772_1

de Elejalde, R., Giuliodori, D., & Stucchi, R. (2015). Employment and innovation: Firm-level evidence from Argentina. *Emerging Markets Finance and Trade*, *51*(1), 27–47. https://doi.org/10.1080/1540496X.2015.998088

Díaz, G. A., Barge-Gil, A., & Heijs, J. (2020). The effect of innovation on skilled and unskilled workers during bad times. *Structural Change and Economic Dynamics*, *52*, 141–158. https://doi.org/10.1016/j.strueco.2019.09.012

Dorn, D. (2015). The Rise of the Machines How Computers Have Changed Work. *UBS Center Public Paper at the University of Zurich.*, *4*.

Dosi, G., Moschella, D., Pugliese, E., & Tamagni, F. (2015). Productivity, market selection, and corporate growth: comparative evidence across US and Europe. *Small Business Economics*, *45*(3), 643–672. https://doi.org/10.1007/s11187-015-9655-z

Dosi, G., & Nelson, R. R. (2013). The Evolution of Technologies: An Assessment of the State-of-the-Art. *Eurasian Business Review*, *3*(1), 3–46. https://doi.org/10.14208/BF03353816

Evangelista, R., & Savona, M. (2003). Innovation, employment and skills in services. Firm and sectoral evidence. *Structural Change and Economic Dynamics*, *14*(4), 449–474. https://doi.org/10.1016/S0954-349X(03)00030-4

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. https://doi.org/10.1093/icc/dtr069

Falk, M., & Hagsten, E. (2018). Employment impacts of market novelty sales: evidence for nine European Countries. *Eurasian Business Review*, *8*(2), 119–137. https://doi.org/10.1007/s40821-017-0098-0

Fan, E. X. (2003). Technological spillovers from foreign direct investment - A survey. *Asian Development Review*, *20*(1), 34–56. https://www.adb.org/publications/technological-spillovers-foreign-direct-investment-survey

Fioravante, D. G., & Maldonado, W. F. L. (2008). *Impacts of Technological Innovation on Employment: The Brazilian Manufacturing Case*. http://www.merit.unu.edu/MEIDE/papers/2009/1236670812_GF.pdf

Foote, C. L., & Ryan, R. W. (2015). Labor- market polarization over the business cycle. *NBER Macroeconomics Annual*, *29*(1), 371–413. https://doi.org/10.1086/680656

Fratocchi, L., & Di Stefano, C. (2020). Do industry 4.0 technologies matter when companies backshore manufacturing activities? An explorative study comparing Europe and the US. In *Knowledge Management and Organizational Learning* (Vol. 9, pp. 53–83). Springer. https://doi.org/10.1007/978-3-030-43589-9_3

Freeman, C., Clark, J., & Soete, L. (1982). Unemployment and technical innovation. In *A study of long waves and economic development*. Printer Publisher.

Freeman, C., & Soete, L. (1987). Factor substitution and technical change. In *Technical change and full employment* (pp. 2187–2183). Basil Blackwell.

Freeman, C., & Soete, L. (1994). *Work for all or mass unemployment? : computerised technical change into the twenty-first century*. Pinter Publishers.

Fundación Cotec. (2020). Informe Cotec 2020. In *800*. https://online.flippingbook.com/view/1027758/42/

Garcia, A., Jaumandreu, J., & Rodriguez, C. (2004). *Innovation and jobs: evidence from manufacturing firm* (Issue 1204). http://mpra.ub.uni-muenchen.de/1204/ MPRA

Globerman, S. (1979). Foreign Direct Investment and "Spillover" Efficiency Benefits in Canadian Manufacturing Industries. *The Canadian Journal of Economics*, *12*(1), 42–56. https://doi.org/10.2307/134570

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Gourvitch, A. (1940). *Survey of economic theory on technological change and employment*. A. M. Kelley. https://books.google.com/books?hl=es&lr=&id=nNm3AAAAIAAJ&oi=fnd&pg=PR11&dq=survey+of+economic+theory+on+technological+change+and+employmnet+&ots=uU-Th9Gvy6&sig=2jBrr8RnjSz0o9Xm-ms6QAgh978

Graetz, G., & Michaels, G. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review*, *107*(5), 168–173. https://doi.org/10.1257/aer.p20171100

Greenan, N., & Guellec, D. (2000). Technological Innovation and Employment Reallocation. *Labour*, *14*(4), 547–590. https://doi.org/10.1111/1467-9914.00146

Greenhalgh, C., Longland, M., & Bosworth, D. (1999). Technological Activity and Employment in in a Panel of UK Firms. *Scottish Journal of Political Economy*, *48*(3), 260–282.

Griliches, Z. (1969). Capital-Skill Complementarity. *The Review of Economics and Statistics*, *51*(4), 465–468.

Griliches, Z. (1979). Issues in Assessing the Contribution of R&D to Productivity Growth. In *Bell Journal of Economics* (Vol. 10, Issue 1, pp. 92–116).

Groshen, E. L., & Potter, S. (2003). Has Structural Change Contributed to a Jobless Recovery? *Current Issues in Economics & Finance*, *9*(8), 1–7. http://ideas.repec.org/a/fip/fednci/y2003iaugnv.9no.8.html%5Cnhttp://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=10775486

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: Evidence from Italian microdata. *Industrial and Corporate Change*, *17*(4), 813–839. https://doi.org/10.1093/icc/dtn022

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* (No. 8; 111). ftp://ftp.zew.de/pub/zew-docs/dp/dp08111.pdf%0ADie

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*(1), 29–43. https://doi.org/10.1016/j.ijindorg.2014.06.001

Hauknes, J., & Knell, M. (2009). Embodied knowledge and sectoral linkages: An input-output approach to the interaction of high- and low-tech industries. *Research Policy*, *38*(3), 459–469. https://doi.org/10.1016/j.respol.2008.10.012

Heijs, J. (2006). El papel de las empresas extranjeras en el desarrollo tecnológico de las economías nacionales. *Revista de Economía*, *830*, 31–54. https://www.researchgate.net/publication/28167251

Heijs, J., Marques, G., & De la Iglesia Villasol, M. (2016). El impacto de las innovaciones de producto y de proceso sobre el empleo industrial. In D. M. Vergara Reyes (Ed.), *Innovación, salarios y eficiencia productiva*. Instituto de Investigaciones Económicas

UNAM. http://eprints.ucm.es/33826/1/DT IAIF 2015 %2897%29 por publicar.pdf

Hicks, J. R. (1932). *The theory of wages*. Macmillan.

Hildenbrand, W. (1981). Short-Run Production Functions Based on Microdata. *Econometrica*, *49*(5), 1095–1125. https://doi.org/10.2307/1912746

Himmelberg, C. P., & Petersen, B. C. (1994). R&D and internal finance: a panel study of small firms in high-tech industries. *Review of Economics & Statistics*, *76*(1), 38–51. https://doi.org/10.2307/2109824

Hirschman, A. (1967). Interdependence and Industrialization. In A. Hirschman (Ed.), *The strategy of economic development*. Yale University Press.

Hobsdawn, E. J. (1952). The Machine Breakers. *Oxford University Press on Behalf of The Past and Present Society*, *1*(1), 57–70. https://www.jstor.org/stable/649989

Horning, B. B. (1994). Labor hoarding and the business cycle. *International Economic Review*, *35*(1), 87–100. https://doi.org/DOI: 10.2307/2527091

ILO. (2015). *World Employment and Social Outlook: Trends 2015*. http://www.ilo.org/global/research/global-reports/weso/2015/WCMS_337069/lang--en/index.htm

Jabbour, L., & Mucchielli, J. L. (2007). Technology transfer through vertical linkages: The case of the Spanish manufacturing industry. *Journal of Applied Economics*, *10*(1), 115–136. https://doi.org/10.1080/15140326.2007.12040484

Jaimovich, N., & Siu, H. E. (2018). The Trend is the Cycle: Job Polarization and Jobless Recoveries. In *National Bureau of Economic Research* (No. w18334; Issue 18334). https://doi.org/10.3386/w18334

Jaumandreu, J. (2003). *Does innovation spur employment? A firm-level analysis using Spanish CIS data* (Issue December). http://www.diw.de/documents/dokumentenarchiv/17/42063/2004-313-V01.pdf

Javorcik, B. S. (2004). Does Foreign Direct Investment Increase the Productivity of Domestic Firms ? In Search of Spillovers through Backward Linkages. *American Economic Review*, *94*(3), 605–627. http://www.jstor.org/stable/3592945

Jenkins, D. T. (1994). *Industrial Revolutions: The Textile Industries* (8th ed.). Blackwell Publishers.

Katsoulacos, Y. (1986). *The employment effect of technical change: a theoretical study of new technology and the labour market*. Wheatsheaf.

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money* (Fisrt Edit, Vol. 99, Issue 2). Macmillan. https://doi.org/10.1111/j.2397-2335.1936.tb04375.x

Kinkel, S., Capestro, M., & Di Maria, E. (2020). Artificial Intelligence and Backshoring Strategies: A German-Italian Comparison. In B. Christiansen & T. Škrinjarić (Eds.), *Handbook of Research on Applied AI for International Business and Marketing Applications* (pp. 227–255). IGI Global. https://doi.org/10.4018/978-1-7998-5077-9

Klette, J., & Førre, S. E. (1998). Innovation and job creation in a smallopen economy-evidence from norwegian manufacturing plants 1982–92. *Economics of Innovation* *and New Technology*, *5*(2–4), 247–272. https://doi.org/10.1080/10438599800000007

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, *29*(2), 210–220. https://doi.org/10.1016/j.ijindorg.2010.05.004

Leitner, S., Pöschl, J., & Stehrer, R. (2011). *Change Begets Change: Employment Effects of Technological and Non Technological Innovations – a Comparison across Countries* (Issue 72). http://eprints.bbk.ac.uk/10505/

Lucchese, M., & Pianta, M. (2012). Innovation and employment in economic cycles. *Comparative Economic Studies*, *54*(2), 341–359. https://doi.org/10.1057/ces.2012.19

Mairesse, J., Wu, Y., Zhao, Y., & Zhen, F. (2014). *Employment Growth and Innovation in China : A Firm Level Comparison across Regions in five Manufacturing Industries*.

Mancebón Torrubia, M., & Lozano Chavarría, P. (2001). La eficiencia productiva: empresa nacional "versus" empresa extranjera. *Información Comercial Española, ICE: Revista de Economía*, *794*, 23–36. https://dialnet.unirioja.es/servlet/articulo?codigo=12630

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). A future that works: Automation, employment, and productivity. In *Mckinsey Global Institute* (Issue January). http://njit2.mrooms.net/pluginfile.php/688844/mod_resource/content/1/Executive Summary of McKinsey Report on Automation.pdf

Marx, K. (1867). *Capital* (First Edit). Foreign Languages Publishing House.

Marx, K. (1969). *Theories of Surplus Value*. Lawrence & Wishart. http://books.google.pt/books?id=msADAAAACAAJ

Matuzeviciute, K., Butkus, M., & Karaliute, A. (2017). Do technological innovations affect unemployment? Some empirical evidence from European countries. *Economies*, *5*(4), 1–19. https://doi.org/10.3390/economies5040048

Meriküll, J. (2010). The impact of innovation on employment. *Eastern European Economics*, *48*(2), 25–38. https://doi.org/10.2753/EEE0012-8775480202

Merino de Lucas, F., & Salas Fumás, V. (1995). Empresa extranjera y manufactura española: efectos directos e indirectos. *Revista de Economía Aplicada*, *3*(9), 105–131.

Meyer-Krahmer, F. (1992). The effects of new technologies on employment. *Economics of Innovation and New Technology*, *2*(2), 131–149. https://doi.org/10.1080/10438599200000010

Mill, J. S. (1848). *The Principles of Political Economy*. M. Kelley. https://doi.org/10.1002/9781118011690.ch20

Montresor, S., & Marzetti, G. V. (2008). Innovation clusters in technological systems: A network analysis of 15 OECD countries for the mid-1990s. *Industry and Innovation*, *15*(3), 321–346. https://doi.org/10.1080/13662710802041679

Nelson, R. R., & Phelps, E. S. (1966). Investment in Humans , Technological Diffusion , and Economic Growth. *American Economic Association*, *56*(1), 69–75. https://www.jstor.org/stable/pdf/1821269.pdf?loggedin=true

Pasinetti, L. L. (1981). *Structural change and economic growth*. Cambridge University Press.

Pellegrino, G., Piva, M., & Vivarelli, M. (2017). *Are Robots Stealing Our Jobs?* (No. 10540; Issue 10540).

Perez, C. (2002). *Technological Revolutions and Financial Capital: The Dynamics of Bubbles and Golden Ages* (Vol. 82, Issue 2). Edward Elgar. https://doi.org/10.2307/20033522

Peters, B. (2005). *Employment Effects of Different Innovation Activities: Microeconometric Evidence*.

Peters, B., Dachs, B., Dünser, M., Hud, M., Köhler, C., & Rammer, C. (2014). *Firm growth, innovation and the business cycle: Background report for the 2014 competitiveness report*. http://hdl.handle.net/10419/110577www.econstor.eu

Peters, B., Hud, M., Dachs, B., & Köhler, C. (2017). *Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries* (No. A12-V3). http://hdl.handle.net/10419/168211

Pianta, M. (2005). Innovation and employment. In J. Fagerberg, D. Mowery, & R. Nelson (Eds.), *The Oxford Handbook of Innovation* (pp. 568–597). Oxford University Press. https://ora.uniurb.it/handle/11576/1889692

Pigou, A. C. (1933). *The theory of unemployment*. Macmillan.

Piva, M., & Vivarelli, M. (2005). Innovation and Employment: Evidence from Italian Microdata. *Journal of Economics*, *86*(1), 65–83. https://doi.org/10.1007/s00712-005-0140-z

Piva, M., & Vivarelli, M. (2018). Technological change and employment: is Europe ready for the challenge? *Eurasian Business Review*, *8*(1), 13–32. https://doi.org/10.1007/s40821-017-0100-x

Porter, M. E. (1993). *The competitive advantage of nations*. Harvard Business School Management Programs.

Ricardo, D. (1821). On the Principles of Political Economy, and Taxation. In P. Sraffa (Ed.), *On the Principles of Political Economy, and Taxation* (1st ed.). Cambridge University Press. https://doi.org/10.1017/cbo9781107589421

Rinne, U., & Zimmermann, K. F. (2012). Another economic miracle? The German labor market and the Great Recession. *IZA Journal of Labor Policy*, *1*(3), 1–21. https://doi.org/10.1186/2193-9004-1-3

Rojas Pizarro, F. B. (2013). *Innovación y empleo en las empresas manufactureras españolas* (No. 201341). http://eprints.ucm.es/21841

Rosenberg, N. (1976). *Perspectives on technology* (First Edit). Cambridge University Press.

Say, J. B. (1803). *A treatise on political economy: or, The production, distribution, and consumption of wealth*. M. Kelley.

Scherer, F. M. (1982). Demand-Pull and Technological Invention: Schmookler Revisted. *The Journal of Industrial Economics*, *30*(3), 225–237.

https://doi.org/10.2307/2098216

Schloss, D. F. (1981). WHY WORKING-MEN DISLIKE PIECE-WORK. *The Economic Review*, *1*(3), 311–326. http://search.proquest.com/openview/9cfed0b24f10fe92/1?pq-origsite=gscholar&cbl=2316

Schmookler, J. (1966). *Invention and economic growth.* Harvard University Press.

Schumpeter, J. A. (1939). *Business cycles : a theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill Book Co.

Schumpeter, J. A. (1947). *Capitalism, Socialism and Democracy* (Second Edi). Harper & Row Publishers.

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. https://doi.org/10.1111/1467-6451.00076

Stanley, T. D. (2005). Beyond publication bias. *Journal of Economic Surveys*, *19*(3), 309–345. https://doi.org/10.1111/j.0950-0804.2005.00250.x

Stanley, T. D., & Doucouliagos, H. (2012). Meta-regression analysis in economics and business. In *Meta-Regression Analysis in Economics and Business*. Routledge. https://doi.org/10.4324/9780203111710

Steuart, J. (1767). *An Inquiry Into the Principles of Political Economy*. Oliver and Boyd.

Stewart, F. (1974). Technology and employment in LDCs. *World Development*, *2*(3), 17–46. https://doi.org/10.1016/0305-750X(74)90092-8

Stiglitz, J. E. (2015). Unemployment and Innovation. In *Institute for New Economic Thinking* (No. 1). https://doi.org/10.2139/ssrn.2585160

Sveikauskas, L. (1981). Technological Inputs and Multifactor Productivity Growth. *The Review of Economics and Statistics*, *63*(2), 275. https://doi.org/10.2307/1924098

Terleckyj, N. (1974). Effects of R&D on the productivity growth of industries: an exploratory study. In *National Planning Association*.

Triguero, A., Córcoles, D., & Cuerva, M. C. (2014). Persistence of innovation and firm's growth: Evidence from a panel of sme and large spanish manufacturing firms. *Small Business Economics*, *43*(4), 787–804. https://doi.org/10.1007/s11187-014-9562-8

UNESCO. (2005). *UNESCO science report: the Current State of Science around the World*.

Utterback, J. M., & Suárez, F. F. (1993). Structure Competition , and Industry. *Research Policy*, *22*(1), 1–21. https://doi.org/10.1016/0048-7333(93)90030-L

van Ophem, H., van Giersbergen, N., van Garderen, K. J., & Bun, M. (2019). The cyclicality of R&D investment revisited. *Journal of Applied Econometrics*, *34*(2), 315–324. https://doi.org/10.1002/jae.2667

Van Reenen, J. (1997). Employment and technological innovation: Evidence from U.K. manufacturing firms. *Journal of Labor Economics*, *15*(2), 255–284. https://doi.org/10.1086/209833

Violante, G. L. (2008). Skill-Biased Technical Change. In S. Durlauf & B. Lawrence (Eds.), *The New Palgrave Dictionary of Economics* (Second Edi).

Vivarelli, M. (1995). *The Economics of Technology and Employment* (E. E. Publishing (ed.)). https://ideas.repec.org/b/elg/eebook/458.html%22%3EThe Economics of Technology and Employment%3C/A%3E%3C/B%3E

Vivarelli, M. (2007). Innovation and Employment: A Survey. *IZA Discussion Series*, *2621*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=969621

Vivarelli, M. (2012). *Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of the Literature* (No. 6291). http://www.iadb.org/publications/search.cfm?

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. https://doi.org/10.2753/JEI0021-3624480106

Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in Italian manufacturing industry. *Research Policy*, *25*(7), 1013–1026. https://doi.org/10.1016/0048-7333(95)00878-0

Vivarelli, M., & Pianta, M. (2003). The employment impact of innovation: Evidence and policy. In *The Employment Impact of Innovation: Evidence and Policy*. Routledge. https://doi.org/10.4324/9780203458686

von Hippel, E. (1976). The dominant role of users in the scientific instrument innovation process. *Research Policy*, *5*(3), 212–239. https://doi.org/10.1016/0048-7333(76)90028-7

Walker, T. (2007). Why economists dislike a lump of labor. *Review of Social Economy*, *65*(3), 279–291. https://doi.org/10.1080/00346760701635809

Welch, F. (1970). Education in Production. *Journal of Political Economy*, *78*(1), 35–59.

Wicksell, K. (1961). *Lectures on political economy*. Routledge & Kegan.

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

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. https://doi.org/10.1093/ICC