UNIVERSIDAD DE SALAMANCA

ESCUELA DE DOCTORADO

PROGRAMA DE DOCTORADO EN CIENCIAS SOCIALES

Tesis doctoral

Technological Change and Employment Polarisation

Doctoranda: Raquel Sebastián Lago

Directores: Dr. Rafael Muñoz de Bustillo Llorente

Dr. José Ignacio Antón

December 2017

I declare that the work presented in this thesis which is not explicitly attributed to another person is my own.

Raquel Sebastián Lago

Salamanca, December 2017

To my family

Acknowledgements

This dissertation is the result of three years of research in the Department of Applied Economics at the University of Salamanca. I also spent four months visiting the Eurofound, another six months visiting the Department of Economics at the University of Vigo, and one month at the Central European University (CEU) in Budapest.

During my PhD, I was funded by the Eduworks Marie Curie Initial Training Network Project (PITN-GA-2013-608311) of the European Commission's 7^{th} Framework Program. I gratefully acknowledge the financial support which made my research and research visits possible. The people that I thank here are just a few of the many who have helped and encouraged me in creating this dissertation.

First, I would like to express my most sincere thanks to my advisors Professor Rafael Muñoz de Bustillo and Dr. José-Ignacio Antón, who have guided me through the last three years. I am truly grateful to them for believing in my work, supporting my research enthusiastically, devoting their time and efforts in training me, and also for helping me to overcome academic difficulties during challenging times. It has been a real privilege to work with you. Thanks for your patience, positive mood and encouragements, which have been essential to my progress. I cannot imagine better advisors than the ones that I have had.

I am also indebted to Dr. Enrique Fernández-Macías for his insightful comments and encouragement. Our stimulating discussions and his hard questions have helped me to substantially improve my research skills. It has been an honour for me to carry out collaborative research with him. I would like to thank the Eurofound for giving me this opportunity by hosting me for more than three months as a visiting researcher. I am also very grateful to Professor Carlos Gradin for his supervision and motivation while I visited the University of Vigo. His valuable suggestions have contributed to the improvement of my work. I thank Dr. Federico Biagi for the funny and wise discussions through which

I have broadened my views of the field of Labour Economics. I would also like to thank Professor Luis Ayala, Professor Kea Tijdens, Dr. Begoña Álvarez, and Dr. Massimiliano Mascherini for their comments on my dissertation, their support, and their trust in my research capabilities.

I would also like to thank all the members in the Applied Economics department at the University of Salamanca, in the Employment Unit at the Eurofound, and in the Economics department at the University of Vigo that I have met over the years. I would also like to express my deepest gratitude to my colleagues Sudipa Sarkar, Fernando Pinto and Rafa Grande (University of Salamanca), Martina Bisello, Elias Gerogiannis and Carlos Vacas (Eurofound), Hugo del Valle-Inclán (University of Vigo), Magdalene Ulceluse (CEU University), and Eloisa Federici and Sofija Pajic (UVA University): thanks for the feedback, the useful comments, and the inspiring conversations; but also for the fun and support during coffee breaks, beers and lunches. I would like to express my gratitude to Dr. Scott Harrison and Simon Naitram for the feedback and help during the writing up.

Looking a little further back in time, another very important person during my academic journey has been Professor Jaime Ortega. He deserves special mention for his encouragement, understanding and mentoring since I began pursuing my Master of Research (MRes) degree.

For their helpful comments, I wish to thank all the participants to the 23rd Public Economics Meeting (Ourense, January 2016), Joint Annual Meeting of the Slovak Economic Association and the Austrian Economic Association (NOeG-SEA) (Bratislava, May 2016), Barcelona Graduate School of Economics Summer Forum (Barcelona, June 2016), 19th Applied Economics Meeting (Sevilla, June 2016), 26th European Association of Labour Economics (EALE) conference (Ghent, September 2016), 24th Public Economics Meeting (Toledo, January 2017), 31st European Society for Population Economics (ESPE) conference (Glasgow, June 2017), 27th EALE conference (St. Gallen, September 2017), and seminars and workshops held at the Eurofound, Amsterdam Institute for Advanced Labour Studies(AIAS), the University of Vigo, the Trinity College, the Central European University (CEU), and the University of Salamanca.

I would like to thank the Eduworks family and all the good friends I have made while attending different conferences (a big thank to my Atlanta friends: Ana Herrero, Borja Gambau, Encarni Murillo, Ignacio González, Javier Martín, Manolo Tránchez, and Vicente Ríos) for their insightful comments and suggestions on my dissertation. During these last three years, we have shared many happy, but also difficult moments, always supporting and caring for each other. I must also thank them for finding the time to cheer me up whenever I have needed it, despite our very busy schedules.

I am also grateful to my non-academic friends: my friends since my childhood in Vigo (Andrea, Antía, Caro, Carola, Cris, Clara, Elena, Iria, Lara, Laura, María, Sabela, and Sara), the friends I have made during my time in Madrid (special thanks go to Ana Laura, Azad, Carlo, Diego, Juancho, Mahmoud, Saray, and Vero), my Saharan friends (Eva, Irene, and Kris), my Brussels family (Ale, Álvaro, Inma, María, Meme, and Rosa), and my Italian crew (Irene, Gila, Uefo, and Vale), who have always struggled to understand exactly what I have been doing. I have really appreciated their positive energy at all times, their understanding of my absence from some important occasions and for their endless support even across oceans.

I do not have words to express my gratitude to Gabriele. He is the person who has suffered most the consequences of my PhD: having to move several times, uncertain future, periods far away from each other, the typical ups and downs of the academic life and their consequent impact in my mood. Thank you so much for being there, for your patience and understanding and for giving me the energy and support to finish this dissertation.

Likewise, words are not enough to transmit my gratitude to my family. I thank my parents for being so supportive, for their care and kindness, for always believing in me, for being so positive regarding my future and for understanding the long periods of absence. I also wish to thank my brothers, Alex, Albe and David, for their patience while I have been doing my PhD and for their availability to help and listen to me at any moment. I also want to mention María, Rosalía, Pepe and Francisco (my grandparents), who are not here anymore but are always with me.

Finally, I want to thank my past self for not having given up during these three years and for maintaining the energy and the enthusiasm to continuously challenge myself and to learn more everyday.

Abstract

A consensus has emerged among labour economists that the structure of employment has changed over time. On the supply side, many industrialised economies experienced the effects of an ageing labour force with greater female participation. This was combined with significant changes in the composition of the workforce, mainly because of rapid education upgrading and migration surges. On the demand side, economists have tried to explain the new shape of the employment structure through technology and trade.

In this dissertation we present five chapters in which we analyse the role of technology and its effect on employment. In the first chapter we present the background of the main theoretical frameworks within which researchers explain how technology shapes the structure of the labour market. We discuss the main difficulties from a conceptual, operational, and empirical point of view. The second chapter contributes to the measurement of this phenomenon. We compare existing measures of task indices using four different databases, paying special attention to the problems associated with measurement. The third chapter contributes to the literature on employment in Spain, providing evidence of job polarisation. That is, we find a decrease in middle-skilled workers characterised by clerical and production occupations, and an increase in high-paying professional occupations and low-paying jobs. Our evidence suggets that changes in employment shares are negatively related to the initial level of routine task intensity. In the fourth chapter, we look at the Spanish provinces. We exploit geographical variation across Spanish local labour markets in their specialisation in routine-intensity industries. The findings are consistent with the importance of technology in explaining the displacement of routine-task work and its subsequent reallocation at the bottom of the employment distribution. However, no significant effect of technological exposure on skilled non-routine cognitive employment is found. In the final chapter, we apply the model presented in the previous two chapters to the case of employment opportunities of migrant workers in Germany.

We explore the effect of an increase in the relative supply of migrants on German natives' task reallocation. The hypothesis is that as low-skilled migrants enter the labour market into predominantly manual-intensive occupations, natives self-relocate to occupations which make use of their comparative advantage: communication skills. We find that an increase in the share of migrant population is indeed negatively associated with the native population's relative supply of manual tasks.

Resumen

La estructura del mercado laboral ha sufrido importantes cambios en los últimos años. Por el lado de la oferta cabría destacar el envejecimiento de la mano de obra y una mayor participación femenina. Ambos efectos se han visto combinados con cambios significativos en la composición de la fuerza del trabajo debido principalmente a la mejora de la educación y al crecimiento de la población migrante. Por el lado de la demanda los economistas han tratado de explicar el cambio en la estructura del empleo a través de la tecnología y el comercio exterior.

De todos los cambios anteriormente mencionados, actualmente se cree que la tecnología es el que más ha afectado a la demanda de mano de obra, siendo dicho cambio único y muy significativo. Con los avances tecnológicos, los trabajadores pueden ser sustituidos y desplazados de los empleos en los cuáles la tecnología tiene un impacto generalizado. La tecnología ha sido y es parte de nuestro progreso pero, al mismo tiempo, ha representado muchos retos para las sociedades, transformando las relaciones económicas y laborales. Por todo ello, en esta tesis presentaremos cinco ensayos en los que abordaremos el efecto que la tecnología tiene en el mercado laboral. A continuación resumimos de forma breve y concisa los ensayos de nuestra tesis.

En el primer capítulo analizamos los principales marcos teóricos a través de los cuales los investigadores explican cómo la tecnología modela la estructura del mercado laboral. A su vez discutimos las principales dificultades conceptuales, operacionales y empíricas a las que los investigadores se ven expuestos. Tras entender los problemas asociados a los marcos teóricos, en el segundo capítulo contribuimos a la medición del fenómeno. Para ello analizamos cuatro bases de datos distintas y comparamos las medidas de índices de tareas, prestando especial atención a los problemas asociados con su operazionalización. En el tercer capítulo describimos la evolución del empleo en España desde un punto de vista tanto gráfico como empírico. En este trabajo evidenciamos la polarización laboral:

por un lado encontramos una disminución de trabajos en la parte central de la distribución salarial, por el otro lado, observamos un crecimiento en la parte baja y alta de la distribución salarial. También comprobamos que los cambios en el empleo se pueden explicar a través del nivel de intensidad inicial de las tareas rutinarias. En el siguiente capítulo extendemos el enfoque de investigación a los mercados de trabajo regionales españoles. En este ensayo explotamos la variación geográfica española que surge a raíz de los distintos niveles de intensidad rutinaria de cada región. Los resultados son consistentes con la teoría. La tecnología explica el desplazamiento del trabajo rutinario y su posterior reasignación en la parte baja de la distribución salarial. Sin embargo, la tecnología no es capaz de explicar el incremento de empleo cognitivo cualificado que se observa en la parte alta de la distribución salarial. En el último capítulo, utilizamos el modelo de los dos capítulos anteriores (capítulo 4 y 5) para abordar el impacto que la población migrante tiene en la población nativa. La hipótesis es la siguiente: a medida que los migrantes con baja cualificación entran en el mercado de trabajo en ocupaciones predominantemente manuales, los nativos se reubican en ocupaciones en las que aprovechan su ventaja comparativa, esto es, las habilidades de comunicación. Dada la importancia de dicho tema y debido tanto a los datos como a los conocimientos de investigación disponibles, analizamos dicho efecto en Alemania.

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Abbreviations

Concept codes

ICT	Information and communication technology
IT	Information technology
SBTC	Skill biased technical change
RBTC	Routine biased technical change
RSH	Routine employment share
RTI	Routine task intensity

Country codes

AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GR	Greece
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxemburg
LV	Latvia
NL	Netherlands
PL	Poland
PT	Portugal
SE	Sweden
SI	Slovenia
SK	Slovakia
UK	United Kingdom
US	United States

Data codes

CAMSIS	Cambridge Social Interaction and Stratification Scale
DE-LFS	German Labour Force Survey
ECHP	European Community Household Panel
EPA	Encuesta de Población Activa
ES-LFS	Spanish Labour Force Survey
EU-LFS	European Union Labour Force Survey
ESS	Encuesta de Estructura Salarial
EWCS	European Working Condition Survey
INE	Instituto Nacional de Estadística
O*Net	Occupational Information Network database
PDII	Princeton Data Improvement Initiative Survey
PIAAC	Programme for the International Assessment of Adult Competencies
SILC	Survey on Income and Living Conditions

International Organisation codes

EU	European Union
Eurofound	European Foundation for the Improvement of Living and Working Conditions
ILO	International Labour Organisation
OECD	Organisation for Economic Co-operation and Development

Occupational and Industrial codes

CNAE-93	Clasificación Nacional de Actividades Económicas 1993
CNO-94	Clasificación Nacional de Ocupaciones 1994
ISCO-88	International Standard Classification of Occupations 1988
ISCO 12	Corporate managers
ISCO 13	General managers
ISCO 21	Physical, mathematical and engineering science profession
ISCO 22	Life science and health professionals
ISCO 23	Teaching professionals
ISCO 24	Other professionals
ISCO 31	Physical and engineering science associate professionals
ISCO 32	Life science and health associate professionals
ISCO 33	Teaching associate professionals
ISCO 34	Other associate professionals
ISCO 41	Office clerks
ISCO 42	Customer service clerks

ISCO 51	Personal and protective services workers
ISCO 52	Models, salespersons and demonstrators
ISCO 71	Extraction and building trades workers
ISCO 72	Metal, machinery and related trades workers
ISCO 73	Precision, handicraft, printing, and trades workers
ISCO 74	Other craft and related trades workers
ISCO 81	Stationary-plant and related operators
ISCO 82	Machine operators and assemblers
ISCO 83	Drivers and mobile plant operators
ISCO 91	Sales and services elementary occupations
ISCO 92	Agricultural, fishery and related labourers
ISCO 93	Labourers in mining construction, and manufacturing
ISCO-08	International Standard Classification of Occupations 2008
SOC 2000	Standard Occupational Classification 2000

1. Introduction - Introducción

1.1 Introduction

1.1.1 Employment polarisation and technological change

This thesis aims to develop a deeper understanding of technology as an important determinant in shaping the structure of labour market. The introduction of new technology has always been a key element of discussion for policy makers and researchers in many academic disciplines. Over time, technological progress has altered the division of labour. In 1930, the British economist, John Maynard Keynes put forward the idea that technological change can lead to increased inequality and higher unemployment rates. According to him "[...] our discovery of means of economizing the use of labour outrunning the pace at which we can find new uses for labour [will result in] technological unemployment" (Keynes, 1930, p.3). A century later the main worry remains: technology is replacing labour, and could lead to greater unemployment rates and increased inequality.

Discussions on how technological progress has affected the labour market have been crucial to understanding the phenomenon. Until recently, the skill-biased technical change (SBTC) has provided the canonical explanation for observed changes in labour demand and wage inequality in advanced economies during the past few decades (Berman et al., 1998; Bound and Johnson, 1992; Katz and Murphy, 1992; Machin and Van Reenen, 1998). In this model, technology replaces low-skilled workers, and favours high-skilled workers, resulting in monotone employment and wage growth along the wage (skill) distribution. In other words, technical change increases the relative productivity of high-skilled labour —and as a consequence, its relative demand— therefore explaining the wage inequality in most developed countries.

However, the SBTC does not provide a satisfactory framework for interpreting recent key trends in labour markets. Specifically, the model is unable to explain the decline in the share of middle-skilled jobs and the simultaneous employment expansion in low-skilled occupations that has occurred in several industrialised economies since the late 1990s. This is the phenomenon of *job polarisation* (Goos and Manning, 2007; Wright and Dwyer, 2003).

In light of this gap, a more nuanced and refined version of the SBTC was put forward. It explains the shift from a monotonic to a U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. The updated theory focuses on the impact of computerisation on the different tasks performed by workers on the job, instead of merely looking at their skills.

In the seminal paper by Autor et al. (2003) (ALM, henceforth) job polarisation is explained through the routine biased technical change (RBTC). They argue that the way jobs are affected by new technology depends on workers' tasks, not on their skills. They divide the tasks along two dimensions: routine versus non-routine, and cognitive against manual. In this model, ALM define routine tasks as those activities which imply a methodological repetition, and are therefore easier to be mechanized. Greater substitutability with computers means that routine tasks are more affected by technological change. Because of falling prices in computerisation, the RBTC predicts the displacement of employment away from routine tasks that are typically located in the middle of the wage distribution towards non-routine tasks that are located at the two tails of the distribution. This induces job polarisation. In contrast to the SBTC, the RBTC allows for employment increases in low-skilled non-routine manual activities that are neither a complement nor a substitute to computer capital. Still, the RBTC hypothesis is not incompatible with SBTC since it does not contradict the idea that computers are complementary to cognitive tasks performed by high-skilled workers.

Due to the increasing importance of the RBTC in explaining the role that technology plays in shaping the structure of labour market, Chapter 2 examines the RBTC. The chapter provides an overview of the theoretical models and empirical databases that surround the notion of how technology affects the labour market.

Despite the importance of the RBTC model, measuring tasks is challenging (Fernández-Macías and Bisello, 2017; Fernández-Macías and Hurley, 2016). There are four main difficulties in evaluating task measurements: representativeness, consistent typologies, consistent definitions, and difficulty to operationalize. Chapter 3 reviews the main difficulties and compares tasks' content using different databases at the European level, paying special attention to problems associated with proper measurement.

This new idea of analysing tasks instead of skills has proven empirically successful, and has been applied to study technological progress and its effect on employment (Autor, 2015; Fernández-Macías and Bisello, 2017; Goos et al., 2014). To our knowledge, the link between technological change and employment market structure has not been studied carefully in Spain. Chapter 4 and Chapter 5 intend to close this gap by analysing the effect that technological change has on Spanish employment. We investigate this relationship at the national and local level.

The next chapter (Chapter 6) extends the RBTC model and advances knowledge on the impact of migration on native employment. We use the RBTC model to explain how native and migrants specialise in different tasks according to their comparative advantage. Due to data constrains and the available research expertise, in contrast to the previous two chapters, we analyse this effect in Germany.

1.1.2 Outline of the thesis

As mentioned above, the second chapter of the thesis contributes to the growing debate about how the introduction of technology affects labour demand. First, we provide some background of the main theoretical frameworks within which researchers have attempted to explain the recent changes in the employment distribution. We discuss the main drawbacks of the SBTC and why the RBTC fits better with a relatively recent phenomenon: the decline in the share of middle-wage occupations relative to high- and low-wage occupations. Second, while the RBTC seems to fit well with changes in the employment distribution, our work reveals that there are some conceptual, operational, and empirical challenges not solved by the RBTC.

After presenting the advantages and drawbacks within the RBTC framework, in Chapter 3, we contribute to the development of task indices to be used for analysing the consequences of technical change. Despite the growing importance of this research, measuring task indices is problematic because task data on an individual/occupation level are not always available. In Chapter 3, we highlight the difficulties of operationalizing the RBTC framework. In this regard, we contribute to the literature by systematically comparing existing measures of task indices using four different databases, paying special attention to the problems associated with proper measurement. To do so, we select the most representative framework and harmonize items across multiple data sources, resulting in a comparable scenario in terms of tasks and definitions. We also make methodological progress with respect to previous studies on tasks by measuring the task content of occupations from European data instead of relying on US sources. Our study contributes further to the literature on tasks, as it includes 25 European countries (16 were included in the study by Goos et al., 2014; 15 were included in the study by Fernández-Macías, 2012) and lengthens the period of analysis (2008 was the last year in the study by Fernández-Macías, 2012; 2010 was the last year in the study by Goos et al., 2014).

In Chapter 4, we contribute to the literature on job polarisation in Spain. We also make methodological progress with respect to previous literature by measuring the task content of occupation using a European survey, the European Working Condition Survey (EWCS), instead of relying on US sources (O*Net). In here, we adopt the task approach to analyse recent changes in the labour market's structure at the job level in Spain. First, evidence of job polarisation is found between 1994 and 2008 using data from the Spanish Labour Force Survey and the Earnings Structure Survey. There is no evidence instead that wages followed the same pattern. After showing the U-shaped relationship between employment share growth and job's location in the wage distribution, we use the task approach to analyse the main determinants behind job polarisation. We find that changes in the employment distribution are negatively related to the initial level of routineness. We then explore the impact of computerisation on tasks where we observe a negative relationship between the use of computer and our routine task intensity measure. Finally, we explore the reallocation of middle-paid workers. To do so, we integrate our main data source with the Survey on Income and Living Conditions (SILC), and we show that middle-paid workers are more mobile over time. However, contrary to our expectations, they do not predominantly reallocate their labour supply to bottom-paid occupations. Our intuition is that the increase at the lower end of the distribution is not only the result of the displacement of national middle-workers, but could also be due to increased migration.

The analysis in Chapter 5 extends the research focus of the previous finding to the Spanish local labour markets. We make use of a new methodology developed by Autor and Dorn (2013) who investigate the extent to which technology is able to explain the displacement of middle-skilled workers towards low-paid occupations. Our main data source is the Spanish Labour Force Survey for the years 1994 and 2008, and we derive the routine task intensity from an additional database, O*Net. We contribute to the literature on job polarisation by providing evidence on the effect of technology on Spanish local labour markets. To the best of our knowledge, this is the first paper which explores this issue in Spain. After exploiting spatial variation across Spanish local labour markets in their initial exposure to technology, we confirm that technology partially explains the decline of middle-paid workers, and its subsequent relocation at the bottom part of the employment distribution. However —and different to the US— technology does not explain the increase found at the top of the employment distribution.

In the last chapter (Chapter 6), we investigate recent changes in the occupational distribution of migrants in Germany and the effects of foreign-born workers on local labour markets. One major concern for governments and policy makers is the effect of migrants on the labour market of receiving countries. Previous research has considered traditional labour markets outcomes such as wages, employment, unemployment, or participation. In this chapter, we adopt a different perspective, building on the task model; we investigate the effect of migration on the specialisation of natives. This chapter aims to determine whether natives, who are assumed to have a comparative advantage relative to immigrants in communication as opposed to manual tasks, are induced to specialize in communication-intensive jobs in response to immigration inflows. We focus on the bottom end of the occupational distribution by looking at the impact of less skilled foreign-born workers on similarly educated native workers. Our main data source is the German Labour Force Survey (DE-LFS) for the years 2002-2014 and we derive our task intensity measures at the occupational level from an additional source, O*Net. Our results show that, in Germany, natives respond to increasing migration by shifting their task supply and providing more communication tasks relative to manual ones. The overall phenomenon of the effect of migration on natives' task reallocation in Germany is substantially higher than the effect found in the US and Spain. Moreover, the effect is significantly larger for recent and for male migrants, pointing to an assimilation effect taking place over time.

1.2 Introducción

1.2.1 Polarización en el empleo y cambio tecnológico

Esta tesis tiene como objetivo entender cuáles son los determinantes en la estructura del mercado laboral, prestando especial atención a la tecnología. La introducción de nueva tecnología ha sido siempre un elemento clave de discusión tanto para los políticos, como para los investigadores de distintas disciplinas académicas. En 1930, el economista británico John Maynard Keynes explicó cómo el cambio tecnológico podía conducir a aumentar la desigualdad y la tasa de desempleo. Según él: "[...] los nuevos descubrimientos tecnológicos están logrando economizar el uso de mano de obra a un ritmo mayor al que se pueden encontrar nuevos usos de mano de obra, y ello, inevitablemente, dará lugar al desempleo tecnológico" (Keynes, 1930, p.3). Un siglo más tarde, la principal preocupación sigue siendo la misma: la tecnología está reemplazando la mano de obra, pudiendo conducir a mayores tasas de desempleo y al aumento de la desigualdad.

El debate generado a lo largo de los años sobre cómo el progreso tecnológico ha afectado al mercado de trabajo ha sido crucial a la hora de entender el fenómeno. Hasta hace poco, la hipótesis según la cual el cambio tecnológico estaba sesgado hacia el trabajo cualificado (en inglés, skill-biased technical change, por lo que llamaremos a esta hipótesis SBTC) era la principal teoría para explicar los cambios en la demanda de trabajo y la desigualdad salarial en las economías desarrolladas en las últimas décadas (Berman et al., 1998; Bound and Johnson, 1992; Katz and Murphy, 1992; Machin and Van Reenen, 1998). En este modelo, la tecnología reemplaza a los trabajadores poco calificados y favorece a los trabajadores altamente cualificados, implicando un incremento mayor de empleo y salario en la parte alta de la distribución salarial. En otras palabras, el cambio técnico aumenta la productividad relativa de la mano de obra altamente calificada —y como consecuencia, su demanda relativa— explicando por lo tanto la desigualdad salarial en la mayoría de los países desarrollados.

Sin embargo, el SBTC no proporciona un marco satisfactorio para explicar los recientes cambios de tendencia en el mercado laboral. En otras palabras, a través de este modelo no se puede explicar la disminución de puestos de trabajo de cualificación media y la expansión simultánea de empleo en ocupaciones de cualificación baja. Dichos cambios se han producido en las economías industrializadas desde finales de los años noventa. La literatura económica lo ha definido como *porlarización en el mercado laboral* (Goos and Manning, 2007; Wright and Dwyer, 2003).

A la luz de los problemas anteriormente descritos, se presentó una versión más matizada y refinada del SBTC. Este nuevo modelo explica el cambio en la distribución de empleos: de una relación monótona creciente, a una relación en forma de U entre el crecimiento del empleo y la distribución salarial de los empleos. La nueva teoría se centra en el impacto de la informatización en las diferentes tareas realizadas por los trabajadores en el trabajo, en lugar de simplemente mirar sus habilidades.

En el influyente estudio de Autor et al. (2003) (ALM, en adelante), la polarización del trabajo se explica a través del cambio técnico rutinario (en inglés, routine-biased technical change, por lo que llamaremos a esta hipótesis RBTC). En este modelo se argumenta que la manera en que los trabajos son afectados por la nueva tecnología depende de las tareas de los trabajadores, no de sus habilidades. Dividen las tareas a lo largo de dos dimensiones: por un lado, rutina versus no rutinaria; por el otro lado, cognitiva versus manual. Asimismo, ALM define las tareas rutinarias, las cuales son más fáciles de mecanizar, como aquellas actividades que implican una repetición metodológica. Una mayor sustitución con los ordenadores significa que las tareas rutinarias se ven más afectadas por el cambio tecnológico. Debido a la caída de los precios en la informatización, el RBTC predice el desplazamiento del empleo lejos de las tareas de rutina, que normalmente se encuentran en el centro de la distribución salarial, a tareas no rutinarias, que se encuentran en las dos colas de la distribución. Esto induce la polarización del trabajo. En contraste con el SBTC, el RBTC permite aumentos de empleo en las actividades manuales no rutinarias de baja cualificación que no son ni un complemento ni un sustituto del capital informático. Sin embargo, la hipótesis RBTC no es incompatible con SBTC, ya que no contradice la idea de que los ordenadores son complementarios a las tareas cognitivas realizadas por trabajadores altamente calificados.

Debido a la creciente importancia del RBTC para explicar el papel que desempeña la tecnología en la actual estructura del mercado de trabajo, el capítulo 2 examina el RBTC. El capítulo ofrece una visión general de los modelos teóricos y de las bases empíricas que rodean la noción de cómo la tecnología afecta al mercado de trabajo.

A pesar de la importancia del modelo RBTC, medir las tareas es un desafío (Fernández-Macías and Bisello, 2017; Fernández-Macías and Hurley, 2016). Dichos autores destacan cuatro dificultades en la evaluación de las medidas de la tarea: representatividad, tipologías consistentes, definiciones consistentes y dificultad en la operacionalización. El capítulo 3 examina las principales dificultades y compara las tareas utilizando diferentes bases de datos a nivel europeo, prestando especial atención a los problemas relacionados con la medición adecuada.

Este nuevo concepto de análisis de tareas en lugar de habilidades ha sido probado empíricamente con éxito. Además se ha aplicado para estudiar el progreso tecnológico y sus efectos en el empleo (Autor, 2015; Fernández-Macías and Bisello, 2017; Goos et al., 2014). Según nuestro conocimiento, el vínculo entre el cambio tecnológico y la estructura del mercado de trabajo no ha sido estudiado en profundidad en España. El capítulo 4 y el capítulo 5 pretenden cerrar esta brecha analizando el efecto que tiene el cambio tecnológico en el empleo español. Investigamos esta relación a nivel nacional y local.

El siguiente capítulo (capítulo 6) extiende el modelo RBTC y avanza en el impacto de la migración en el empleo nativo. Utilizamos el modelo RBTC para explicar cómo los nativos y los migrantes se especializan en diferentes tareas según su ventaja comparativa. Debido a las limitaciones de datos y la experiencia de investigación disponible, en contraste con los dos capítulos anteriores, analizamos este efecto en Alemania.

1.2.2 Esquema de la tesis

Como se mencionó anteriormente, el segundo capítulo de la tesis contribuye al creciente debate sobre cómo la introducción de la tecnología afecta a la demanda de trabajo. En primer lugar, ofrecemos algunos antecedentes de los principales marcos teóricos dentro de los cuales los investigadores han intentado explicar los cambios recientes en la distribución del empleo. Asimismo, discutimos los principales inconvenientes del modelo SBTC y por qué el RBTC encaja mejor con un fenómeno relativamente reciente: la disminución en ocupaciones de salarios medios y el crecimiento en ocupaciones de salarios altos y bajos. En segundo lugar, tras observar que el RBTC encaja mejor con los cambios en la distribución del empleo, nuestro trabajo revela que siguen existiendo algunos problemas conceptuales, operativos y empíricos dentro de dicho modelo.

Después de presentar las ventajas y los inconvenientes dentro del RBTC, en el capítulo 3 desarrollamos los índices de trabajo que después serán utilizados para analizar las consecuencias del cambio tecnológico. A pesar de la creciente importancia de esta investigación, la medición de los índices de tareas es problemática ya que los datos de tareas a un nivel individual/ocupacional no siempre están disponibles. A su vez, también destacamos las dificultades de operacionalización del marco del RBTC. En este sentido, aportamos a la literatura la comparación sistemática de las medidas existentes de los índices de tareas utilizando cuatro diferentes bases de datos, prestando especial atención a los problemas asociados con la siguiente medición. Para ello, seleccionamos el marco más representativo y armonizamos los elementos a través de múltiples fuentes de datos, resultando en un escenario comparable en términos de tareas y definiciones. También hacemos progresos metodológicos con respecto a los estudios previos sobre tareas, midiendo el contenido de tareas de las ocupaciones a partir de datos europeos en lugar de utilizar datos estadounidenses. Además, nuestro estudio contribuye a la literatura sobre las tareas de dos formas complementarias: en primer lugar incluimos 25 países europeos (Goos et al., 2014 incluyeron 16 países, mientras que Fernández-Macías, 2012 utilizó 15 países europeos) y, en segundo lugar, alargamos el período de estudio hasta 2015 (2008 fue el último año en el estudio de Fernández-Macías, 2012; 2010 fue el último año en el estudio de Goos et al., 2014).

En el capítulo 4, contribuimos a la literatura sobre la polarización del empleo en España. También hacemos progresos metodológicos con respecto a la literatura anterior midiendo el contenido de la tarea de la ocupación utilizando una encuesta europea, la Encuesta de Condiciones de Trabajo Europea (EWCS), en lugar de depender de fuentes estadounidenses (O*Net). En este sentido, adoptamos el enfoque de la tarea para analizar los cambios recientes en la estructura del mercado de trabajo a nivel laboral en España. En primer lugar, la evidencia de la polarización del empleo se encuentra entre 1994 y 2008 utilizando datos de la Encuesta de Población Activa (EPA) y de la Encuesta de

Estructura Salarial (EES). No hay evidencia en cambio que los salarios siguieran el mismo patrón. Después de mostrar la relación en forma de U entre el crecimiento del empleo compartido y la ubicación del trabajo en la distribución de los salarios, utilizamos el enfoque de tareas para analizar los principales determinantes detrás de la polarización del empleo. Encontramos que los cambios en la distribución del empleo están negativamente relacionados con el nivel inicial de rutina. A continuación, exploramos el impacto de la informatización en las tareas, donde se observa una relación negativa entre el uso de los ordenadores y nuestra medida de la intensidad de rutina de la tarea. Finalmente, analizamos la reasignación de trabajadores con salarios medios. Para ello, integramos nuestra principal fuente de datos con la Encuesta sobre Ingresos y Condiciones de Vida (SILC), y mostramos que los trabajadores con salarios medios son más móviles a lo largo del tiempo. Sin embargo, contrariamente a nuestras expectativas, estos no reasignan predominantemente su oferta de mano de obra a las ocupaciones con salarios bajos. Nuestra intuición es que el aumento en el extremo inferior de la distribución salarial no es sólo el resultado del desplazamiento de los trabajadores intermedios nacionales, sino que también puede deberse al aumento de la migración.

El análisis del capítulo 5 extiende el foco de investigación de los hallazgos anteriores a los mercados de trabajo locales españoles. Así, hacemos uso de una nueva metodología desarrollada por Autor and Dorn (2013) que investiga hasta qué punto la tecnología es capaz de explicar el desplazamiento de los trabajadores con cualificaciones medias hacia las ocupaciones mal remuneradas. Nuestra principal fuente de datos es la Encuesta de Población Activa (EPA) de España para los años 1994 y 2008, y derivamos la intensidad de las tareas rutinarias de una base de datos adicional, O*Net. Además, contribuimos a la literatura sobre la polarización del empleo aportando evidencia sobre el efecto de la tecnología en los mercados de trabajo locales españoles. Hasta donde sabemos, este es el primer artículo que explora este tema en España. Después de explotar la variación espacial en los mercados de trabajo locales españoles en su exposición inicial a la tecnología, confirmamos que la tecnología explica en parte la disminución de los trabajadores con salarios medios y su posterior reubicación en la parte inferior de la distribución del empleo. Sin embargo —a diferencia de los EE.UU. — la tecnología no explica el aumento se encuentra en la parte superior de la distribución del empleo.

En el último capítulo (capítulo 6), investigamos los cambios recientes en la distribución ocupacional de los migrantes en Alemania y los efectos de dichos trabajadores en los mercados laborales locales. Una preocupación importante para los gobiernos y los encargados de formular políticas es el efecto de los migrantes en el mercado de trabajo de los países receptores. Las investigaciones anteriores han considerado los resultados tradicionales de los mercados laborales, como los salarios, el empleo, el desempleo o la participación. En este capítulo, adoptamos una perspectiva diferente, basándonos en el modelo de tarea, investigamos el efecto de la migración sobre la especialización de los nativos. Este capítulo pretende determinar si los nativos, que se supone que tienen una ventaja comparativa en relación con los inmigrantes en la comunicación en contraposición a las tareas manuales, son inducidos a especializarse en los trabajos intensivos en comunicación en respuesta a los flujos de inmigración. Al examinar el impacto de los trabajadores extranjeros menos capacitados en trabajadores nativos con educación similar, nos enfocamos en el extremo inferior de la distribución ocupacional. Nuestra principal fuente de datos es la Encuesta Alemana de Población Activa (DE-LFS) para los años 2002-2014 y derivamos nuestras medidas de intensidad de tareas a nivel ocupacional a partir de una fuente adicional, O*Net. Nuestros resultados muestran que, en Alemania, los nativos responden al aumento de la migración desplazando su oferta de tareas y proporcionando más tareas de comunicación relativas a las manuales. El fenómeno general del efecto de la migración en la reasignación de tareas de los nativos en Alemania es sustancialmente más alto que el efecto encontrado en Estados Unidos y España. Por otra parte, el efecto es significativamente mayor para los migrantes recientes y para los hombres, lo que indica un efecto de asimilación que tiene lugar a lo largo del tiempo.

2. A review on routine biased technical change

2.1 Introduction

In recent years, the topic of inequality has gain major interest both in policy and academic circles. There is evidence for an increase of wage inequality in the United States and in most of the European countries. In the case of US in 2000, the wage ratio was 4.5: the best-paid 10 per cent in the US earned on average 4.5 times as much as the worst-paid 10 per cent, while in 2010 it increased to 6.7 per cent. The income ratio was 5.9 per cent, while in 2014 was 7.2 per cent (data from World Wealth Income database). However, there are differences in the increase of inequality across countries (Atkinson, 2015a). This represents a shift in secular trends in income distribution, which in the previous decades was becoming more rather than less equal (Atkinson, 2015a).

On wage inequality, the economic literature highlights the role of demand shocks, particularly those based on technology, as the driving forces behind these changes. The conventional wisdom of this literature is what Acemoglu and Autor (2011) refer to as the skill-biased technical change (hereafter, SBTC): better trained workers benefit more from new technologies than those with less training, thereby creating a "skill-bias" in the evolution of labour demand (Katz and Murphy, 1992). Technology in this model has a monotonically upgrading effect on the occupational structure in terms of skills. That is, the higher is the level of skill, the higher is the increase in demand. The implication is that we should observe a higher increase in employment in the higher-skilled occupations relative to the lower-skilled ones. The SBTC hypothesis has been proved empirically successful in accounting for the growth in the skill premia in the United States as well as among advanced nations throughout the twentieth century.

Despite its virtue, skill-biased technological change alone cannot explain a prominent and relatively recent phenomenon: the decline in the share of middle-wage occupations relative to high- and low-wage occupations. This phenomenon has been defined as *job polarisation* (Goos and Manning, 2007).

While the main drivers behind job polarisation are still subject to some debate, the main candidate is the routinization hypothesis (Autor et al., 2003) (hereafter called RBTC). The basic idea of this model is that technological developments, including artificial intelligence, robotics, and more generally advancements in Information and Communication Technology (ICT), have made possible the replacement of workers by machines performing routine tasks. This process is driven by the declining price of computer capital. This labour-capital substitution reduces the relative demand of labour in middle-wage occupations due to the increasing ability of machines to perform routine tasks, which characterise these occupations. The innovative aspect of this model is that it predicts that computerisation has a non-linear effect on labour demand.

Despite the importance of RBTC, the conceptual and operational framework seems to be underdeveloped (Fernández-Macías and Hurley, 2016). First, there are some problems with the definition of routine occupations. For instance, in workers' surveys, it is not easy for respondents to answer whether their job might be done by a computer or some other machine. Second, most research focuses just on the routine and cognitive dimensions, to which an *ad hoc* additional dimensions is added, such as manual (Autor and Dorn, 2013; Autor and Handel, 2013) or services (Goos et al., 2010) depending on their particular interest. And third, the RBTC is very difficult to operationalize as there is no perfect data source (Fernández-Macías and Bisello, 2017). The most common approach to identify tasks is through O*Net. In this case, tasks are identifies with the help of experts at the occupational level. The downside of this approach is that there is no variation in job tasks among the workers of the same occupation. Moreover, O*Net refers to the US labour market and it might not be perfectly applicable to the EU.

In the light of the above remarks, the objectives of this chapter are threefold. First, we present a detailed review of the theoretical and empirical debates that surround the notion of how technology affects the labour demand. Second, we explain why the RBTC seems to fit well with the job polarisation phenomenon. Third, our work also reveals the main conceptual, operational, and empirical challenges not solved by the RBTC. With this aim, Section 2.2 provides a summary of the main theoretical frameworks within which researchers have attempted to explain the phenomenon. Section 2.3 looks at the empirical evidence that have been provided by researchers. Section 2.4 presents a discussion of the main concepts. In Section 2.5, we present the main operationalization problems between the definitions and the variables used by researchers. Section 2.6 features a detail discussion on the measurement of the phenomenon. A summary and conclusions are presented in Section 2.7 (look at Appendix A for a description of all the data sources).

2.2 Theoretical framework

2.2.1 Introductory remarks

Technological progress has been highlighted as the dominant cause driving the changes in labour demand (Goos and Manning, 2007; Manning, 2004). It is well known that innovations affect labour demand in a powerful and important way. Over time, workers might be substituted by technology and displaced from jobs allocated into sectors in which technological advance has a pervasive impact. For example, during the first Industrial Revolution, major technological advances like the mechanization of textiles, lead to a significant substitution of artisans for unskilled labour, resulting in an occupational downgrading. In contrast, in the modern age, information and communication technologies have stimulated the demand for managerial and professional jobs over production workers (Goldin and Katz, 1996). Overall, from the second Industrial Revolution (the beginning of the twentieth century) until the end of the 1990s, technology has fostered an increasing demand for more qualified workers (Goldin and Katz, 2007). However, there is no accepted unified theory regarding how technology affects the labour market. The following sections give an overview of the two more prominent theories trying to explain the phenomenon.

2.2.2 Canonical model: Skill-Biased Technical Change

Measuring the impact of technological advances on the employment structure relies on the classification of skills of workers. In this respect, the trend towards an increasing utilisation of high-skill labour force is known as skill-biased technological change (henceforth, SBTC).

According to Acemoglu and Autor (2011), SBTC is based on two assumptions. First, labour markets can be classified accordingly with workers' skills, typically by selecting two distinct categories: skilled (high-educated) and unskilled (low-educated) workers. In particular, this classification implies that any given job is assigned to a given category, and workers from the other category cannot perform it. Second, in the canonical model, technology is exogenous, meaning that the forms innovations take are not influenced by the skill composition of the workforce itself. Firms do not choose technologies that complement a certain type of labour input on the basis of its relative abundance. They can only determine quantities of skilled and unskilled workers to employ.

The basic idea behind SBTC is that new technologies that foster productivity are "skill-biased", meaning that higher educated workers are more able to use new technologies than less educated workers (Tinbergen, 1974, 1975). Indeed, the increasingly important new information and communication technologies (ICT) are complementary to skilled labour. This non-neutral technological change makes higher educated workers more productive for employers and therefore increases the demand for this type of workforce. At the same time, less educated workers are less productive in relative terms. The SBTC hypothesis predicts that the demand for skilled jobs is rising relative to that for unskilled jobs. In conclusion, the model predicts a positive monotonic relation between skills and employment growth (Acemoglu, 2002).

Evidence of such relationship is provided when skills are measured in terms of education. First, at the aggregate level of the economy, both employment (quantities) and wages (prices) of college workers in the US have strongly risen since the early 1980s and through the 1990s in comparison with these magnitudes for less educated workers (Katz and Murphy, 1992). Second, at the firm and industry level, there is a striking correlation between the adoption of computer-based technologies and an increased demand for high-skilled workers (Fernandez, 2001). Finally, ample micro-econometric research and several case studies document a statistical correlation between the use of new technologies, such as computers, and either the employment share of skilled workers (Bartel and Lichtenberg, 1987) or their wage across industries (Autor et al., 1998). These studies firmly establish that the new technologies are deployed with better-qualified and better-paid labour. These empirical evidences support the SBTC prediction. Hence during the 90s, SBTC became the standard explanation in labour economics to account for the deteriorating wage and employment of less qualified workers.

However, there are two problems with the SBTC theoretical framework. First, this model is unable to explain the recent evidence of growing employment for low-skilled jobs (Autor et al., 2006; Goos and Manning, 2007; Wright and Dwyer, 2003). Hence, it does not provide an entirely satisfactory framework for interpreting recent key trends in labour markets. Secondly, the SBTC relies on a simplistic classification of skilled and unskilled jobs. This classification is unable to capture the interrelations between the labour market and technological progress (feedbacks) and, mainly relies on workers' education rather than what they actually do (e.g., tasks). For these reasons, some authors started to investigate not only skill requirements, but how the task content of jobs is relevant to explain the effect of technological change on the demand.

2.2.3 From Skill-Biased Technical Change to Routine Biased Technical Change

In the light of the above remarks, a more nuanced and refined version of the SBTC was put forward to explain changes in the employment structure, focusing on the impact of computerisation on the different tasks performed by workers on the job (Acemoglu and Autor, 2011).

Autor et al. (2003) (hereafter, ALM) provide the so-called "routinisation" hypothesis (or routine biased technical change, RBTC). They argue that how occupations are affected by new technologies depends to a large extent on the tasks workers perform, rather than on their skills. Therefore, in order to measure how the role of computerisation affects the labour market, ALM proposes a new classification based on a two-dimensional typology: routine, as opposed to non-routine, and manual, as opposed to cognitive, content. The cognitive element can be further divided into analytical and interactive subsets (Table 2.1 for details). Overall, the authors identify five categories of tasks:

- *Routine manual tasks*: repetitive physical labour that can be easily replicated by machines and automated. These tasks are typical of production and operative occupations. It includes occupations like assemblers and machine operators.

- *Routine cognitive tasks*: repetitive labour involving the processing of information. These tasks are characteristic of clerical and administrative occupations, for example, a bank teller or a telephone switchboard operator. The Information Technology (IT) revolution of the 1980s had a similar effect as to what mechanization did to routine manual jobs a century earlier, these tasks can be easily performed by computers.

- *Non-routine cognitive tasks*: non-repetitive or non-codifiable work involving the production, processing and manipulation of information. These tasks, which are carried out mainly within managerial, professional and creative occupations, are usually performed by high-skilled workers. Examples of occupations with non-routine cognitive tasks are judges, psychologists, lawyers or medical doctors. According to

ALM, these occupations are not only difficult to replace with machines, but technologies like personal computers are even considered to play a complementarity role.

In turn, *non-routine cognitive tasks* are divided in two groups:

- *Non-routine interactive*: tasks that demand creativity, flexibility and complex communication (managerial and interpersonal tasks).
- *Non-routine analytic*: tasks requiring problem solving and quantitative reasoning.

- *Non-routine manual tasks*: non-repetitive tasks of a physical nature. It includes occupations such as bus drivers, cabinet makers or plumbers. The ALM framework does not explicitly predict neither strong substitution nor strong complementarity with computers, because this category is not supposed to be directly affected by technological change. Indeed, non-routine manual tasks (typical of service occupations) are difficult to automate as they require direct physical proximity or flexible interpersonal communication and rely on dexterity. At the same time, they do not need problem solving or managerial skills to be carried out, hence there is limited room for complementarity.

In summary, firms substitute routine tasks for technology, while technology complements non-routine tasks. Therefore, capital-labour substitutions result in two effects: first, increasing employment and earnings for jobs in non-routine non-manual tasks and second, decreasing employment and earnings for routine jobs. The innovative aspect of this model is that it predicts that computerisation has a non-linear effect on labour demand.

Table 2.1: Categories of workplace tasks according to Autor et al. (2003)

	Routine Tasks	Non Routine Tasks
	Analytic and Interactive Tasks	
Example	Record-keeping	Forming/testing hypothesis
	Calculation	Medical diagnosis
	Repetitive customer service	Legal writing
		Persuading/selling
		Managing others
Computer impact	Substantial substitution	Strong complementarities
	Manual Tasks	
Examples	Picking or sorting	Repetitive assembly
	Janitorial services	Truck Driving
Computer impact	Substantial substitution	Limited opportunities for substitution or complementarity

Source: Autor et al. (2003; p. 1286).

2.3 Empirical evidence on RBTC

As already discussed, the RBTC hypothesis provides a more refined framework than the SBTC model for interpreting recent key trends in the labour market. One of the most important characteristics in this framework is that they distinguish between tasks and skills. According to Acemoglu and Autor (2011, p. 1045), a task is defined as a "unit of work activity that produces output (good and services)" whereas a skill is a "worker's endowment of capabilities for performing various tasks". Tasks are actions that workers perform in their jobs and they might change as the latter are changing due for example to technical changes. In this literature, researchers are interested in the tasks respondents are required to perform in their given job, not the skills or competencies respondents may or may not have in order to perform these tasks.

In what follows, we briefly review this literature, paying attention to the type of tasks that each study identifies as the most important. Table 2.2 presents the main results of each paper, together with the specification of the domains considered, and the identified relationship between technology and routinization.

As can be seen in Table 2.2, there are just two studies that follow the original ALM taxonomy (Goos and Manning, 2007; Spitz-Oener, 2006). Five papers consider a three-fold classification of tasks by bringing together the two routine categories. To be more precise, Autor et al. (2006), Autor and Handel (2013), Autor and Dorn (2013), Goos et al. (2014), and Fonseca et al. (2016) classify tasks into abstract, routine and manual. In this case, routine is defined as in the ALM model, whereas the abstract category refers to tasks that require problem-solving and managerial tasks with high cognitive demand, and manual tasks are those requiring physical effort and at the same time requiring adaptability and flexibility, making them difficult to automate.[1] Different from most studies in the literature, Matthes et al. (2014), Fernández-Macías and Hurley (2016) and Fernández-Macías and Bisello (2017) propose three new frameworks to measure tasks. Matthes et al. (2014) define five domains: analytic, interactive, manual, routine and autonomy. The most innovative idea is that they decided to define routine *ex negativo*, that is, by asking respondents whether their jobs are in some ways non-routine. Fernández-Macías and Hurley (2016) add for the first time the "social interaction task". They argue that since social interaction is by definition of human nature, it would seem in principle resilient to computerisation and therefore relevant as well in this respect. Finally, Fernández-Macías and Bisello (2017) divide the tasks in two groups: the first one in terms of the object of work (where they include physical, intellectual, and social tasks). The second group in

[1]In an earlier version, Goos et al. (2010) introduce the concept of service tasks (instead of manual) alongside abstract and routine. In here, service tasks are defined as taking care of others, tending to be in the low-skilled and non-routine quadrant.

terms of the method and tools used in the work (where they include work organization and technology).

On the empirical side, all the papers in Table 2.2 present evidence for the occurrence of RBTC.[2] They show that a decline in the usage of routine skills is shown to be correlated with the level of computer adoption at the occupation and industry level.

The RBTC model has been used by several studies as a conceptual framework to investigate changes in the employment structure at the occupational and sectorial level, specifically the phenomenon of job polarisation (Autor and Dorn, 2013; Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2010)

Goos and Manning (2007) are the first to formalise the relationship between the substitution of routine tasks and job polarisation. They look at the relationship between the median wage of occupations and their task content on the evolution of the UK employment structure since the 1970s. The results of their analysis point out that the UK exhibits a pattern of polarisation with rises in employment shares in the highest- and lowest-wage relative to the middle-wage for the period 1979-1999. Furthermore, they are able to link low-wage occupations with non-routine manual tasks, middle-wage occupations with the routine tasks and high-wage jobs with cognitive non-manual tasks. Hence, this work suggests that job polarisation naturally emerges from substantial substitution, and subsequent displacement, of workers performing routine tasks and complement cognitive non-routine activities as predicted by ALM.

[2] It must be noted that Matthes et al. (2014) and Fernández-Macías and Bisello (2017) just present a new framework; therefore, in their papers, they do not investigate the RBTC hypothesis.

Table 2.2: Task categories

Name of the study	Year	Country	Task categories	Routine tasks
Autor, Levy and Murnane (ALM)	2003	US	Routine manual Routine cognitive Non-routine analytic Non-routine interactive Non-routine manual	YES
Autor, Kazt, and Kearney (AKK)	2006	US	Abstract Routine Manual	YES
Spitz-Oener	2006	Germany	Follow ALM (2003)	YES
Goos and Manning	2007	UK	Follow ALM (2003)	YES
Autor and Handel	2013	US	Follow AKK(2006)	YES
Autor and Dorn	2013	US	Follow AKK(2006)	YES
Matthes et al.	2014	Germany	Analytic Interactive Manual Routine Autonomy	YES
Goos, Manning and Salomons	2014	EU-15	Follow AKK(2006)	YES
Fonseca et al.	2014	Portugal	Follow AKK(2006)	YES
Fernández-Macías and Hurley	2016	EU-15	Cognitive task Routine task Social task Trade intensity	YES
Fernández-Macías and Bisello	2017	EU-15	Work (physical, intellectual, and social) Tools (work organisation and technology)	YES

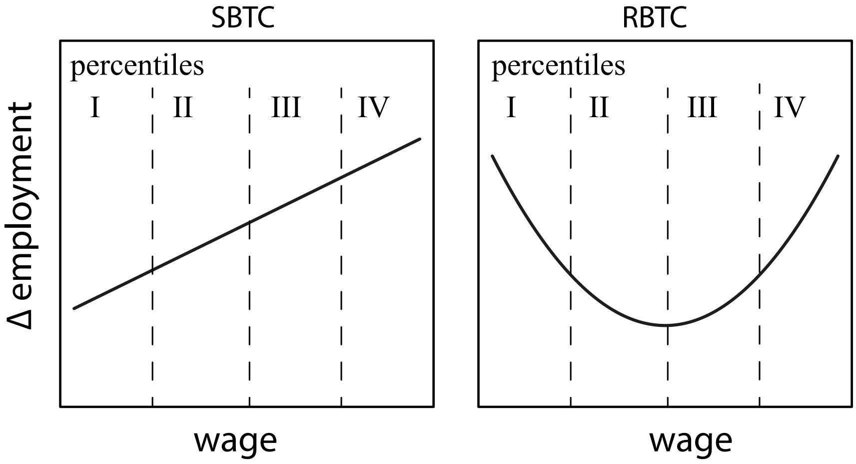
Source: Author's analysis from the references quoted in the table.

In addition to the previous evidence, a later paper by Autor et al. (2006) follows the model proposed by Goos and Manning (2007) and shows that the US labour market experienced a polarising trend as well, with routine tasks losing ground relative to non-routine tasks. In a more recent work, Goos et al. (2014) find evidence for job polarisation by looking at the whole Europe: the four lowest-paid and the eight highest-paid occupations increase their employment share, while the nine middle-paid occupations experience significant decreases. They find that employment between 1993 and 2006 is positively correlated with the importance of abstract and service tasks, and negatively correlated with routine tasks. On the contrary, one exception is Fernández-Macías (2012): they find very heterogeneous results among European countries and do not show evidence of generalised job polarisation.[3] Finally, evidence for job polarisation is found in Germany by different authors from 1979 to 1999 (Spitz-Oener, 2006) and from mid-1980s until 2008 (Kampelmann and Rycx, 2011).

While the SBTC postulates an increase in demand for highly educated workforce and a decrease for low-educated workers, the routinization model argues that technology would affect negatively mid-range jobs, while leading to growth in both high- and low-end jobs, which results in the polarisation of the employment structure. Empirical evidence suggests that RBTC might offer a more convincing explanation to recent developments in the demand for labour and skills in many industrialised economies (Figure 2.1 for more details). However, it still presents some serious challenges from a conceptual, empirical, and operational point of view as it is discussed in the next sections.

[3]It should be emphasised that the methodology used in these analyses is not the same. On the one hand, Goos et al. (2014) classify the jobs in three categories (good, middling, and bad jobs), which have uneven sizes in terms of number of occupations (8-9-4) and in terms of employment shares in the first year of the period studied (29 per cent, 49 per cent, and 22 per cent, respectively). On the other hand, Fernández-Macías (2012) classifies jobs in five equally size groups (showing the 20 per cent of population in each quintile)

Figure 2.1: Skill-Biased Technical Change vs Routine Biased Technical Change



Source: Author's elaboration.

2.4 Conceptual problems: capturing routine

The RBTC, introduced by ALM, has replaced SBTC explanation as the most conventional approach to explain changes in the structure of labour market induced by technological change. As discussed above, the main difference emerges from the more sophisticated definition of tasks: cognitive-manual and routine-non routine tasks. However, the bi-dimensional subdivision of tasks introduces conceptual problems on the definitions itself.

The main problem is related to the definition of routine tasks, which, according to ALM, comprise those which are programmable, expressible in rules, codificable and imply a methodological repetition of procedure. This definition makes a strong conceptual link between jobs with high-routine content and technology (Fernández-Macías and Hurley, 2016). In particular, it suggests a priori that technology will replace the jobs with high-routine content and not the others. As a result of this definition, low-routine jobs are for instance those held by both managers and waiters, thus either high-educated (skilled) or low-educated (unskilled) workers, while high-routine jobs are performed by middle-skilled workers. Thus, the hollowing out of middle-skilled jobs is biased by the definition of routine tasks.

The definition of routine stated above is problematic in itself. For example, what is perceived as routine from workers' point of view may not be so from the perspective of machine execution, and this poses a further challenge to the operationalisation of the concept as highlighted by Matthes et al. (2014). For instance, driving of a motor vehicle is considered as a non-routine task, because even though it is a commonplace everyday task, the procedures by which it is actually accomplished are not sufficiently understood in order to write computer routines to replace it (however this is changing rapidly). Nevertheless, one could argue that most people would consider such a task routine simply because it is a commonplace and everyday task (Matthes et al., 2014, p.279). In the same line, Green (2012) also raises some doubts on the validity of the categorization between routine and non-routine tasks, which is often ambiguous. He explains that in many cases it is not possible to determine a priori which activities are routine and therefore programmable. Finally, despite a relative coherence in the definition of what is routine work, limitations in data availability and lack of uniformity among surveys questionnaires inevitably lead to a different choice of variables that are actually used for the analyses (Autor and Handel, 2013).

Another conceptual problem is the possible overlap that could exist between routine and cognitive tasks. To have a unique and clear representation of the structure of employment, we aim to find an orthogonal dimension of tasks. Instead, almost by definition, a routine task is a task performed with little cognitive effort and vice versa (Eurofound, 2014). Thus, one can argue that the addition of a second axis is unnecessary or misleading. Part of this explanation may lie in the term "cognitive". Whereas the concept of routine is very clear with a precision definition, there is not a proper definition of the cognitive axis. Sometimes, cognitive task are related to problem solving, and in this case there is an overlap between the two axes; if a task is routine, it requires few problem solving. Sometimes, cognitive tasks are defined as a task involving information processing. In this case, the overlap is not necessary since there could be routine information processing tasks (Eurofound, 2014). The non-orthogonality of the model also relates to same operational problems, which is discussed in the next section.

Moreover, ALM does not distinguish between domestic and foreign labour, and hence they rule out the possibility that routine tasks performed by domestic workers are either replaced with capital or alternatively offshored abroad for a lower economic cost. Recently, Blinder (2009) and Acemoglu and Autor (2011) provide a unified framework which incorporates globalisation and international trade (particularly, offshoring), allowing for the possibility of trade in tasks. Hence, alongside technological change, other forces which affect patterns of wages and employment are considered.

Finally, either SBTC or RBTC theories point to within-industry shifts in occupational composition and tend to dismiss the importance of the sectorial redistribution of jobs (between-industry shifts): from manufacturing to services. Autor and Dorn (2013) suggest that it is necessary to have a better understanding of the rapid rise of employment and wages in service occupations. Handel (2001) explains that this increase is in part due to three factors: population aging contributing to employment growth in the health care sector; the growth of female labour force participation, which stimulates market demand for services previously produced mostly in the home, such as meals or childcare and, lastly, the growth of the Welfare State.

2.5 The operationalization of the RBTC

Another relevant issue is the mismatch between the definitions of tasks proposed and the operationalization of theoretical concepts. Indeed, not only is the classification of tasks into different typologies inconsistent between the original work by ALM (2003) and following papers, but also the choice and the number of variables used to create task indices is often arbitrary.

Table 2.3 summarizes the operationalization of the RBTC in ten fundamental papers defending the RBTC/polarisation hypothesis. As previous argued, the ALM model is bi-dimensional, which leads to the consideration of four broad categories: routine-manual, routine-cognitive, non-routine manual, non-routine cognitive (in turn, subdivided into non-routine cognitive interactive and analytical). There are four papers that follow this classification: Cortes et al. (2014); Goos and Manning (2007); Kampelmann and Rycx (2011); and Spitz-Oener (2006). In four papers, the two routine (cognitive and non-cognitive) categories are conflated into one, leading to a three-fold classification: abstract, routine, and manual (Autor and Dorn, 2013; Autor and Handel, 2013; Autor et al., 2006; Goos et al., 2009, 2014).[4] Two papers present a new framework (Akcomak et al., 2013; Fernández-Macías and Hurley, 2016).

The main problem in the operationalization is that there are several indicators used to classify tasks that do not seem to be justified by the RBTC framework. For example, "managerial tasks" are included in the abstract or cognitive category. Indeed, while it seems reasonable to assume that cognitive effort is required in order to perform managerial

[4]In an ealier version, Goos et al. (2010) introduce the concept of service tasks (instead of manual) alongside abstract and routine. In here, service tasks are definied as taking care of others, tending to be in the low-skilled and non-routine quadrant.

tasks, these sorts of tasks are a feature of the social organization of work. The same can be said about "quality control" as an indicator of routine. Quality control might be routine and repetitive in traditional production line jobs that involve mostly manual work and basic tasks with machines, but not necessary in other activities. Therefore the routine content of some jobs could be overestimated or underestimated when relying on this variable category.

The introduction of some indicators for identifying routine tasks might be problematic. For instance, Autor and Handel (2013) introduce the "absence of face-to-face interactions with customer" as a parameter to identifying routine. This is arguable; whether there is interaction or not with customers does not necessarily affect the routine content of the occupation. The absence of face-to-face interaction usually has to do with chances of offshoring a certain job and it is an indicator for identifying jobs that are predominantly located at the middle level (Blinder, 2009). As a result, high-routine jobs are performed by middle-skilled workers and therefore, the hollowing out of middle-skilled jobs is biased by the definition of routine tasks. A similar case happens when "social interactions and care" is used to classify non-routine non-cognitive category at the bottom of the distribution.

As we can observe in Table 2.3 , there are also some inconsistencies between different applications of the same RBTC hypothesis. For example, the category of "non-routine manual" is measured as: "hand-eye-foot coordination" in the first two papers; "care and social interaction" in Goos et al. (2010); "time spent performing physical activities" in Autor and Handel (2013); "repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving and accommodating" in Spitz-Oener (2006). Another good example is "routine manual". In the first two papers (Autor et al., 2003; Goos and Manning, 2007) is measured as “finger dexterity”, Goos et al (2010) also include “operation monitoring, equipment maintenances, quality control and arm-hand steadiness”. In the paper by Autor and Handel (2013), the variables are completely different: “short repetitive tasks, absences of face-to-face interactions with customers”. However, they all refer to the same category of the RBTC framework, which in the first case was described as “non-routine, non cognitive tasks” and in the second “routine manual”.

More problematic is perhaps the classification of cognitive (as opposed to manual) tasks. These are usually split into analytical and interactive (or interpersonal) activities. In some cases the cognitive dimension is more about problem-solving and analytic skills, in others is related to information-processing tasks. Also, managerial tasks (such as direction, evaluation, and planning) sometimes are included in the analytical category (Spitz-Oener, 2006) and other times in the interactive one (Autor et al., 2003).

Akcomak et al. (2013) have used an alternative classification approach using factor analysis, claiming that a clear-cut division into routine and non-routine tasks is problematic. Seven distinct factors have been identified in the British Skill Survey (BSS): literacy, problem-solving, checking, planning, number, physical and interactive skills.

Finally, Fernández-Macías and Hurley (2016) have used a new framework to measure the RBTC hypothesis arguing that in the ALM the cognitive task and the routine task overlap in reverse. Different from previous cases, routine refers to a sequence of actions that is carried out regularly and identically; as an adjective, it is synonym of repetitive and standardized.

Table 2.3: Operationalization of the RBTC in 9 key papers

1. Autor, Levy and Murnane, 2003 (p. 1283)	
Typologies	Non-routine analytic, non-routine interactive,routine cognitive, routine manual, non-routine manual.
Definitions	*Routine*: “tasks that require the methodical repetition of an

	unwavering procedure". No definition of *analytic* or *cognitive*; only of *non-routine cognitive tasks*: "tasks demanding flexibility, creativity, generalized problem-solving and complex communications".
Variables used	*Non-routine analytic*: quantitative reasoning requirements. *Non-routine interactive*: direction, control and planning (managerial and interpersonal tasks). *Routine cognitive*: adaptability to work requiring set limits, tolerances and standards. *Routine manual*: finger dexterity. *Non-routine manual*: eye-hand-foot coordination.
2. Goos and Manning 2007 (p. 119) - Follow ALM (2003)	
3. Autor, Katz and Kearney, 2006 (p. 192)	
Typologies	Abstract, routine, manual.
Definitions	*Abstract*: "problem-solving and managerial tasks. These are not well structured and require non-routine cognitive skills". *Routine*: "cognitive or physical tasks that follow closely prescribed sets of rules and procedures and are executed in a well-controlled environment". *Manual*: "do not require abstract problem-solving or managerial skills but are nevertheless difficult to automate because they require some flexibility in a less than fully predictable environment".
Variables used	Not specified.
4. Spitz-Oener, 2006 (pp. 239-240; 243)	
Typologies	Nonroutine analytical, nonroutine interactive, routine cognitive, routine manual, non-routine manual.
Definitions	*Routine* (both manual and cognitive): "are well defined in the sense that they are expressible in rules such that they are easily programmable and can be performed by computers at economically feasible costs (Levy and Murnane 1996)". *Non-routine tasks*: 'are not well defined and programmable and, as things currently stand, cannot be accomplished by computers". *Analytical*: "refers to the ability of workers to think, reason, and solve problems encountered in the workplace". *Interactive*: "refers not only to communication skills -that is, the ability to communicate effectively with others through speech and writing- but also to the ability to work with others, including coworkers and customers".
Variables used	*Non-routine analytical*: researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules. *Non-routine interactive*: negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel. *Routine cognitive*: calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature. *Routine manual*: operating or controlling machines and equipping

	machines. *Non-routine manual*: repairing or renovating houses/apartments/ machines/vehicles, restoring art/monuments, and serving or accommodating.
5.Goos, Manning and Salomons, 2010 (p. 9)	
Typologies	Three categories: abstract, routine and service tasks
Definitions	*Routine*: "those which computers can perform with relative ease, such as jobs that require the input of repetitive physical strength or motion, as well as jobs requiring repetitive and non-complex cognitive skills". The non-routine dimension is split into abstract and service. No definition of *abstract tasks*, just examples: "complex problem-solving' ([such as] ... needed by engineers and medical doctors)". Examples of *service tasks* are "caring for others ([such as] ... needed by hairdressers and medical doctors)".
Variables used	*Routine*: operation monitoring, equipment maintenance, quality control, manual and finger dexterity, arm-hand steadiness. *Abstract*: managerial tasks, problem-solving, information-processing, technical and data analysis, interaction with computers. *Service*: assisting and caring for others, social interaction, selling, active listening, working directly with the public.
6. Autor and Handel, 2013 (pp. S70-71)	
Typologies	Three categories: Abstract, routine, manual
Definitions	*Abstract*: "abstract problem-solving, and creative, organisational and managerial tasks". *Routine*: "routine, codifiable cognitive and manual tasks that follow explicit procedures". *Manual*: "non-routine manual job tasks that require physical adaptability".
Variables used	*Abstract*: document-reading, mathematics, problem-solving of at least 30 minutes, supervision of other workers. *Routine*: short repetitive tasks, absence of face-to-face interactions with customers. *Manual*: time spent performing physical tasks.
7. Autor and Dorn, 2013 - Follow Autor, Katz, and Kearney (2006)	
8. Akcomak, Kok and Rojas-Romagasa (2013)	
Typologies	Abstract, services and routine
Definitions	*Routine* (both manual and cognitive): "are well defined in the sense that they are expressible in rules such that they are easily programmable and can be performed by computers at economically feasible costs (Levy and Murnane 1996)". *Nonroutine tasks*: "are not well defined and programmable and, as things currently stand, cannot be accomplished by computers"
Variables used	*Service*: people (dealing with people), selling (selling a product or service), listen (Listening carefully to colleagues), product (knowledge of particular products or services), and special (specialist knowledge or understanding)

	Routine: faults (spotting problems or faults), noerror (checking things to ensure no errors), mistake (noticing when there is a mistake), calca (adding, subtracting, multiplying and dividing numbers), percent (calculations using decimals, percentages or fractions), stats (Calculations using more advanced mathematical or statistical procedures) *Abstract*: solutn (thinking of solutions to problems), analyse (analysing complex problems in depth), teach (teaching people), speech (making speeches/ presentations), writelg (writing long documents with correct spelling and grammar), readlg (reading long documents such as long reports, manuals, articles or books), planoth (planning the activities of others), teamwk (working with a team of people)
9. Kampelmann and Rycz (2011)	
Typologies	Non-manual non-routine, Non-manual routine, Manual non-routine and manual routine
Definitions	*Routine/non-routine*: "Our operationalisation of routine tasks is based on whether a work post is characterised by diversity and monotony of procedures, arguing that the less diversified and the more monotone a job is, the more it is possible to identify the underlying rules and procedures and, in fine, replace them with technology". *Manual/non-manual*: "distinction between physical and nonphysical work appears to be most pertinent"; "the more physical a job is, the more it is likely to involve complex eye-hand coordination absent in nonphysical jobs".
Variables used	*Routine/non-routine*: "Do you carry out diverse tasks?" and "Does your work allow you to constantly learn new things that are useful for your professional development?". *Manual/non-manual*: "Do you have to perform physically demanding work in your job?"
10. Fernández-Macías and Hurley (2016)	
Typologies	Cognitive, routine task, social interaction task and trade intensity
Definitions	*Cognitive*: "Adaptability to work requiring set limits, tolerances and standards". *Routine*: Refers to a sequence of actions that is carried out regularly and identically; as an adjective, it is synonym of repetitive and standardized. *Social Interaction*: No definition. *Trade intensity*: No definition.
Variables Used	*Cognitive*: (a) complex tasks; (b) use of computers at work; (c) use of internet at work; (d) number of years of formal education necessary to perform the job adequately *Routine Manual*: (a) repetitive hand or arm movements; (b) repetitive hand movements of less than 1 or 10 min; (c) monotonous tasks; (d) dealing with unforeseen problems (reverse coded) *Social Interaction*: (a) whether the current job requires direct interaction with non-colleagues; (b) whether the pace of work is

	determined by the demands from customers. *Trade intensity*: the index comes from the 1995-2007 average of domestic value-added of exports (that is, eliminating the value of intermediate imports) and the 1995-2007 average of the gross value added of imports relative To gross output.

Sources: Author's analysis from the references quoted in the table.

2.6 Empirical measurements: data sources

From Table 2.4 we can see that there are two main options for measuring the task content of different types of jobs: (1) direct measures, drawing from occupational databases based on the assessment of experts (e.g., O*Net), and (2) self-reported, aggregating the answers of individual workers to surveys on skills and working conditions (e.g., IAB/BIBB, BBS, PDII, PIAAC, and EWCS).

One of the main problems to be highlighted in ALM's empirical approach has to do with their exclusive reliance on O*Net, which does not allow for a comparison over time, even if this database is regularly updated. Thus, studies using this database are limited to analyse exclusively changes in the extensive margin, and assume that the task-content is fixed within occupations. As can be seen in Table 2.4, O*Net has been used in eight out of sixteen studies. Other surveys used for this purpose in the literature are the BIBB/IAB for Germany (see, e.g., Spitz-Oener, 2006), the Princeton Data Improvement Initiative (PDII) for the US (see e.g., Autor and Handel, 2013), the British Skills Surveys (BBS) for the UK (see, e.g., Green, 2012, and Akcomak et al., 2013), the Programme for the International Assessment of Adult Competencies (PIACC) for 24 OECD countries (Fernández-Macías and Bisello, 2017) and the European Working Condition Survey (EWCS) for 15 European countries (Fernández-Macías and Bisello, 2017;

Fernández-Macías and Hurley, 2016) and for Spain (Sebastian, 2017).

Table 2.4: Empirical measurement of the RBTC in 15 key papers

Name of study	Year	Dataset	Country	Data
Autor et al.	2003	O*Net	US	1977 and 1991
Goos and Manning	2007	O*Net	UK	1977
Autor, et al.	2006	O*Net	UK	Not specified
Spitz-Oener	2006	BIBB/IAB	Germany	1979, 1985/86, 1991/92, 1998/99, 2006, 2012
Kampelmann and Rycz	2011	SOEP	Germany	1985, 1987,1989,1995 and 2001 1989, 1995 and 2001
Green	2012	BBS	UK	1997, 2001, 2006
Autor and Dorn	2013	O*Net	US	1977
Autor and Handel	2013	PDII	US	1977
Akcomak, et al.	2013	BBS	UK	1997, 2001, 2006
Goos et al.	2014	O*Net	EU-15	1977
Matthes et al.	2014	NEPS	Germany	2012
Anghel et al.	2014	O*Net	Spain	*same as GMS
Fonseca et al.	2015	O*Net	Portugal	Not specified
Fernández-Macías and Hurley	2016	EWCS	EU-15	Not specified
Fernández-Macías and Bisello	2017	O*Net, EWCS, and PIAAC	EU-15	Not specified
Sebastian	2017	EWCS	Spain	1995, 2000, 2005, 2010

Notes: BBS (British Skill Survey), BIBB/IAB (German Federal Institute for Vocational Training/Research Institute of the Federal Employment Service), EWCS (European Working Condition Survey), NEPS (National Education Panel Study), O*Net (Occupational Information Network), PIAAC (Programme for the International Assessment of Adult Competencies), PDII (Princeton Data Improvement Initiative), and SOEP (German Socio-Economic Panel).
Source: Author's analysis from the references quoted in the table.

Using workers' surveys to infer the task content of jobs and occupations has advantages and disadvantages. On the one hand, it allows to study the variability in task content within each occupation or job type. As discussed in the analytical framework, jobs can be understood as coherent bundles of tasks: this implies that workers in the same occupation or type of job should carry out similar tasks. But to some extent this is an empirical question that can be explicitly analysed using workers' surveys. Not all workers within the same job carry out exactly the same tasks, as such the extent of dispersion in task content within jobs and the reasons behind it, is a very valid research question. On the other hand, gathering information on tasks from workers introduces a potential bias in our measurement, since the workers' answers may reflect other things beside the task content in strict terms.

2.7 Summary and conclusions

In this chapter, we contribute to the growing debate about how the introduction of technology affects labour demand. First, we provide some background of the main theoretical frameworks within which researchers have attempted to explain the recent changes in the employment distribution. We discuss the main drawbacks of the SBTC and why the RBTC fits better with a relatively recent phenomenon: the decline in the share of middle-wage occupations relative to high- and low-wage occupations.

Second, we review the most important empirical studies using the RBTC model. Overall, the prevailing economic literature provides empirical support to the RBTC model: cheaper computerisation progressively replaces human labour in routine tasks, thereby leading to an increase in the relative demand for workers performing non-routine tasks.

Third, while the RBTC seems to fit well with changes in the employment distribution, this theory presents challenges from a conceptual, operational, and empirical point of view. The first relevant issue is the conceptual problems that arise trying to capture routine. In the RBTC model, routine task is defined as tasks that can be replace by machine. However, what is perceived as routine for workers (everyday task) may not be so from the perspective of the machine execution. Another conceptual problem is the possible overlap (in reverse) between routine and cognitive tasks. Many routine codificable tasks require by definition fewer cognitive tasks.

Moreover, we find inconsistencies between the theory and the operationalization of these concepts into indices. This is the case of operationalization of routine and cognitive tasks that include some indicators that are not specified in the theoretical arguments. For example, routine task index includes measures of quality controls, but this item is unrelated to the theoretical definition. The same happens with cognitive task index. Whereas the definition involve problem solving and information processing, cognitive task index often includes measures of managerial responsibilities, being again unrelated to the theoretical concept.

Finally, there is not a perfect database. On the one hand, self-reported sources allow studying the variability in task content within each occupation or job type, whereas this cannot be study using occupational database. On the other hand, self-reported sources are prone to introduce potential bias in the measurement while occupational databases provide more objectives measures.

In conclusion the body of literature is still far from a model that perfectly explains how technology affects the labour demand. As already stated, the RBTC has some challenges. However, it serves to put some pieces into their right location: cheaper computerisation progressively replaces human labour in routine tasks, leading to an increase in the relative demand for workers performing non-routine tasks.

3. How can the task approach be operationalised?

3.1 Introduction

Analysing the tasks that people undertake on a daily basis has helped economists to gain insights into micro-level behaviours. Task model information on the activities performed by workers has been collected, answering research questions regarding the structure of the economy and its implications. More precisely, the task model has played an important role in explaining the role of technology in increasing wage inequality and identifying jobs with a high risk of being transferred abroad.

Despite the importance of task measures, measuring tasks is challenging. There are four main difficulties involved in evaluating task measurements: representativeness, consistent typologies, consistent definitions, and operationalization difficulties. First, information on tasks is not commonly collected by representative data sources. Thus, while one could ask which tasks a worker performs in his/her job, the question is far from trivial and prone to introducing a potential bias into the measurement. Some researchers use skills, for which proxies such as education and experience are broadly collected by surveys. Despite the fact that they are connected, as skills are necessary to perform tasks, skills and tasks are not the same; the former refers to workers' knowledge and the latter to their ability to use knowledge and apply it.

Second, researchers lack shared consistency concerning the typologies of tasks (Fernández-Macías and Hurley, 2016). For example, the original taxonomy introduced by Autor et al. (2003) classifies tasks along two main axes: routine (as opposed to non-routine) and cognitive (as opposed to manual). More recent studies (Autor and Dorn, 2013; Autor and Handel, 2013) consider instead a threefold classification of tasks by combining the two routine categories into one. More precisely, these are abstract, routine, and manual.[1]

Third, researchers lack consistency among definitions of tasks. For example, as Biagi and Sebastian (2017) point out, the category of "non-routine manual" labour is measured as: 1) "hand-eye-foot coordination" by Autor et al. (2003), 2) "time spent performing physical activities" by Autor and Handel (2013), and 3) "care and social interaction" by Goos et al. (2014).

Fourth, the task approach is very difficult to operationalize, as there is no perfect data source (Fernández-Macías and Bisello, 2017). Two types of source can be distinguished, occupational databases and worker surveys. First, occupational databases identify tasks by expert judgements. To the authors' knowledge, the Occupational Information Network database (O*Net) is the only source in which information is collected at the occupational level. The main drawback when using occupational-level information is that researchers do not take into account possible variations in tasks among workers in the same occupation (Autor and Handel, 2013). The second type of data source is a workers' survey. This type of source asks workers about highly complex concepts, such as their job's task composition, producing potential measurement errors.[2] The main data sources known

[1]For more information refer to the recent survey by Biagi and Sebastian (2017).

[2]For instance, workers who are unhappy in their jobs can exaggerate the amount of time that they devote to routine tasks, workers who are new in their jobs can have limited knowledge of what they

in this category are: the Princeton Data Improvement Initiative Survey (PDII) for the US, the British Skill Survey (BSS) for the UK, and the Qualification and Career Survey (BIBB/IAB) for Germany. At the European level, two important surveys include the Programme for the International Assessment of Adult Competencies (PIAAC) and the European Working Condition Survey (EWCS). With the exception of the EWCS, databases collect data at one moment of time.

In light of these drawbacks, the objectives of this chapter are threefold. First, we compare tasks' content using different databases at the European level, paying special attention to the problems associated with proper measurement. Accordingly, we select the most representative framework and harmonize items across multiple data sources, resulting in a comparable framework in terms of tasks and definitions. Second, we analyse two different definitions of tasks but use the same data source (the PIAAC). Third, we present the evolution of the task approach in the EU-26 between 2005 and 2015 using the EWCS. This study determines whether changes in the task content of occupations are due to changes within occupations (in the intensive margin) or between occupations (the extensive margin). Significant contributions to the literature on understanding tasks are made by comparing harmonized frameworks. We also make practical progress with respect to previous studies on tasks by measuring the task content of occupations from European data instead of relying on US sources. Our study contributes further to the literature on tasks, as it includes 25 European countries (15 were included in the study by Fernández-Macías, 2012; and 16 were included in the study by Goos et al., 2014) and enlarges the period of analysis (2008 was the last year in the study by Fernández-Macías,

are actually required to do, and so on. Furthermore, there can be inconsistencies in the classification of workers across occupational levels and sectors, which can be particularly negative for our purposes (every misclassified worker would bias the occupation-level task scores).

2012; and 2010 was the last year in the study by Goos et al., 2014).

The study is organized as follows. In Section 3.2 we highlight the importance of analysing the task approach and explain the task framework used through the chapter. In Section 3.3 we discuss the general approaches to measuring task content. Section 3.4 describes the main databases used in our analysis: the EWCS, PIAAC, PDII, O*Net, and European Labour Force Survey (EU-LFS). The fifth section presents and discusses the main results of the analysis. The last section summarizes the main conclusions of this chapter.

3.2 Theoretical framework

A growing body of research uses the task approach to measure occupational changes. Despite the fact that several questions can be answered through this approach, arguably the most important one concerns the impact that technology has on changes in the labour demand and wage inequality.

Measuring the impact of technology has always been among the priorities in social sciences. It is well known that, when technology is introduced into the labour market, it affects the labour demand in a non-trivial and non-unique way. Over time, workers are substituted by technology and displaced from jobs allocated to sectors in which technological advance has a pervasive impact.

As we have seen in previos chapters, before the task approach, the natural way of measuring the effect of technology on the labour demand was through skill-biased technical change (SBTC). The concept of skills that underlies this model is very simple: workers are characterized within a dichotomy of low-skilled and high-skilled. In this model technical change increases the relative productivity of high-skilled (versus low-skilled) labour and therefore its relative demand: hence the observed expansion of wage inequality in most developed economies (Berman et al., 1998; Bound and Johnson, 1992; Katz and Murphy, 1992; Machin and Van Reenen, 1998)

At the turn of the century, the evidence of growing employment for low-skilled jobs in the US and the UK, a phenomenon known in the literature as *job polarisation* (Autor et al., 2006; Goos and Manning, 2007), enabled the reformulation of the SBTC. Due to this observation of non-linear changes in the labour demand by skill level, a more nuanced and refined version of SBTC was put forward, focusing on the impact of computerisation on the different categories of workplace tasks.

Autor et al. (2003), (ALM) develop the so-called "routinization" hypothesis (or routine biased technical change, RBTC), the alternative version of SBTC. It shares the central idea of SBTC (technological progress is the main driver behind changes in the labour demand and wages); however, the authors argue that the way in which occupations are affected by new technologies depends to a large extent on the tasks that workers perform rather than on their skills. To measure how technology affects the labour market, ALM propose a new classification based on a two-dimensional typology: routine as opposed as non-routine and manual as opposed to cognitive tasks. The cognitive element can be divided further into analytical and interactive subsets.

As we know, the theory of routine biased technical change (RBTC) argues that recent technological change is biased towards replacing labour in routine tasks (tasks that are easy to codify and automate). Since routine tasks are located in the middle of the occupation distribution and non-routine tasks at the top and at the bottom, RBTC argues that this mechanism has two effects: first, the employment and wages in the middle of the distribution decrease; second, the employment and wages increase (or at least remain stable) in the higher- and lower-qualified groups. Hence, the polarisation effect of recent technical change is explained by RBTC.

RBTC is richer than SBTC. First, RBTC is a non-linear and multidimensional approach: four axes (routine as opposed as non-routine and cognitive as opposed as manual) affect the impact of technology on the labour demand instead of a single continuum of skills. Second, they differentiate between skills and tasks. Skills refer to the human capability to perform tasks, whereas tasks are units of work that produce output. Technology affects the production process, and consequently two effects are generated: first, changes in tasks, and second, the demand for skills. Due to this differentiation, this model allows a more detailed analysis of the effect of technology on the labour demand.

The original model by ALM has sparked a growing literature and has been applied for different periods and countries, but the domains considered remain under discussion (Fernández-Macías and Hurley, 2016).[3] Autor et al. (2006) and more recently Autor and Dorn (2013) reformulate the ALM model by bringing together the two routine categories. They consider a threefold classification and classify tasks into abstract, routine, and manual. While this new classification shares the routine definition of the ALM model, the abstract category refers to tasks requiring problem solving and managerial tasks with high cognitive demand and the manual tasks refer to those requiring physical effort and time adaptability, both task categories therefore being difficult to automate. Different from most studies in the literature, a new measure of "social interaction" is introduced by Fernández-Macías and Hurley (2016). They argue that since social interaction is by

[3]This well-known phenomenon has been found in the US (Autor and Dorn, 2013; Autor et al., 2006), the UK (Akcomak et al., 2013; Goos and Manning, 2007), Germany (Spitz-Oener, 2006), Sweden (Adermon and Gustavsson, 2015), and Spain (Sebastian, 2017). Regarding Europe results are more controversial. On the one hand, Fernández-Macías (2012) find very heterogeneous results among European countries. On the other hand, Goos et al. (2009, 2014) conclude that on average the employment strucutre in Europe has been polarising between 1993 and 2006.

definition of human nature, it would seem in principle resilient to computerisation and therefore relevant. Moreover, Matthes et al. (2014) and Fernández-Macías and Bisello (2017) propose two new frameworks to measure tasks, but they are not yet implemented in the literature.

However, despite the growing importance of understanding tasks, one question remains unsolved among economists: how can we measure tasks properly? The next section tackles this question.

3.3 Measuring the task approach

Before proceeding with our analysis of tasks in Europe, it is important to reflect on the concept of tasks, emphasizing the differences between tasks and skills, and the different approaches to measurement.

3.3.1 Tasks versus skills

As a starting point, we need to clarify the concept of tasks, specifically how it differs from the concept of skills. According to Autor and Acemoglu (2011, p.1045), tasks are defined as "a unit of work activity that produces output", whereas a skill is "a worker's endowment of capabilities performing various tasks". On the one hand, when economists talk about tasks, they consider the units of work needed to transform input into output. Consequently, depending on the complexity of the production process, a combination of different types of tasks might be required. Tasks are therefore performed in the workplace, and, if the production process changes (for example due to technology or international trade), the tasks will change as well. On the other hand, skills refer to workers' qualifications. A job's tasks and a worker's skills might coincide; however, it might happen that the worker lacks some skills to perform the required task, resulting in under- or overqualification, respectively.

We cannot neglect the possibility that the two concepts are interconnected, as, when workers perform a task, it will lead to training on the skills necessary to perform it properly. At the same time, having certain skills will lead employees to match their jobs better, and they will have to perform tasks requiring these skills. However, tasks and skills are not interchangeable; whereas the former is related to the ability to use knowledge and apply it in a given context, the latter refers to the possession of knowledge. They are two different concepts, and it is essential to differentiate between them.

In this chapter we are interested in understanding workers' tasks to perform their jobs and not the skills that workers may need to perform these tasks. The main reason behind this choice is that, while there is a large body of literature addressing the issue of measuring skills, no research focuses on understanding the task perspective.

3.3.2 Measurement of tasks (operationalization of tasks)

In this section we take the model of Autor and Dorn (2013) as the foundation for the analysis of the European labour market.[4] Their theoretical model presents a general equilibrium of routine task replacement. The five original task measures of Autor et al. (2003) are combined to produce three task aggregates. Therefore, non-routine interactive and non-routine analytic in the ALM model are combined in the "abstract task measure"; routine cognitive and routine manual are merged in the "routine task measure"; and finally non-routine manual tasks in the original model correspond to the "manual task

[4]As we already mentioned, in this literature, there are other two different frameworks: Matthes et al. (2014), and Fernández-Macías and Bisello (2017). We follow Autor and Dorn (2013) as they create a Routine Task Intensity (RTI). Thanks to the RTI Index we can measure the importance of routine tasks in each country.

measure".

We then follow Autor and Dorn (2013) in creating a routine task intensity measure (RTI) to compare our findings in the literature. This measure aims to capture the importance of the routine tasks compared with the task components of countries. We standardize our indices with a mean of 0 and a standard deviation of 1. The RTI is then calculated as follows:

$$RTI_c = \ln T^R_{c,t} - \ln T^A_{c,t} - \ln T^M_{c,t} = \ln \frac{T^R_{c,t}}{T^A_{c,t} T^M_{c,t}} \tag{3.1}$$

where $\ln T^R_{c,t}$, $\ln T^A_{c,t}$, and $\ln T^M_{c,t}$ are the routine, abstract, and manual inputs in each country c in year t. This measure rises with the importance of routine tasks in each country and declines with the importance of abstract and manual tasks.

3.4 Data and methodology

This section is concerned with an explanation of the data sets as well as the construction of the tasks (see the Appendix B for further details about its derivation). In this work we make use of five different data sources that include information on the task content of different types of jobs and the European Labour Force Survey, which includes information on occupations. The surveys on task measures are presented first, followed by the EU-LFS.

3.4.1 Workers' survey data versus occupational databases

At present there are two main options for measuring the task content of different types of jobs: (1) self-reported, aggregating the answers of individual workers to surveys on skills and working conditions (e.g., EWCS, PIAAC, and PDII), and (2) direct measures, drawing from occupational databases based on the assessment of experts (e.g., O*Net).[5] Before proceeding with the description of each database, we first provide a more detailed description of each kind of source.

Workers' survey data

The data contained in these sources are measured at the level of individual workers and contain their replies to questions about their tasks at work. In this work we use three different European/international sources: the European Working Condition Survey (EWCS), the Programme for the International Assessment of Adult Competencies (PIAAC), and the Princeton Data Improvement Initiative Survey (PDII).[6] The first two surveys are at the European level, and the latter is conducted in the US. None of these sources are aimed at measuring task content, but they still contain variables that are strongly related to some of our categories of tasks and therefore can be used as proxies. Information on self-reported measures is obtained by asking workers the intensity of the tasks performed at work.

Using workers' survey data has advantages and disadvantages. On the one hand, they allow researchers to study the variability in task content within each occupation or job type. Workers in the same occupation could carry out different tasks; therefore, using a workers' survey, the extent of dispersion in the task content within occupations and the main drivers behind it can be analysed. On the other hand, self-reports are prone to

[5]The EWCS and PIAAC are at the European level. The NEPS is performed in Germany. The PDII and O*Net are from the US.

[6]Other workers' survey data are the "UK Skill Survey" for the UK, the "Qualification and Career Survey" for Germany, and the "German National Educational Panel Study" (NEPS) for Germany. We reject these three surveys as they are not conducted at the European level and therefore assume that the task composition is the same inside Europe.

introducing potential bias into the measurement. Respondents may have the tendency to overestimate and upgrade their positions at work.

Occupational databases

Occupational databases compile standardized assessments from occupational specialists on a range of variables measuring task content, skill requirements, job characteristics, and so on. Therefore, tasks are measured directly, providing a more objective measure. To the best of our knowledge, there is just one source in this category, and it is from the US: the Occupational Information Network data set (O*Net).[7] The only problem with using the O*Net is that the task content is for the US and it is just for one moment of time.

3.4.2 Occupational databases

European Working Condition Survey (EWCS)

The European Working Condition Survey (EWCS) is administered by the European Foundation for the Improvement of Living and Working Conditions (Eurofound) and has become an established source of information about working conditions and the quality of work and employment. With six waves (one every five years) having been implemented since 1990, it enables the monitoring of long-term trends in working conditions in Europe. During each wave information on employment status, working time arrangements, work organization, learning and training, and work-life balance, among others, is collected. In this research we focus on the last three waves (2005-2015). The five repeated cross-sections cover altogether 180,000 individuals (men and women), respectively 12,819 in

[7]The Dictionary of Occupational Titles (DOT) is the O*Net's predecessor.

1990, 15,986 in 1995, 21,803 in 2000, 29,680 in 2005, 43,816 in 2010, and 43,850 in 2015. Sampling weights adjusted for responses are used through the analysis. We restrict the analysis to individuals aged from 16 to 65. We classify occupations according to the ISCO-88 nomenclature at the two-digit level.[8]

As already stated, we follow Autor and Dorn (2013) as closely as possible to derive our task intensity measures at the occupational level (see Table 3.1 for more information about comparable items among surveys).[9] For the abstract tasks, we retain responses on "learning new things", "solving unforeseen problems", and "assessing yourself the quality of your job".[10] For the manual tasks, we select questions on "physical strength" (e.g., carrying or moving heavy loads), "skill or accuracy in using fingers/hands" (e.g., repetitive hand or finger movements), and "physical stamina" (e.g., painful positions at work).[11] For the routine tasks, we opt for the routine activities performed within the respondents' job: "does your main job involve (1) dealing with people, (2) repetitive tasks, (3) dealing with customers?".[12] The items for manual and routine tasks are on a seven-point scale ranging from one ("all of the time") to seven ("never"). These variables on the Likert scale are then normalized to range from zero to one. After collapsing each index at the ISCO-88 two-digit level, weighting each observation for the country sampling weight, we merge the EWCS index with the EU-LFS. Therefore, the employment figures of each country are used for weighting the indices.

[8]One of the advantages of this survey is that, in 2010 and in 2015, occupations are at the ISCO-88 two-digit level and at the ISCO-08 two-digit level. Therefore, we do not need a crosswalk to convert occupations.

[9]Their definitions are widely discussed in the literature; see Biagi and Sebastian (2017) for a review.

[10]These three items are closed questions (1=yes, 2=no).

[11]The questions provide answers in intensity frequencies (1=all of the time, 2=almost all of the time, 3=around three-quarters of the time, 4=around half of the time, 5=around one-quarter of the time, 6=almost never, 7=never).

[12]The questions provide answers in intensity frequencies (1=all of the time, 2=almost all of the time, 3=around three-quarters of the time, 4=around half of the time, 5=around one-quarter of the time, 6=almost never, 7=never).

Programme for the International Assessment of Adult Competencies (PIAAC)

The Programme for the International Assessment of Adult Competencies (PIAAC) is a survey carried out by the OECD in 24 countries in 2012. The main aim of this survey is to provide an analysis of the level and distribution of the skills used in the workplace. The data sample contains 166,000 observations of adults aged between 16 and 65 years. The survey contains information about their personal background, education and training current work status, work history, and different types of activities performed in the workplace. Particularly, using data from the workers' responses on the activities conducted at work, we construct measurements of task intensities.

To measure the task framework at the two-digit occupational level,[13] we construct the three task measures from Autor and Dorn (2013): routine, manual, and abstract.[14]

We convert the occupational codes from the ISCO-08 into the ISCO-88 using the crosswalk made available by Ganzeboom.[15] This classification makes our results easily comparable with the other data sources. We exclude occupations for which the data appear to be unreliable: army (ISCO 1), legislators and senior officials (ISCO 11), and agricultural, fishery, and related labourers (ISCO 92). The respondents are asked how often certain tasks are performed at work on a five-point scale ranging from one ("never")

[13]Most of the countries display the occupation at the four-digit occupation level (Belgium, Cyprus, the Czech Republic, Denmark, Spain, France, Italy, the Netherlands, Norway, Poland, Slovakia, and the United Kingdom). However, there are four countries (Germany, Ireland, Portugal, and Sweden) with occupations at the two-digit level and three countries (Austria, Estonia, and Finland) at the one-digit level.

[14]Autor and Dorn's analysis follows Autor, Katz, and Kearney (2006), who collapse the five original task measures from Autor, Levy, and Murnane (2003) into three: abstract (which includes cognitive and interpersonal non-routine), routine (which includes manual and cognitive routine), and manual (non-routine manual) tasks.

[15]Available at: http://www.harryganzeboom.nl/isco08/qa-isco-08.htm

to five ("every day"). These variables on the Likert scale are then normalized to range from zero to one.

To implement the definitions of each particular task, we follow the existing literature as closely as possible by selecting the abilities from the PIAAC that resemble those available in the study by Autor and Dorn (2013) (see Table 3.1 for more information about comparable items among surveys). For the abstract tasks, we retain the following items: "read diagrams", "write reports", "prepare charts, graphs, or tables", "use simple algebra or formulas", "face complex problems", "persuading and influencing people", and "negotiating with people". For the manual tasks, we resort to responses on "skill or accuracy in using hands/fingers" (e.g., to assemble or repair) and "physical work" (e.g., to work on physical activities). Finally, for the routine tasks, we select four items regarding the frequency and repetitiveness of the job (change the sequence of tasks, change how you work, change the speed of work, and change the working hours) and three items regarding the lack of adaptation (learn work-related things from co-workers, learning by doing, and keeping up to date with new products/services).[16]

The task measures are collapsed at the ISCO-88 two-digit occupation for the pooled data set, weighting each observation for the country sampling weight. The final data set is then merged with the EU-LFS data by occupation. Finally, the abstract, manual, and routine indicators are derived as an average of the selected elements mentioned above.

[16]For the lack of flexibility, they could respond in intensity of frequencies ranging from "not at all" to "to a very high extent" (intermediate answers were "very little", "to some extent", and "to a high extent"). For the lack of adaptation, the answers were on a scale of time frequencies ranging from "never" to "every day" (intermediate answers were less than once a month, less than once a month but at least once, and at least once a week but not every day).

Table 3.1: A comparison of task measures among the PDII, the EWCS, and the PIAAC

Autor and Handel (2013) - PDII	EWCS	PIAAC
Abstract	Abstract	Abstract
1) The length of the longest document typically read as part of the job 2) The frequency of mathematical tasks involving high school or higher maths 3) The frequency of problem-solving tasks requiring at least 30 minutes to find a good solution	Does your main paid job involve: 1) Learning new things? 2) Solving unforeseen problems on your own? 3) Assessing yourself the quality of your own work?	1) Read diagrams, maps, or schematics 2) Write reports 3) Prepare charts, graphs, or tables 4) Use simple algebra or formulas 5) Use simple algebra or formulas 6) Persuading/influencing people 7) Persuading/influencing people
Routine	Routine	Routine
1)Complete absence of face-to-face interactions with: 1.1. Customers and clients 1.2. Suppliers or contractors 1.3. Students or trainees 2) The proportion of the working day spent performing short and repetitive task	1) (Not) dealing with people 2) Your pace of work depends on direct demands from people such as customers ? 3) Short repetitive tasks 3.1) 1 minute 3.2) 10 minute	1) Learn work-related things from co-workers 2) Learning by doing from tasks performed 3) Keeping up to date with new products 4) Change sequence of tasks 5) Change how do you work 6) Change speed of work 7) Change working hours
Manual	Manual	Manual
1) The proportion of the working day spent performing physical tasks, such as standing or operating machines or vehicles	1) Does your job involve ? 1.1. Tiring or painful positions? 1.2. Carrying or moving heavy loads? 1.3. Repetitive hand and/or finger movements?	1) Hand/finger skill accuracy 2) Physical work

Sources: Author's analysis from the references quoted in the table.

Princeton Data Improvement Initiative Survey (PDII)

The Princeton Data Improvement Initiative Survey collects data on the cognitive, interpersonal, and physical job tasks that workers perform in their jobs. The data are available on Alan Krueger's web page.[17] The PDII covers 2,500 workers. Sampling weights adjusted for the response rate are used throughout the analysis.[18] We restrict our analysis to individuals aged 18 to 65 (211 observations are dropped). We retain only those occupations that appear with at least 5 observations (168 observations are dropped). We also drop observations for which task information is missing (35 observations are dropped).

Differently from the US O*Net database, the original purpose of which was an administrative evaluation by Employment Services offices of the fit between workers and occupations, the PDII was conducted exclusively for research purposes.[19] Like the O*Net, the PDII displays occupations using the International Occupation Classification (SOC2000). Therefore, we convert the SOC2000 into the International Standard Classification of Occupations (ISCO-88) using a crosswalk made available by the CAMSIS project.[20]

To calculate the task measures, we follow the work by Autor and Dorn (2013) (see Table 3.1 for more information about comparable items among surveys). Four items are selected for abstract tasks: (1) the length of the longest document typically read as part of the job, (2) the frequency of mathematical tasks involving high school or higher maths, (3) the frequency of problem-solving tasks requiring at least 30 minutes to find a good solution, and (4) the proportion of the day spent managing or supervising other workers. These questions are on a five-point scale ranging from one ("at least once a week") to

[17]Available at: http://krueger.princeton.edu/pages/princeton-data-improvement-initiative-pdii
[18]See Felstead et al. (2007) for further details.
[19]The study was directed by the following researchers: Alan Krueger, Ed Freeland, and Bill Barron.
[20]Available at: http://www.cardiff.ac.uk/socsi/CAMSIS/occunits/us00toisco88v2.sps

five ("never").[21] These variables on the Likert scale are then normalized to range from zero to one. A single item is identified as a manual task: the proportion of the working day spent performing physical tasks, such as standing, operating machines or vehicles, or making or fixing things by hand. This question is on a four-point scale ranging from one ("almost all the time") to four ("almost none of the time").[22] These variables on the Likert scale are then normalized to range from zero to one. One item is selected for routine tasks: (1) the proportion of the working day spent performing short, repetitive tasks and complete absence of face-to-face interactions with: (a) customers or clients, (b) suppliers or contractors, and (c) students or trainees. This question is on a three-point scale ranging between one ("a lot"), two ("some"), and three ("none"). These variables on the Likert scale are then normalized to range from zero to one. In the last step, we merge the PDII measures and the EU-LFS using the ISCO-88 at the two-digit level, weighting each occupation for the occupation sampling weight of each country.

Occupational Information Network data set (O*Net)

The O*Net database is the primary project of the O*Net program promoted by the US Department of Labour. In the O*Net analysts at the Department of Labor assign scores to each task according to standardized guidelines to describe their importance within each occupation.[23] Therefore, the O*Net is a primary source of occupational information, providing data on the key attributes and characteristics of occupations. It replaces the Dictionary of Occupational Titles (DOT), which was used for earlier research, prominently by Autor et al. (2003) and Autor and Dorn (2013). O*Net data are collected

[21] The questions provide answers in intensity frequencies (1=once or more every week, 2=at least once a week, 3=at least once a month, 4=less than once a month, 5=never).

[22] The questions provide answers in intensity frequencies (1=almost all the time, 2=more than half of the time, 3=less than half of the time, 4=almost none of the time).

[23] We use version 11.0 of the survey, available at: http://www.onet.org

for 812 occupations based on the Standard Occupation Classification (SOC2000). The SOC2000 data are matched to the International Standard Classification of Occupations (ISCO-88) using a crosswalk made available by the CAMSIS project.[24] Like previous authors using the O*Net data set with European data, we do so under the assumption that the occupations examined in the US and in Europe are not particularly different with regard to the specified job contents. As already mentioned, Autor and Dorn (2013) base their task measures on the DOT —O*Net's previous version. We thus use the same task measures, which are: "arm-hand steadiness" and "manual dexterity" for the manual aspect; "GED maths" and "administration and management" for the abstract tasks; and "finger dexterity" and "customer and personal services" for the routine aspect. Finally, we merge the occupational task requirements from the O*Net at the ISCO-88 two-digit level with their corresponding ISCO-88 two-digit level at the European level, weighting each occupation for the occupation sampling weight.

3.4.3 European Union Labour Force Survey (EU-LFS)

The second source of data for this research is the European Labour Force Survey (EU-LFS), administered by Eurostat. It consists of the compilation and homogenization of national labour force surveys carried out by the European statistical authority. In this research we focus on the data from 2005 to 2014, a period during which we can find the required degree of detail in the information on workers' occupational status variable and there is no substantial methodological (e.g., a new occupational classification) change in the variables of interest.[25] It includes information on the labour market status of more

[24] Available at: http://www.cardiff.ac.uk/socsi/CAMSIS/occunits/us00toisco88v2.sps

[25] Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, and the United Kingdom have occupational information from 1995, Hungary and Sweden from 1996, the Czech Republic, Finland, Poland, and Romania from 1997, Lithuania, Latvia,

than 1.5 million individuals in the 28 European Union countries, Norway, Switzerland, Iceland, Turkey, and Macedonia. The last four countries, Malta, and Romania (with the variable occupation only available at the 1-digit level) are not included here. Specifically, this data source contains information on the personal and labour market characteristics of individuals, including occupation, coded through ISCO-88 (until 2010) and ISCO-88 (from 2011 to 2014) at the 3-digit level. As already mentioned, we convert occupation codes using the crosswalk made available by Ganzeboom.

3.5 Results

3.5.1 Comparing different databases: the EWCS, PIAAC, PDII, and O*Net

Although, as it often happens in economic analysis, the availability of data leaves very few degrees of freedom at the moment of choosing the type of items as well as the type of analysis, we consider it to be important to explore the extent to which using one or other data source can lead to different conclusions in terms of the quality of the task measures. To determine the level of consistency of the different indicators, we look at the results from the application of different data sources using the same definition (reviewed above —see Table 3.1) to the EWCS, PIAAC, PDII, and O*Net surveys.

In Table 3.2 we present the three task measures (abstract, routine, and manual) for the twenty-six EU countries in 2014. As already stated, the task measures are constructed using similar items.

and Slovakia from 1998, Cyprus from 1999, Estonia from 2000, and Croatia from 2002.

Table 3.2: Distribution of abstract, manual, and routine tasks based on the EWCS, PIAAC, PDII, and O*Net

		Abstract				Routine				Manual			
Country		EWCS	PIAAC	PDII	O*Net	EWCS	PIAAC	PDII	O*Net	EWCS	PIAAC	PDII	O*Net
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10	(11)	(12)
Austria	AT	80.22	34.56	42.54	40.49	45.39	46.11	53.62	39.20	28.68	60.21	58.73	29.94
Belgium	BE	80.04	34.72	42.11	41.08	44.77	46.40	53.44	38.18	29.40	57.89	56.57	28.42
Bulgaria	BG	63.59	30.90	40.04	37.29	45.05	47.99	53.75	42.07	32.72	66.47	63.39	30.91
Cyprus	CY	69.20	32.14	40.75	39.42	53.64	47.41	53.79	38.23	44.55	59.27	58.55	28.26
Czech Republic	CZ	70.80	34.02	41.41	39.77	45.76	47.41	53.78	40.96	25.53	62.52	61.71	31.81
Germany	DE	75.20	35.67	42.41	41.32	44.94	45.98	53.68	38.69	24.28	58.22	56.58	29.72
Denmark	DK	**89.65**	35.74	43.11	41.59	46.59	45.86	53.41	37.43	25.68	57.02	55.47	27.86
Estonia	EE	84.83	33.49	41.39	39.65	50.18	47.42	53.87	40.45	35.04	61.95	61.49	30.47
Spain	ES	79.79	32.11	40.68	39.09	52.15	47.90	53.79	39.07	39.02	61.62	61.10	29.99
Finland	FI	83.88	36.39	43.89	41.74	49.19	45.29	53.59	38.52	30.96	58.44	56.42	28.89
France	FR	80.52	33.74	41.43	40.06	47.62	46.81	53.79	38.70	38.95	59.66	58.48	29.41
Greece	GR	66.09	31.89	42.00	39.01	**61.15**	46.47	54.29	41.05	42.98	63.45	62.29	30.26
Hungary	HU	59.46	32.54	40.59	38.91	41.55	48.07	54.27	41.37	28.78	63.22	62.79	31.28
Ireland	IE	79.12	34.18	42.35	40.59	44.72	46.04	54.01	39.15	27.06	59.64	58.13	29.37
Italy	IT	70.21	32.71	40.66	39.19	48.12	47.62	53.80	39.68	27.24	61.37	60.61	30.33
Lithuania	LT	72.85	33.26	42.13	39.42	57.27	46.47	54.09	41.32	34.08	62.56	61.91	30.33
Luxembourg	LU	86.81	**40.21**	**45.72**	**44.06**	48.57	42.35	53.93	35.77	32.61	**49.09**	**45.93**	**24.00**
Latvia	LV	62.86	32.26	41.16	38.95	48.38	47.66	54.11	40.44	30.38	62.61	62.65	30.48
Netherlands	NL	85.92	35.93	42.91	41.65	41.58	45.27	53.65	37.28	26.17	56.13	54.43	27.61
Norway	NO	88.21	37.68	44.75	42.58	43.83	44.71	52.94	37.55	**23.69**	56.89	54.38	28.34
Poland	PL	77.11	32.11	41.76	38.40	45.79	46.26	54.12	**42.93**	30.73	66.37	61.23	30.46
Portugal	PT	74.52	30.57	40.46	38.91	52.84	47.73	53.97	40.14	33.33	64.10	61.97	30.48
Sweden	SE	88.75	37.02	43.99	42.03	41.48	45.13	53.17	37.49	33.49	56.96	54.82	28.24
Slovenia	SI	81.92	33.11	41.79	38.49	44.62	46.29	**54.51**	42.61	34.53	64.38	58.48	29.62
Slovakia	SK	65.41	31.91	39.72	38.33	44.47	**48.74**	53.87	41.21	31.06	64.78	64.84	32.23
United Kingdom	UK	82.94	35.67	42.61	41.57	44.31	45.61	53.72	37.28	29.23	56.57	55.08	27.90

Notes: Countries are arranged in alphabetical order. The cells highlighted are the highest value in the column; those in bold are the lowest value in the column. Columns (1) to (12) report normalized task measures in 2014, ranging [0,100].
Sources: Author's analysis from the EWCS (2015), PIAAC, O*Net, PDII, and EU-LFS (2014).

We first examine the abstract measure. Several remarks can be made when analysing the information provided by the four different databases (Table 3.2). First, the percentage of tasks varies considerably from one survey to another in abstract tasks. For example, in Denmark it ranges from 89.65 per cent using the EWCS, to 35.74 per cent with the PIAAC, 43.11 per cent with the PDII, and 41.59 per cent with the O*Net. Regarding the dispersion within each survey, it ranges from 20 per cent exploiting the EWCS (59.46 per cent being the lowest in Hungary and 89.65 per cent the highest in Denmark), 10 per cent using the PIAAC (30.57 per cent in Portugal and 40.21 per cent in Luxembourg), 6 per cent using the PDII (45 per cent in Slovakia and 39 per cent in Luxembourg), and 5 per cent with the O*Net (37 per cent being the lowest in Bulgaria and 44 per cent the highest in Luxembourg).

We then rank the countries from the highest to the lowest level of abstract tasks (Table 3.3). On the one hand, the Northern countries, Luxembourg, and the Netherlands always have the highest percentages, Luxembourg being pointed out twice as the country with the highest level among the European countries (in the PIAAC and O*Net). On the other hand, the Eastern countries and Mediterranean countries have the lowest percentages. While for the highest percentages the countries are almost the same among the four surveys (Denmark, Sweden, Norway, Finland, Luxembourg, and the Netherlands), there is much variety when analysing the lowest percentages (Slovakia and Bulgaria appear in four surveys, Hungary in three surveys, Portugal and Greece in two surveys, and finally Latvia, Poland, Italy, and Spain in one survey). Therefore, when evaluating and implementing new policy measures, we need to take care with the lowest percentages in abstract tasks. This is particularly the case of Spain and Italy; whereas they both rank in the middle of the distribution of countries using the EWCS and PDII, this is not the case when conducting the analysis with the PIAAC and O*Net.

In all cases the Eastern and Mediterranean countries seem to be the least equipped to deal with the challenges of digitalization, being the ones with the lowest percentages in abstract tasks. This probably suggests that the challenges of digitalization and technology for these countries might need very tailored and specific labour market policies to address this specific situation.

Table 3.3: The five countries with the highest and lowest abstract index

	EWCS	PIAAC	PDII	O*Net
Five countries	Hungary	Portugal	Slovakia	Bulgaria
with the	Latvia	Bulgaria	Bulgaria	Slovakia
lowest	Bulgaria	Greece	Portugal	Poland
abstract	Slovakia	Slovakia	Hungary	Slovenia
index	Greece	Spain	Italy	Hungary
Five countries	Denmark	Luxembourg	Luxembourg	Luxembourg
with the	Sweden	Norway	Norway	Norway
highest	Norway	Sweden	Sweden	Sweden
abstract	Luxembourg	Finland	Finland	Finland
index	Netherlands	Netherlands	Denmark	Netherlands

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, O*Net, and EU-LFS (2014).

Second, turning to routine tasks, the coefficient for routine tasks does not differ widely across the surveys (Table 3.2). In the case of Latvia, it ranges from 40.44 per cent to 54.11 per cent using the O*Net and PDII, respectively (48.38 and 47.66 are the intermediate levels using the EWCS and PIAAC).

The percentage of routine tasks varies from 41.48 per cent to 61.15 per cent, Sweden being the lowest in routine tasks and Greece being the highest using the EWCS, from 42.35 per cent (in Luxembourg) to 48.74 per cent (Slovakia) using the PIAAC, from 52.94 per cent (in Norway) to 54.51 per cent (in Slovenia) using the PDII, and from 35.77 per cent (again in Luxembourg) to 40.14 per cent (in Poland) using the O*Net. We confirm again that the differences between countries are quite remarkable using the EWCS (the dispersion range being 20 per cent), while there are narrow for the other three surveys (the PIAAC, O*Net, and EWCS).

Differently from the abstract index, we observe some differences when we compare the highest-scoring and the lowest-scoring countries among the surveys (Table 3.4). As we expected, the lowest routine index is among the Northern countries (Norway, Sweden, Finland, and Denmark) as well as Luxembourg and the United Kingdom. On the opposite side of the spectrum, we find Eastern countries (Slovakia, Hungary, Slovenia, Bulgaria, and Latvia) and three Mediterranean countries (Greece, Portugal, and Spain) with the highest level of the routine index.

Table 3.4: The five countries with the highest and lowest routine index

	EWCS	PIAAC	PDII	O*Net
Five countries	Sweden	Luxembourg	Norway	Luxembourg
with the	Hungary	Norway	Sweden	United Kingdom
lowest	Netherlands	Sweden	Denmark	Netherlands
routine	Norway	Netherlands	Belgium	Denmark
index	United Kingdom	Finland	Finland	Sweden
Five countries	Greece	Slovakia	Slovenia	Poland
with the	Latvia	Hungary	Greece	Slovenia
highest	Cyprus	Bulgaria	Hungary	Bulgaria
routine	Portugal	Spain	Poland	Hungary
index	Spain	Portugal	Latvia	Latvia

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, O*Net, and EU-LFS (2014).

One surprising case is Hungary: using the EWCS it ranks as the country with the second-lowest routine index (only Sweden performs better), while under the PIAAC, O*Net, and PDII it is among the five countries with the highest routine index. More analysis must be performed to reach any conclusion.

This index is particularly interesting, since technological change is biased towards replacing labour in routine tasks. Therefore, Eastern and Mediterranean countries will have to face the challenges of adapting to the changes in the digital economy in any case. A very important question in this case would be how to develop ways of allowing the workers without the required skills to benefit from these new niches and minimize the losses and risks. In this respect well-designed active labour market policies are called to have a central role. This is not a trivial issue, as the international evidence on active labour market policies suggests that in many cases some of these interventions (particularly in developed countries) have had, at best, only small positive effects on the labour market outcomes of workers. In this context it is possible that a close partnership with firms and forcing the technological change might be essential.

Finally, concerning manual tasks, the coefficients vary across different surveys (Table 3.2). According to the EWCS, the manual index varies from 23.69 per cent to 44.55 per cent, Norway being the country with the lowest and Cyprus the country with the highest manual index percentage. Using the PIAAC source, it is remarkable that the range of estimation is 49-66 per cent, Luxembourg being the lowest and Bulgaria the highest manual index. While the PDII reveals figures that are not very different from the previous ones of 45-64 per cent (Luxembourg and Slovakia), the percentages of the O*Net are very low in this survey: 24-29 per cent (for Luxembourg and Slovenia, respectively).

Turning now to Table 3.5, we find the same pattern as for abstract and routine: Northern countries, Luxembourg, and the Netherlands among those with the lowest levels of the manual index, while Eastern and Mediterranean countries are among the ones with the highest levels. Particularly relevant is the Luxembourgish case: in three cases out of four, it scores the lowest level of manual tasks among the twenty-five European countries.

As in the routine index, there is an odd case: the Czech Republic. According to the

EWCS, it is the country with the third-lowest routine tasks (only exceeded by Norway and Germany), while measuring it with the O*Net it is the country with the fourth-highest routine tasks (preceded by Hungary, Bulgaria, and Latvia).

Table 3.5: The five countries with the highest and lowest manual index

	EWCS	PIAAC	PDII	O*Net
Five countries	Norway	Luxembourg	Luxembourg	Luxembourg
with the	Germany	Netherlands	Norway	Netherlands
lowest	Czech Republic	United Kingdom	Netherlands	Denmark
manual	Denmark	Norway	Sweden	United Kingdom
index	Netherlands	Sweden	United Kingdom	Sweden
Five countries	Cyprus	Bulgaria	Slovakia	Slovakia
with the	Greece	Poland	Bulgaria	Czech Republic
highest	Spain	Slovakia	Hungary	Hungary
manual	France	Slovenia	Latvia	Bulgaria
index	Estonia	Portugal	Greece	Latvia

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, O*Net, and EU-LFS (2014).

Table 3.6, Table 3.7, and Table 3.8 show the correlation among the three task indices at the individual level under the different survey alternatives. Some remarks can be made from the information provided below: first, the results obtained for the abstract indices are quite similar, and the pairwise correlation between the indices is tight, PIAAC-O*Net being the one with the highest correlation (0.963) and EWCS-PDII the one with the lowest correlation (0.691).

Table 3.6: Correlation of the abstract index based on the different surveys at the country level (2014)

	EWCS	PIAAC	PDII	O*Net
EWCS	1			
PIAAC	0.723	1		
PDII	0.691	0.827	1	
O*Net	0.743	0.963	0.818	1

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, and O*Net.

Turning now to the routine index, it becomes clear that the pairwise correlation between the EWCS and any other source is very low (0.149, 0.362, and 0.174, respectively, with the PIAAC, PDII, and O*Net), whereas the correlation using the other three surveys is a little higher but still far from being ideal. More precisely, the PDII and O*Net have the highest correlation (0.662), followed by the PIAAC and O*Net (0.654) and by the PIAAC and PDII (0.537).

Table 3.7: Correlation of the routine index based on the different surveys at the country level (2014)

	EWCS	PIAAC	PDII	O*Net
EWCS	1			
PIAAC	0.149	1		
PDII	0.362	0.537	1	
O*Net	0.174	0.642	0.662	1

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, and O*Net.

Regarding the correlation of manual tasks among the four different surveys, we can conclude that, while the pairwise correlations among the PIAAC, the PDII, and the O*Net are almost perfect and very close to one, this is not the case between the EWCS and the previous three data surveys.

Table 3.8: Correlation of the manual index based on the different surveys at the country level (2014)

	EWCS	PIAAC	PDII	O*Net
EWCS	1			
PIAAC	0.217	1		
PDII	0.226	0.937	1	
O*Net	0.175	0.903	0.952	1

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, and O*Net.

The implications of these wild differences among the three indices using different data surveys in the countries of the sample would be less important if one survey was clearly superior to the others when addressing the task approach. Unfortunately this does not seem to be the case. As far as we know, which of these measures is superior for the measurement of the task approach is not a long-debated issue in the literature. Nevertheless, the answer is far from clear, as all the definitions and surveys have their drawbacks and limitations.

As explained before, following Autor and Dorn (2013), we now combine these measures to create a summary measure of routine task intensity (RTI) by country, calculated as:

$$RTI_{c,2015} = \ln T^{R}_{c,2015} - \ln T^{A}_{c,2015} - \ln T^{M}_{c,2015} = \ln \frac{T^{R}_{c,2015}}{T^{A}_{c,2015} T^{M}_{c,2015}} \tag{3.2}$$

where $\ln T^{R}_{c,2015}$, $\ln T^{A}_{c,2015}$, and $\ln T^{M}_{c,2015}$ are the routine, abstract, and manual inputs in each country c in 2015. This measure rises with the importance of routine tasks in each country and declines with the importance of abstract and manual tasks.In the last step, we standardize our indices with a mean of 0 and a standard deviation of 1.

Table 3.9 shows the distribution of the RTI based on the EWCS, PIAAC, and O*Net. As we expected, Northern countries and Luxembourg obtain the lowest values, while the Eastern and Mediterranean countries obtain the highest RTI values. The percentage of the routine task index varies from -1.71 to 2.53, Norway being the highest in the RTI and Greece being the lowest using the EWCS, from -3.03 (in Luxembourg) to 1.44 (Bulgaria) using the PIAAC, from -3.11 (in Luxembourg) to 1.52 (in Slovakia) using the PDII, and from 2.89 (again in Luxembourg) to 1.35 (in Bulgaria) using the O*Net. Particularly relevant is the Luxembourgish case: in 3 out of 4 surveys (PIAAC, PDII, and O*Net), it obtains the lowest RTI index.

Analysing Table 3.10, we find the same pattern as before: the Northern countries, Luxembourg, and the Netherlands are among the ones with the lowest levels of RTI, while Eastern and Mediterranean countries are among the ones with the highest levels. On this occasion the results are very similar to those reported earlier. Among the lowest levels of the RTI, two countries (Norway and Netherlands) are in four surveys and Denmark and Luxembourg are in three surveys. On the other side of the spectrum, particularly relevant are the Bulgarian, Slovak, and Portuguese cases: in three out of four surveys, they score the highest level of manual tasks among the twenty-six European countries.

Table 3.9: Distribution of the RTI based on the EWCS, PIAAC, PDII, and O*Net

Country		EWCS	PIAAC	PDII	O*Net
		(1)	(2)	(3)	(4)
Austria	AT	-0.59	-0.18	-0.10	0.01
Belgium	BE	-0.55	-0.42	-0.49	-0.67
Bulgaria	BG	0.65	1.44	1.02	1.35
Cyprus	CY	2.04	0.37	0.11	-0.40
Czech Republic	CZ	-0.53	0.35	0.77	0.90
Germany	DE	-0.98	-0.62	-0.41	-0.29
Denmark	DK	-1.27	-0.78	-0.84	-1.05
Estonia	EE	0.21	0.39	0.69	0.52
Spain	ES	0.98	0.69	0.63	0.25
Finland	FI	-0.20	-0.82	-0.71	-0.60
France	FR	0.63	0.01	0.03	-0.14
Greece	GR	2.53	0.73	0.58	0.69
Hungary	HU	0.15	0.79	1.15	1.01
Ireland	IE	-0.80	-0.18	-0.14	-0.16
Italy	IT	-0.11	0.51	0.57	0.43
Lithuania	LT	1.15	0.37	0.60	0.68
Luxembourg	LU	-0.19	**-3.03**	**-3.11**	**-2.89**
Latvia	LV	0.68	0.73	0.89	0.65
Netherlands	NL	-1.41	-1.00	-0.98	-1.15
Norway	NO	**-1.71**	-1.30	-1.38	-1.07
Poland	PL	-0.19	0.95	0.48	1.18
Portugal	PT	0.72	1.25	0.86	0.60
Sweden	SE	-0.72	-1.12	-1.13	-1.02
Slovenia	SI	-0.08	0.56	0.15	0.91
Slovakia	SK	0.31	1.17	1.52	1.31
United Kingdom	UK	-0.71	-0.86	-0.75	-1.06

Notes: Countries are arranged in alphabetical order. The cells highlighted are the highest value in the column; those in bold are the lowest value in the column. Columns (1) to (12) report the normalized task measures in 2014.
Sources: Author's analysis from the EWCS (2015), PIAAC, O*Net, PDII, and EU-LFS (2014).

Table 3.10: The five countries with the highest and lowest RTI index

	EWCS	PIAAC	PDII	O*Net
Five countries	Norway	Luxembourg	Luxembourg	Luxembourg
with the	Ncetherlands	Norway	Norway	Netherlands
lowest	Denmark	Sweden	Sweden	Norway
RTI	Germany	Netherlands	Netherlands	United Kingdom
index	Ireland	United Kingdom	Denmark	Denmark
Five countries	Greece	Bulgaria	Slovakia	Bulgaria
with the	Cyprus	Portugal	Bulgaria	Slovakia
highestt	Latvia	Slovakia	Hungary	Poland
RTI	Spain	Poland	Portugal	Hungary
index	Portugal	Hungary	Latvia	Slovenia

Sources: Author's analysis from the EWCS (2015), PIAAC, PDII, and O*Net.

3.5.2 Comparing different definitions of RTI

So far we have investigated whether the same definition of the task approach using four different surveys outlines similar results. We now change the objective, and we analyse whether two different definitions of the same construct (in this case the RTI) using the same source (in this case the PIAAC) produce different results. To do so we perform the analysis first using Marcolin et al.'s (2016) definitions and then we compare it with Biagi and Sebastian's (2017) definitions.

Different from our definition, Marcolin et al. (2016) build on information about the extent to which workers can modify the sequence of their tasks and decide the type of tasks to be performed on the job. This captures the degree of codifiability of such tasks.

Table 3.11 shows the RTI values using the two different definitions. The percentage of the RTI varies from -2.96 to 0.99, Luxembourg being the lowest and Spain being the highest using Marcolin's et al. (2016) definition, while Biagi and Sebastian's (2017) definition reveals figures that are not particularly different from the previous ones, the

RTI varying from -3.03 to 0.73 for Luxembourg and Greece, respectively. The correlation between the two measures is very high (0.87), suggesting that the two definitions are very close.

Table 3.11: Distribution of the RTI based on the EWCS, PIAAC, PDII, and O*Net

Country		Marcolin et al. (2016)	Biagi and Sebastian (2017)
		(1)	(2)
Austria	AT	-0.45	-0.18
Belgium	BE	-0.39	-0.42
Bulgaria	BG	1.55	1.44
Cyprus	CY	0.32	0.37
Czech Republic	CZ	0.72	0.35
Germany	DE	-0.39	-0.62
Denmark	DK	-0.45	-0.78
Estonia	EE	0.74	0.39
Spain	ES	0.99	0.69
Finland	FI	-0.85	-0.82
France	FR	-0.02	0.01
Greece	GR	-0.40	0.73
Hungary	HU	1.14	0.79
Ireland	IE	-0.21	-0.18
Italy	IT	0.50	0.51
Lithuania	LT	-0.12	0.37
Luxembourg	LU	**-2.96**	**-3.03**
Latvia	LV	1.09	0.73
Netherlands	NL	-0.79	-1.00
Norway	NO	-1.47	-1.30
Poland	PL	0.23	0.95
Portugal	PT	0.71	1.25
Sweden	SE	-1.09	-1.12
Slovenia	SI	0.39	0.56
Slovakia	SK	1.57	1.17
United Kingdom	UK	-0.35	-0.86

Notes: Countries are arranged in alphabetical order. The cells highlighted are the highest value in the column; those in bold are the lowest value in the column. Columns (1) to (12) report the normalized task measures in 2014.
Sources: Author's analysis from the PIAAC and EU-LFS (2014).

Table 3.12 presents the five countries with the lowest and highest RTI index for each definition. We can see that the two definitions are very close when we look at the lowest and highest RTI values. First, considering the lowest values, four countries out of five are in both definitions: Luxembourg, Sweden, Norway, and the Netherlands. Turning now to the highest RTI values, three out of five are in both definitions: Slovakia, Hungary, and Bulgaria.

Table 3.12: The five countries with the highest and lowest RTI index

	Marcolin et al. (2016)	Biagi and Sebastian (2017)
Five countries	Luxembourg	Luxembourg
with the	Norway	Norway
lowest	Sweden	Sweden
RTI	Finland	Netherlands
index	Netherlands	United Kingdom
Five countries	Spain	Bulgaria
with the	Latvia	Portugal
highest	Hungary	Slovakia
RTI	Bulgaria	Poland
index	Slovakia	Hungary

Sources: Author's analysis from the PIAAC and EU-LFS (2014).

3.5.3 Evolution of the task framework in the European Union: 2005-2015

As mentioned above, for good or bad, the decision regarding the type of indicator to use when estimating the task framework for a group of countries over time is often taken in accordance with the availability of data. That is the case when measuring the task framework in the long run for a large number of EU countries. For a given year and a large group of countries, as we have seen in the previous section, there is a rich source to address the task framework homogeneously from different angles (PIAAC). However, if we want to study the size and evolution of the task framework in the EU during a relatively long period of time (2005-2015 in our case), we find ourselves limited to the use of the EWCS, which allows the estimation of the task framework at three moments of time (2005, 2010, and 2015) in twenty-five European countries. We exclude Norway from our analysis, because the 2005 EWCS does not have weight information on this country.

As explained before, changes in the task structure rely on changes within occupations (i.e., the intensive margin) and between occupations (i.e., the extensive margin). One positive characteristic of the EWCS is that it allows us to decompose the changes in the three indicators (abstract, manual, and routine) into changes in the intensive and extensive margins.

For the analysis we decompose the changes in the three indicators using the following equation:

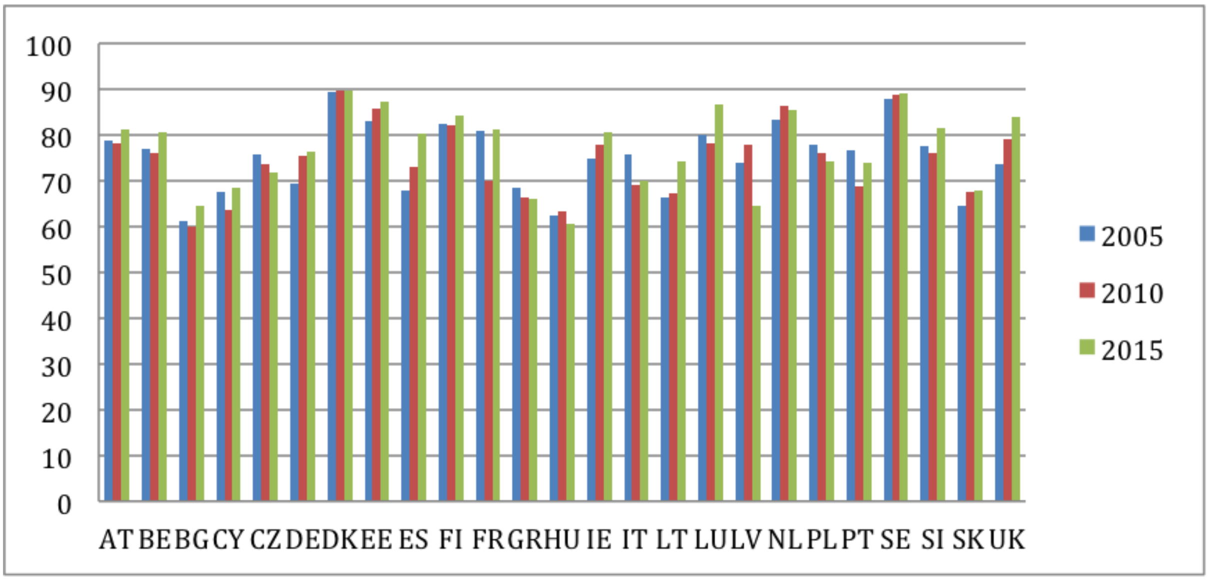
$$\Delta \mathrm{T}_k = \sum_j \Delta \mathrm{E}_j \gamma_{jk} + \sum_j \Delta \gamma_{jk} \mathrm{E}_j \tag{3.3}$$

where $\Delta \mathrm{T}_k$ is the change in the importance of task k between 2005 and 2015; $\Delta \mathrm{E}_j$ is the change in the employment share in the national employment of occupation j, and γ_{jk} represents the average share of task k in occupation j. Finally, $\Delta \gamma_{jk}$ is the change in the share of task k in occupations, and E_j is the average share of occupation j. The first term on the RHS of the equation is the extensive margin; that is, the task importance is held constant (and represents the average task importance over the two years) and time variation relies on changes across occupations. The second term is the intensive margin, for which occupational employment is held constant while the importance of tasks within occupations is allowed to vary over time.

Table 3.13, Table 3.14, and Table 3.15 decompose the changes in the importance of the three tasks groups into changes at the intensive and the extensive margin. The first three columns of the tables present the importance of each particular task in 2005 and 2015 and the change between 2005 and 2015. In addition, the last two columns show the decomposition of these changes into changes at the intensive and the extensive margin.

Figure 3.1 reproduces the abstract index for the twenty-five European countries in 2005, 2010, and 2015. Two points stand out from the analysis of the figure. First, the Northern countries (Denmark, Sweden, and Finland) and Luxembourg had the highest level of abstract index in 2005 and this remained so in 2015. At the same time, Hungary, Latvia, Bulgaria, Slovakia, and Greece had the lowest level of routine in 2005 and this continued in 2015. Second, while the UK and Luxembourg showed a large increase from 2005 to 2015, Greece and Hungary experienced a small setback. This has enormous implications: the countries with a lower abstract index are not becoming closer to the leaders but moving further away from them. The only exception is Spain: whereas in 2005 it was among the countries with a lower abstract index, it achieved an enormous increase, performing among the best countries in 2015.

Figure 3.1: Evolution of the abstract index in 25 European countries using the EWCS



Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

In Table 3.13 we present the decomposition of abstract changes into changes at the intensive (within occupations) or the extensive margin (between occupations). In other words we analyse whether the change in abstract tasks is due to changes within occupations (different occupations change their task composition) or changes between occupations (the same occupation changes its task composition). There are some important facts. First, the increasing importance of the abstract tasks is normally due to changes at the intensive margin,[26] with the exception of Austria, Denmark, France, Finland, and Sweden, for which it occurs at the extensive margin. In the latter countries, their abstract index is increasing in occupations that did not previously require abstract tasks. In the case of France it is due to a mixed effect: a decrease at the intensive level and an increase at the extensive level, the latter being higher than the former. In France occupations with a high level of abstract tasks are now demanding other types of tasks (a decrease at the intensive level), while occupations with a lower level of abstract tasks are now demanding them (an increase at the extensive level). Second, the decreasing importance of the abstract tasks in the Czech Republic, Greece, Hungary, Italy, Latvia, Poland, and Portugal is at the intensive level (within occupations) with no exception. Occupations that were previously demanding abstract tasks no longer require them. Therefore, we can conclude that, while the Nordic countries are increasing their abstract tasks due to changes in occupations that did not require abstract tasks earlier (changes at the extensive margin), in the rest of Europe it is due to changes that were already demanding abstract tasks (changes at the intensive margin).

[26]Belgium, Bulgaria, Germany, Estonia, Spain, Ireland, Lithuania, Luxembourg, the Netherlands, Slovenia, Slovakia and the United Kingdom.

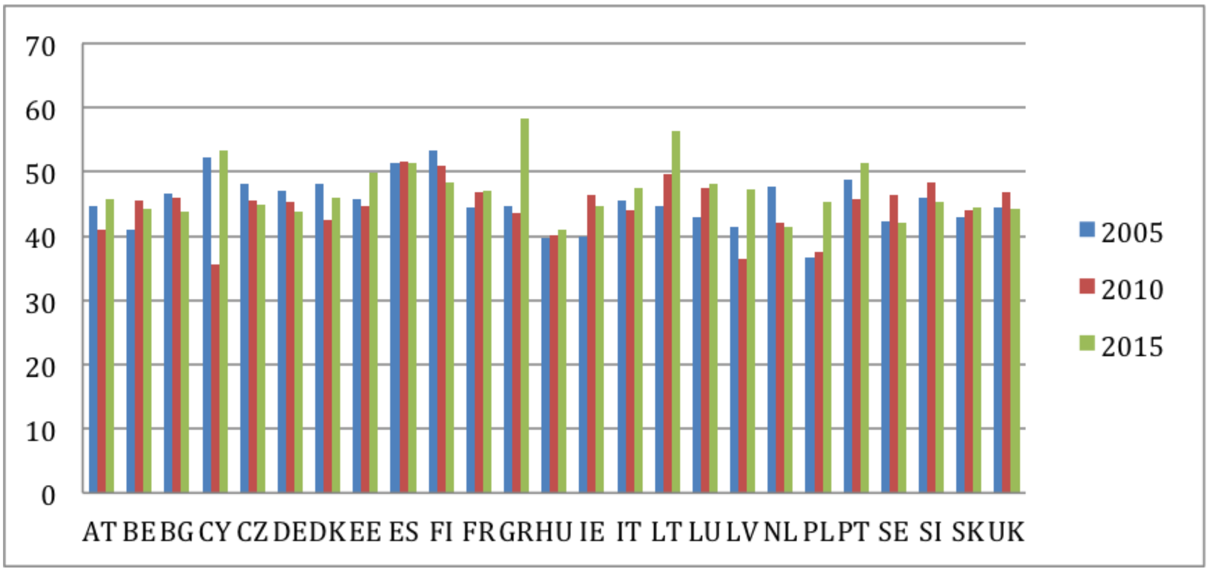
Table 3.13: Abstract task shifts, extensive and intensive margins

Country		Importance in 2005	Importance in 2015	Change 2015-2005	Extensive margin	Intensive margin
		(1)	(2)	(3)	(4)	(5)
Austria	AT	78.68	81.30	2.62	2.02	0.60
Belgium	BE	77.04	80.65	3.61	0.41	3.20
Bulgaria	BG	61.11	64.59	3.48	1.05	2.43
Cyprus	CY	67.49	68.62	1.13	1.05	0.08
Czech Republic	CZ	75.89	71.83	-4.06	1.18	-5.24
Germany	DE	69.36	76.38	7.02	1.12	5.90
Denmark	DK	89.35	89.81	0.46	0.46	0.00
Estonia	EE	83.13	87.29	4.16	1.36	2.80
Spain	ES	67.85	80.31	12.46	1.20	11.26
Finland	FI	82.51	84.32	1.81	0.96	0.85
France	FR	80.99	81.34	0.35	0.76	-0.41
Greece	GR	68.46	66.05	-2.41	0.81	-3.22
Hungary	HU	62.50	60.46	-2.04	0.58	-2.62
Ireland	IE	75.00	80.66	5.66	1.69	3.97
Italy	IT	75.80	70.11	-5.69	0.50	-6.19
Lithuania	LT	66.32	74.33	8.01	1.89	6.12
Luxembourg	LU	79.91	86.78	6.87	1.90	4.97
Latvia	LV	73.92	64.52	-9.40	1.69	-11.09
Netherlands	NL	83.30	85.49	2.19	0.90	1.29
Poland	PL	77.76	74.26	-3.50	0.85	-4.35
Portugal	PT	76.57	73.86	-2.71	1.40	-4.11
Sweden	SE	87.79	89.11	1.32	0.96	0.36
Slovenia	SI	77.53	81.56	4.03	0.78	3.25
Slovakia	SK	64.65	67.95	3.30	0.86	2.44
United Kingdom	UK	73.67	84.04	10.37	2.06	8.31

Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

In Figure 3.2 we reproduce the routine index for 25 countries from 2005 to 2015, and it shows that there is considerable variation across countries. While the Northern countries and Hungary show a decrease in the routine index between 2005 and 2010, there is an increase for the rest of the European countries. Particularly, the highest positive changes in the routine index are achieved by the Netherlands (6.27 per cent) and Finland (5.06 per cent), while the highest negative changes are reported for Greece (-13.70 per cent) and Lithuania (-11.65 per cent).

Figure 3.2: Evolution of the routine index in 25 European countries using the EWCS



Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

Turning now to Table 3.14, we analyse the decomposition of routine changes into changes at the intensive (within occupation) or at the extensive (between occupation) margin. There are two important remarks to be made here: first, different from the abstract tasks, all the changes (positives and negatives) are explained by the intensive margin (within occupations), meaning that routine occupations were increasing/decreasing their routine in 2015. Therefore, when we observe an increase/decrease in routine tasks, it is because routine occupations are increasing/decreasing their routine tasks. Second, in all the European countries, the extensive margin is negative. Therefore, non-routine occupations are decreasing their routine over time.

Table 3.14: Routine task shifts, extensive and intensive margins

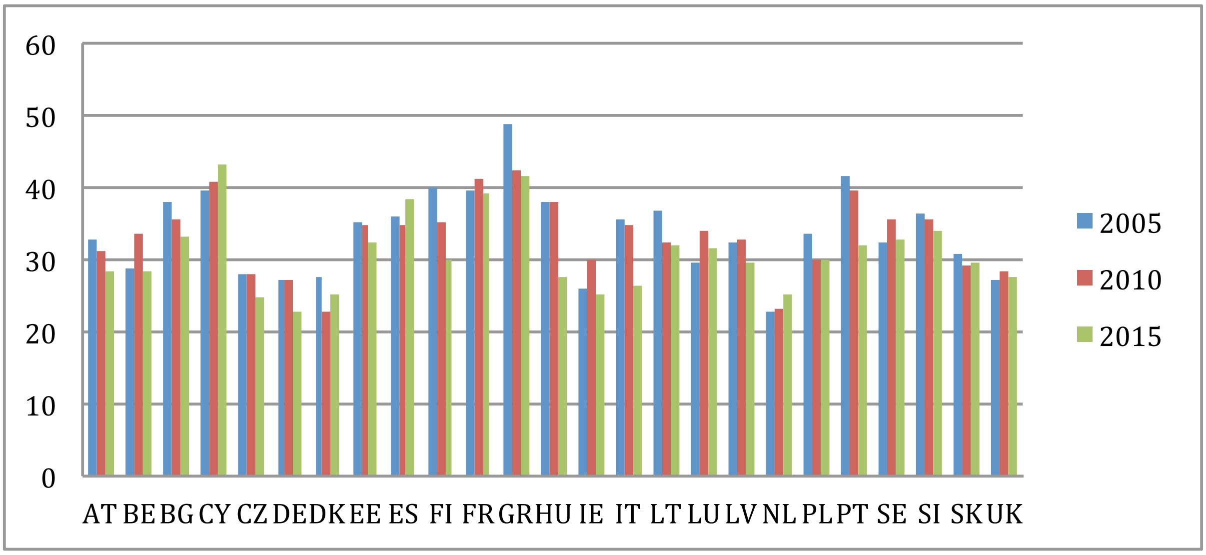
Country		Importance in 2005	Importance in 2015	Change 2015-2005	Extensive margin	Intensive margin
		(1)	(2)	(3)	(4)	(5)
Austria	AT	44.78	45.83	1.05	-0.47	1.52
Belgium	BE	40.93	44.22	3.29	-0.20	3.49
Bulgaria	BG	46.57	43.87	-2.70	-1.35	-1.35
Cyprus	CY	52.20	53.35	1.15	-0.77	1.92
Czech Republic	CZ	48.12	44.96	-3.16	-0.13	-3.03
Germany	DE	47.06	43.83	-3.23	-0.41	-2.82
Denmark	DK	48.19	46.02	-2.17	-0.95	-1.22
Estonia	EE	45.84	49.88	4.04	-0.10	4.14
Spain	ES	51.38	51.38	0.00	-1.37	1.37
Finland	FI	53.40	48.34	-5.06	-0.40	-4.66
France	FR	44.47	47.06	2.59	-0.62	3.21
Greece	GR	44.59	58.29	13.70	-1.01	14.71
Hungary	HU	39.72	41.02	1.30	-0.37	1.67
Ireland	IE	39.83	44.60	4.77	-0.64	5.41
Italy	IT	45.53	47.43	1.91	-0.35	2.26
Lithuania	LT	44.75	56.38	11.63	-1.47	13.10
Luxembourg	LU	42.87	48.06	5.19	-1.00	6.19
Latvia	LV	41.42	47.28	5.86	-0.97	6.83
Netherlands	NL	47.73	41.46	-6.27	-0.37	-5.90
Poland	PL	36.69	45.31	8.62	-0.42	9.04
Portugal	PT	48.87	51.44	2.57	-1.79	4.36
Sweden	SE	42.33	42.08	-0.25	-0.34	0.09
Slovenia	SI	45.99	45.24	-0.75	-0.38	-0.37
Slovakia	SK	42.98	44.49	1.51	-0.30	1.81
United Kingdom	UK	44.37	44.27	-0.10	-0.91	0.81

Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

Finally, in Figure 3.3 we show the evolution of the manual tasks in the 25 European countries from 2005 to 2015. On the one hand, the Netherlands (22.65 per cent) and

Germany (27.08 per cent) had the lowest level of manual tasks in 2005. However, they followed different trajectories: whereas the German level of manual tasks decreased almost by 5 points in 2015 (now being the country with the lowest level of manual task), the Dutch level of manual tasks increased by almost 3 points (no longer ranking among the first countries with the lowest level of manual tasks). On the other hand, Greece and Portugal had the highest levels of manual tasks in 2005 (48.51 per cent and 41.74 per cent, respectively) and this remained the case in 2015; however, both countries decreased their manual tasks by 7 and 10 points, respectively. On average countries are converging in manual tasks (the differences among countries are decreasing).

Figure 3.3: Evolution of the manual index in 25 European countries using the EWCS



Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

Table 3.15: Manual task shifts, extensive and intensive margins

Country		Importance in 2005	Importance in 2015	Change 2015-2005	Extensive margin	Intensive margin
		(1)	(2)	(3)	(4)	(5)
Austria	AT	32.86	28.38	-4.48	-0.92	-3.56
Belgium	BE	28.67	28.47	-0.20	-0.20	-0.00
Bulgaria	BG	38.19	33.18	-5.01	-2.30	-2.71
Cyprus	CY	39.69	43.39	3.70	-2.35	6.05
Czech Republic	CZ	27.92	24.61	-3.31	-1.11	-2.20
Germany	DE	27.08	22.76	-4.32	-1.13	-3.19
Denmark	DK	27.60	25.35	-2.25	-1.05	-1.20
Estonia	EE	35.09	32.28	-2.81	-1.39	-1.42
Spain	ES	35.98	38.39	2.41	-2.86	5.27
Finland	FI	39.83	30.06	-9.77	-1.58	-8.19
France	FR	39.46	39.11	-0.35	-1.25	0.90
Greece	GR	48.91	41.67	-7.24	-1.86	-5.38
Hungary	HU	38.19	27.74	-10.45	-0.79	-9.66
Ireland	IE	26.07	25.17	-0.90	-1.32	0.42
Italy	IT	35.77	26.44	-9.33	-1.15	-8.18
Lithuania	LT	36.69	32.07	-4.62	-2.73	-1.89
Luxembourg	LU	29.51	31.56	2.05	-3.05	5.10
Latvia	LV	32.55	29.59	-2.96	-1.49	-1.47
Netherlands	NL	22.65	25.17	2.52	-0.54	3.06
Poland	PL	33.40	30.13	-3.27	-1.59	-1.68
Portugal	PT	41.74	31.82	-9.92	-1.97	-7.95
Sweden	SE	32.48	32.66	0.18	-1.45	1.63
Slovenia	SI	36.34	34.18	-2.16	-1.33	-0.83
Slovakia	SK	30.69	29.51	-1.18	-0.88	-0.30
United Kingdom	UK	27.15	27.70	0.55	-0.98	1.53

Notes: The indices are computed at the two-digit occupation level in 2005, 2010, and 2015 using the EWCS for each country. Then they are merged with the EU-LFS in 2005, 2010, and 2014 (2015 is still not available) for each country.
Sources: Author's analysis from the EU-LFS (2005, 2010, 2014) and EWCS (2005, 2010, 2015).

In terms of the changes at the extensive and intensive margins, there are some patterns to summarize (Table 3.15). First, in all the countries, the extensive margin is negative; therefore, non-manual occupations are now demanding fewer manual tasks. Second, in general European countries have decreased their manual tasks, and this occurs at the intensive margin (having a negative effect within occupations) and at the extensive margin (having a negative effect between occupations); therefore, it is mainly explained by a decrease in manual tasks in manual task occupations and at the same time a decrease in manual tasks in non-manual task occupations, the intensive margin being more important than the extensive margin. Second, there is one exception to the previous scenario: countries with a positive change in manual tasks at the intensive margin: Cyprus, Spain, Luxembourg, the Netherlands, Sweden, and the United Kingdom. In this second scenario, the increase in manual tasks relies on a positive effect within occupations; therefore, manual task occupations are now demanding more manual tasks.

3.6 Conclusions

In this chapter we contribute to the measurement of task indices to be used for analysing and comparing the European countries, drawing on different international databases (the EWCS, PIAAC, PDII, and O*Net). First, we briefly review the existing databases and assess their differences by comparing the task content at the European level. On the one hand, the PIAAC, PDII, and O*Net are quite similar in the results that they show. On the other hand, the EWCS differs widely from the previous databases. One good example is the Hungarian case: using the EWCS, it ranks as the country with the second-lowest routine index (only Sweden performs better), while under the PIAAC, O*Net, and PDII it is among the five countries with the highest routine index. Overall, our results indicate that the Northern countries, Luxembourg, and the Netherlands show the lowest values in the RTI, while the Eastern (Bulgaria and Slovakia, in particular) and Mediterranean countries appear with the highest values in the RTI. This index is particularly interesting, since it provides a summary index that increases with the routine task importance and decreases with the non-routine manual and abstract task importance. Therefore, the Eastern and Mediterranean countries will have to deal with the challenges of new technology.

Second, having shown an analogous framework in terms of definitions, in the next step we select two different definitions of the routine task index and apply the same database (PIAAC). As we expected, the results are close enough and the two definitions give almost the same results. As previously stated, the Northern countries perform well in abstract tasks while the Eastern and Mediterranean countries perform well in manual and routine tasks.

Finally, we present the evolution of the task approach in the EU-25 between 2005 and 2015 using the EWCS and highlight whether the changes in the task content are due to the intensive margin (within occupations) or the extensive margin (between occupations). Our results show two different features: firstly, a sharp reduction in the importance of manual and routine tasks consistent with a gradual shift from manufacturing to services; secondly, abstract tasks increase their relevance throughout the period for almost every country. Generally the results are in line with the routinization hypothesis: routine tasks decrease over time, while abstract tasks become more important. Moreover, when we look at the extensive and intensive margins, there are two interesting conclusions that we would like to highlight. First, the extensive margin is positive in abstract tasks but negative in routine and manual tasks. This suggests that routine occupations are increasing their abstract tasks and decreasing their routine tasks. Second, changes in routine occupations are mainly explained by the intensive margin. Therefore, when we observe an increase/decrease in routine tasks, it is because routine occupations are increasing/decreasing their routine tasks and vice versa.

4. Explaining job polarisation in Spain from a task perspective

4.1 Introduction

Debate concerning the structural evolution of the division of labour and its impact on job quality has been a central theme in social sciences for the last 200 years. In the late 1990s, the idea has been that technology is skilled biased, favouring high-skilled workers and substituting low-skilled workers. While skill-biased technical change (SBTC) is a good explanation for the increase in the upper tail distribution of the labour force composition, it cannot explain a recent phenomenon: the decline in the share of middle occupations relative to low- and high-skilled occupations. This phenomenon has been defined as *job polarisation* (Goos and Manning, 2007; Wright and Dwyer, 2003).

The main drivers behind job polarisation are still subject to some debate, however, the main candidate is the routinization hypothesis (Autor et al. 2003, hereafter called ALM). Due to continuously cheaper computerisation, technology replaces human labour in routine task. This labour-capital substitution reduces the relative demand for workers performing routine occupations, while leading to an increase in the relative demand for workers performing non-routine tasks. Since routine workers are characterised for being in the middle of the employment distribution, this can explain the hollowing out effect.

The notion that middle-paid (skilled) jobs have been disproportionately destroyed and that the job distribution has hollowed out in the middle has been identified as a key aspect of contemporaneous rising labour market inequality (Acemoglu and Autor, 2011; Goos et al., 2009, 2014).[1] Therefore, understanding how the employment structure evolves is crucial for governments and policy makers. Firstly, they need to understand whether the occupational change can transform societies into one with a large middle-class or one where the middle-class is more divided. Secondly, they also need an accurate understanding on occupational employment in order to anticipate future skills needs and job opportunities.

Despite the importance of this topic, the results of research assessing the existence and degree job polarisation in Spain are mixed, where little has been done to understand the different results reported by researchers. For example, Anghel et al. (2014) conclude that the employment structure has been polarising between 1997 and 2012, while Oesch and Rodríguez Menés (2011) and Muñoz de Bustillo and Antón (2015) show a pattern of progressive upgrading for the same period (top-wage occupations expanding at the expenses of bottom-wage occupations). Moreover, two recent studies covering Spain, based on the European Labour Force Survey, diverge in their results. Goos et al. (2009, 2014) conclude that, on average, the employment structure in Spain has been polarising between 1993 and 2006. Using the same period of analysis, Fernández-Macías (2012) conversely shows an upgrading process and does not provide evidence of a pervasive polarisation.[2]

Focusing on the Spanish case, this chapter makes major contributions to understand-

[1] The terms *paid* and *skilled* are interchangeable in this essay.

[2] It must be noted that the methodology is not exactly the same.

ing the evolution of the employment and wage structure in four complementary ways. First, we shed some light to the literature on employment polarisation in Spain, providing evidence of job polarisation in our sample; between 1994 and 2008, the employment share in Spain increased at the two extremes of the job wage distribution, while it decreased for middle income earners. We also contribute to widen the literature on employment remuneration in line with employment trends. In the US, Autor and Dorn (2013) find a clear correspondence between employment and wages. However, the polarisation of wages does not seem to be common in Spain, as there is no evidence that changes in pay followed the same pattern as changes in occupations. This contrasts with standard labour markets models, predicting that a positive demand shock increases both employment and earnings.

Second, methodological progress is made with respect to previous studies on job polarisation in European countries. In this study we measure the task content of occupations from a European survey data (information on Spain is included), instead of relying on US sources like Anghel et al. (2014). Therefore, no assumption on task composition and the impact of technology between the two countries is needed. Moreover, the EWCS (European Working Condition Survey) allows for time dynamics to measure routine tasks.[3] Using this survey, jobs are classified as abstract, routine and manual tasks similar to the ALM model. This allows us to examine the association between employment changes and the task content of occupations. The evolution of the task's content is also analysed performing a shift-share analysis, exploring whether the changes of the task content of occupation are due to changes within occupations (intensive margin) or between occupa-

[3]The widely used O*Net task database from the US has information for only one point in time, and thus, is not suitable to analyse changes over time. The EWCS has three comparable waves (2000, 2005, and 2010) that allows us to analyse changes in the task content of occupations.

tions (extensive margin).

Third, the main hypothesis of the ALM model is tested: technology substitutes routine task while it complements non-routine task. In doing so, a pseudo-panel analysis finds a negative relationship between computers and routine tasks, and a positive association between computer and abstract tasks. Analysing manual tasks, there is a negative relationship between computer and manual tasks. Therefore, the ALM predictions are verified for routine and abstract tasks, but not for manual task.

Finally, the role of job polarisation within the reallocation of middle-skilled workers is analysed. To investigate this phenomenon, the main data source is integrated with an additional dataset, the Survey on Income and Living Conditions (SILC). Taking advantage of the new database, the analysis builds on questions on previous occupations. Two findings are made: in line with the ALM, middle-skilled workers become more mobile over time. However, contrary to the model's expectations, it is found that workers predominantly shift towards high-skilled occupations.

The chapter is organised as follows. Section 4.2 clarifies the main concepts and provides a review of the literature. Section 4.3 describes the data and methods used for analysis. In Section 4.4, the evidence on labour market polarisation, on both employment and pay rules, is presented. Section 4.5 investigates the task content of occupations. Section 4.6 looks at the impact of computer adoption on tasks. Section 4.7 analyses the occupational mobility of middle-paid workers. Finally, Section 4.8 summarizes the main conclusions of the chapter.

4.2 Literature review

Job polarisation refers to the relative job growth in the lower and upper tail of the wage distribution relative to the middle-wage ones. This well-known phenomenon has been found in the US (Autor and Dorn, 2013; Autor et al., 2006; Wright and Dwyer, 2003), the UK (Goos and Manning, 2007; Salvatori, 2015), Germany (Dustmann et al., 2009; Kampelmann and Rycx, 2011; Spitz-Oener, 2006), and Sweden (Adermon and Gustavsson, 2015). With respect to Europe, results are more controversial. On the one hand, Goos et al. (2009, 2014) show that on average the employment structure in Europe has been polarizing from 1993 to 2006. On the other hand, Fernández-Macías (2012) find heterogeneous results in Western European countries and conclude that there is not a clear and universal pattern of a pervasive polarisation.[4] As for Spain, conclusions also diverge between polarisation (Anghel et al., 2014) and occupational upgrading (Muñoz de Bustillo and Antón, 2015; Oesch and Rodríguez Menés, 2011).

While in the US wage polarisation has occurred hand with hand with job polarisation (Autor et al., 2006), papers based on European countries do not find the same result. Differently from job polarisation, wage polarisation refers to the relative wage growth in the lower and upper tail of the wage distribution relative to the middle-wage ones. Goos and Manning (2007) failed to find wage polarisation for the UK despite the strong evidence of job polarisation. Antonczyk et al. (2010), and Kampelmann and Rycx (2011) show little evidence of wage polarisation in Germany. Finally, Massari et al. (2014) study

[4]The main differences between Goos et al. (2009, 2014) and Fernández-Macías (2012) are in terms of categories, and in terms of employment population in each category. On the one hand, Goos et al. (2009, 2014) classify the jobs in three categories (good, middling, and bad jobs), which have uneven sizes in terms of number of occupations (8-9-4) and in terms of employment shares in the first year of the period studied (29 per cent, 49 per cent, and 22 per cent, respectively). On the other hand, Fernández-Macías (2012) classifies jobs in five equally size groups (showing the 20 per cent of population in each quintile).

the European labour market as a whole and conclude that there is no evidence of wage polarisation. With regards to Spain specifically, there is not a single study which explores this phenomenon.

Different theories have tried to explain the main drivers behind the phenomenon. While there are some explanations based on supply mechanisms (skill composition), almost all the theoretical explanations are based on three different demand mechanisms. The first mechanism is the propensity to offshore activities, which is not the same in all occupations. According to Blinder (2009), certain jobs are potentially more vulnerable to offshoring than others. They show that production jobs are easier to reallocate in low-income countries than service jobs. In the second place, Autor and Dorn (2013) explain that wage inequality increases income in the top earners and as a consequence, increasing the demand for bottom-paid job services. It is well known that these two factors affect specific occupations. However, the economic literature suggests that these two factors play a minor role in explaining the demand shift towards skilled workers in advanced countries (Acemoglu and Autor, 2011; Katz and Autor, 1999).

On the contrary, the most prominent theory accounting for job polarisation is the well-known routinisation hypothesis, called routine biased technical change (formulated by Autor et al. 2003, RBTC). In their seminal paper, ALM propose a classification of tasks along two different dimensions: routine (as opposed to non-routine) and manual (as opposed to non-manual, or also called cognitive) tasks. Routine tasks are defined as those that "require methodical repetition of an unwavering procedure" (ALM, 2003, p.1283). The cognitive dimension generally refers to tasks that require gathering and processing of information and problem solving (analytic), as well as those that need creativity, flexibility, and communication in order to be performed (interactive).

Autor et al. (2006), and Autor and Dorn (2013) reformulate the ALM model by bringing together the two routine categories. They consider a three-fold classification scheme, where tasks are classified into abstract, routine, and manual. While this new classification shared the routine definition of the ALM model, the abstract category refers to tasks requiring problem solving and managerial tasks with high cognitive demand, and the manual tasks refers to those ones requiring physical effort and time adaptability, being therefore both tasks categories difficult to automate. More recently, Fernández-Macías and Bisello (2017) propose a new framework to measure tasks. They divide the tasks in two groups: the first one in terms of the object of work (where they include physical, intellectual, and social tasks). The second in term of the method and tools used in the work (where they include work organization and technology).

In the ALM model, the way in which occupations are affected by new technologies depends to a large extent on the tasks they perform, rather than on their skills (normally measured using educational level).[5] Two hypotheses are then formulated. The first hypothesis is that since routine tasks are easy to codify, and therefore easy to replicated by machines, the ALM model predicts the progressive substitution of technology for labour in routine tasks. The second hypothesis is that abstract tasks are characterised by complex analytical thinking, flexibility, creativity, and communication tasks, among others. These types of tasks are not only difficult to be replaced by machines, but they are also complementary to computer technologies. Therefore, the ALM model predicts complementarity between technology and abstract tasks. No assumptions are made regarding manual tasks.

Goos and Manning (2007), and Autor and Dorn (2013) use the ALM model to ex-

[5]Goos and Manning (2007) and Goos et al. (2009, 2014) also refer to this phenomenon as *routinisation*.

plain the polarisation phenomenon: since routine tasks are located in the middle of the occupation distribution, and non-routine tasks at the top and at the bottom, the ALM indicate that two key effects occur: first, employment and wages in the middle of the distribution decreased. Second, employment and wages increased (or at least remain stable) in the higher and lower qualified groups. Hence, the polarisation effect of recent technical change is explained by the RBTC. In summary, the ALM model provides a strong theoretical foundation to develop a deeper understanding of how technology may be impacting the Spanish labour market.

4.3 Data

Three different datasets covering the period 1994-2008 are used in the analysis. Data on the evolution of jobs and socio-demographic characteristics come from the Spanish Labour Force Survey. Data on the evolution of wages come from the Structure of Earnings Survey. Data on tasks come from the European Working Condition Survey. Below, each data set is described in detail.

4.3.1 Spanish Labour Force Survey

The primary data source used is the Spanish Labour Force Survey (*Encuesta de Población Activa* EPA, in Spanish) administered by the National Institute of Statistics. The EPA was carried out quarterly from 1964 to 1968, then biannually from 1969 to 1974, and finally quarterly again from 1975 onwards. The EPA is used to estimate employment and unemployment within the ILO framework and is the basic source by which researchers can construct data series on occupations.

Although the data is compiled quarterly and available from all years since 1964, the analysis focuses on the period 1994-2008 where the second quarter of each relevant year is sampled to avoid seasonality problems. The total sample size is 57,231, 66,636, and 69,809 individuals for 1994, 2000, and 2008, respectively. The EPA contains data on employment status, weekly hours worked, two-digit occupational level (CNO-94) and one-digit industry level (CNAE-93), education, region, nationality, sex, age, and the population in each cell among others. The dataset is weighted to reflect employment in absolute numbers.

For the purpose of our analysis, the EPA is far from ideal. The main problem is the lack of income data necessary to rank selected job cells on earnings-based quality. To overcome this problem, we merge it with the Structure of Earnings Survey.

4.3.2 Structure of Earnings Survey

The Structure of Earnings Survey (in Spanish, *Encuesta de Estructura Salarial*, EES) is administered by the official statistical office. This survey consists of a random sample of workers from private-sector firms of at least 10 employees in the manufacturing, construction, and service sectors.

The sampling takes place in two stages. First, firms are randomly sampled from the Social Security General Register of Payments records. Second, from each of the selected firms, workers are randomly selected. The survey collects detailed information on workers' wages; personal characteristics such as gender, age, educational attainment, and nationality; and job characteristics, including sector, occupation, contract, job type, firm size, and ownership.

For the period under study, the survey has been carried out three times (1995, 2002 and 2006). In 2002, the coverage of the survey is extended to include some non-market services (educational, health, and social services sectors) that are not included in the 1995 wave. Throughout our chapter, to measure job polarisation, we use the 1995 wave rather than the 2002 or the 2006, as results remain invariant and is closer to the base year of the period of analysis. Moreover, to measure wage polarisation, all three cohorts and all wages are deflated to the year 1995 using the Consumer Price Index (CPI).

4.3.3 Measuring the task content of jobs

In order to establish the task content of each job's measures, information on the activities performed by workers on the job is required. Task measures at the job level are derived from an additional source, the European Working Condition Survey (EWCS). Unlike previous studies on job polarisation in Spain (Anghel et al., 2014), this study does not rely on the US O*Net survey to derive data on job task requirements.[6] Hence, there is no need to assume that the task composition is the same in the two countries. Moreover, as we mentioned before, there are two different features between the US O*Net and the EWCS. Firstly, while the original purpose of the US O*Net is an administrative evaluation by Employment Services offices of the fit between workers and occupations, the EWCS is conducted for research. Secondly, differently from the US O*Net where analysts at the Department of Labour assign scores to each task according to standardised guidelines, the EWCS derive individual tasks measures. This means that the EWCS presents a higher level of subjectivity, giving the advantage of a more precise idea of the tasks performed within each occupation.[7]

The EWCS is administered by the European Foundation for the Improvement of

[6] We use the same database as Fernández-Macías and Hurley (2016).

[7] Autor and Handel (2013), who use a similar type of survey as the EWCS, prove that their data have a greater explanatory power for wages than those derived from the O*Net.

Living and Working Conditions (Eurofound) and has become an established source of information about working conditions and the quality of work and employment. With six surveys (one every five years) having been conducted since 1990, it enables monitoring of long-term trends in working conditions in Europe. At each time point, information on employment status, working time arrangements, work organisation, learning and training, and work-life balance among others is collected. In this research, four surveys (1995-2010) are used for analysis. These four repeated cross-sections cover, 15,986 in 1995, 21,803 in 2000, 29,680 in 2005, and 43,816 in 2010. Sampling weights adjusted for responses are used through the analysis. The analysis is restricted to individuals aged from 16 to 65. Jobs are classified according to the ISCO-88 nomenclature at the two-digit level and NACE, Rev. 1.1 at the one-digit level.

The same framework as Autor et al. (2003), and Autor and Dorn (2013) is used to estimate the effects of job polarisation.[8] Their classification is based on a three-dimensional typology: abstract, routine, and manual. For the abstract tasks, responses on "learning new things", "solving unforeseen problems", and "assessing yourself the quality of your job" are retained.[9] For the manual tasks, questions on "physical strength" (e.g., carrying or moving heavy loads),"skill or accuracy in using fingers/hands"(e.g., repetitive hand or finger movements), and 'physical stamina" (e.g., painful positions at work) are selected.[10] For routine tasks, routine activities people performed within their job are used to classify positions: "does your main job involve (1) dealing with people, (2) repetitive tasks, (3) dealing with customers".[11]

[8] In the literatura there are two more frameworks: (1) Matthes et al. (2014) and (2)Fernández-Macías and Bisello (2017). For more information look at Biagi and Sebastian (2017).

[9] These three items are closed questions (1=yes, 2=no).

[10] Questions provide answer in intensity frequencies (1=all of the time, 2=almost all of the time, 3=around 3/4 of the time, 4=around half of the time, 5=around 1/4 of the time, 6=almost never, 7=never).

[11] Questions provide answer in intensity frequencies (1=all of the time, 2=almost all of the time,

The items for manual and routine tasks are on a 7-point Likert scale ranging from 1 ("all of the tim") to 7 ("never"). These variables are then normalized to range from 0 to 1. After collapsing each index at the job level (ISCO-88 two-digit level and NACE, Rev. 1.1 one-digit level), weighting each observation for the sampling weight, the EWCS index is merged into the EPA. Therefore, the employment figures of Spain are used for weighting the indices (See Appendix B for further information).

Following Autor and Dorn (2013), this study creates a routine task intensity measure (RTI) to compare findings to those in the literature. This measure aims to capture how important the routine tasks are compared to tasks components of countries. Indices are standardized with a mean of 0 and a standard deviation of 1. As presented in previous chapters, the RTI is then calculated as follow:

$$RTI_{1994} = \ln T^R_{1994} - \ln T^A_{1994} - \ln T^M_{1994} = \ln \frac{T^R_{1994}}{T^A_{1994} T^M_{1994}} \tag{4.1}$$

where T^R, T^A, and T^M are the routine, abstract, and manual inputs in Spain in 1994. This measure is rising in the importance of routine tasks in Spain and declining in the importance of abstract and manual tasks.

Before proceeding with the analysis, Table 4.1 shows correlation between the EWCS and O*Net.[12] A positive correlation is found between the two surveys being the RTI with the highest correlation (0.882) and routine task with the lowest correlation (0.622). The results indicate that both surveys are close enough, indicating that the EWCS is a suitable measure.

3=around 3/4 of the time, 4=around half of the time, 5=around 1/4 of the time, 6=almost never, 7=never).

[12] US Census 2000 codes are matched to the International Standard Classification of Occupations.

Table 4.1: Correlation between EWCS and O*Net

	EWCS Survey Abstract	EWCS Survey Routine	EWCS Survey Manual	EWCS Survey RTI
	(1)	(2)	(3)	(4)
O*Net Abstract	0.706			
O*Net Routine		0.622		
O*Net Manual			0.866	
O*Net RTI				0.882

Notes: Correlations are computed at 2-digit occupation level.
Sources: Author's analysis from the EWCS (2000) and O*Net.

4.4 The evolution of employment and pay rules in Spain

4.4.1 The evolution of employment

The starting point of the analysis is to investigate the pattern of employment change in the Spanish labour market, acting as a preliminary step for the subsequent analysis. Unless otherwise noted, throughout this chapter employment is modelled by occupation (ISCO-88 two-digit level) and by industry (NACE, Rev. 1.1 at one-digit level). All earnings data used in this article refer to hourly wages deflated to the year 1995, using the Consumer Price Index (CPI). Employment share is computed from EPA data, while the employment ranking is based on the mean wage from the 1995 EES data.[13]

A common way of analysing the development of jobs is through graphical illustration.

[13]We merge the EPA with the EES, and two filters are applied to the final data. First, we drop workers associated with the primary sector, public administration and defense (These correspond to the industries (NACE, Rev. 1.1) A, B, C, L and Q, and the occupations (ISCO) 11, 61 and 92.). Second, we retain only those jobs which appear in both surveys and with at least 5 observations. After applying both filters, we reduce the total number of jobs from 218 to 160 jobs. See Appendix C for details on the measures discussed in this section.

For this, the employment shares by each job are computed, along with changes over time. To avoid bias due to small jobs drive dominating results, each job is weighted by its total employment. Jobs are ranked according to their initial mean wage.[14] Then, the percentage point change in employment share is plotted against the ln mean hourly wage. If the structure of employment has polarised, it is expected that employment in bottom- and top-paid jobs increased, while it decreased in the middle of the distribution.

Figure 4.1 corresponds to the evolution of Spanish employment between 1994 and 2008. As noted already, employment shares are measured by two-digit occupations (ISCO-88) and by one-digit sectors of activity (NACE, Rev. 1.1). Earnings are measured by the logarithm of hourly mean in each job in 1995. The employment changes in Spain shows a clear pattern of job polarisation, in which the higher and lower part of the wage distribution has increased while shrinking the middle-wage part. A U-shaped curve can be clearly detected in the evolution of employment shares, when jobs are ranked according to the hourly mean wage.

Using the parametric graph, a more rigorous test for job polarisation can be conducted. In order to do so, the following model of the quadratic form is estimated as proposed by Goos and Manning (2007):

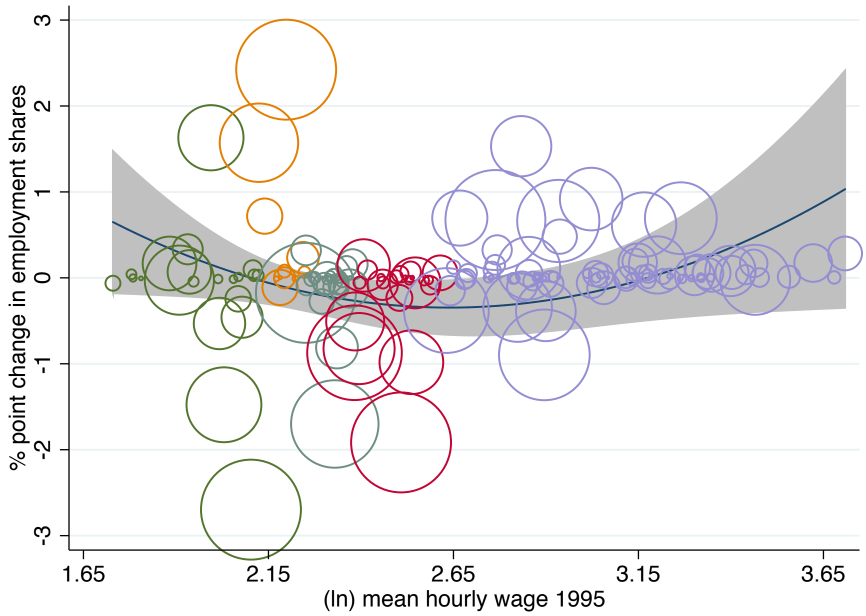
$$\Delta \ln E_j = \beta_0 + \beta_1 \ln(\mathrm{w}_{j,\text{t-1}}) + \beta_2 \ln(\mathrm{w}_{j,\text{t-1}})^2 \tag{4.2}$$

where $\Delta \ln E_j$ is the change in the ln employment share of job j between the initial and the final year considered, $\ln(\mathrm{w}_{j,\text{t-1}})$ is the logarithm of the mean wage of job j in t-1, and $\ln(\mathrm{w}_{j,\text{t-1}})^2$ is the square of the initial mean wage. A U-shaped relationship between the employment growth and the wages implies that the linear term is negative and the

[14] The shape of the graph does not change if median average wage are used for determining job quality.

quadratic term is positive.

Figure 4.1: Employment shares growth in Spain (1994-2008) by mean hourly wage



Notes: Scatter plot and quadratic prediction curve. The dimension of each circle corresponds to the number of observations within each ISCO-88 two-digit occupation and NACE, Rev. 1.1 one-digit occupation in 1994; the grey area shows 95 per cent confidence interval. Employment shares are measured in terms of workers. Colours represent the quintile of each job (grey colour represents the first, third, and fifth quintile. Black colour represents the second and fourth quintile).
Sources: Author's analysis from the EPA (1994, 2008) and EES (1995).

Table 4.2, panel (1) and (2), presents the results of the OLS regression using weekly hours worked as a measure for employment shares rather than expressing them in terms of bodies. Moreover, the equation in two time periods is estimated: 1994-2000 (short period), and 1994-2008 (long period). Equation (1) is estimated by weighting each job by its initial employment share in 1994 to avoid that results are biased by compositional changes in small jobs. All regression coefficients have the expected sign and are significant at the 1 per cent level. For the longest period (1994-2008), the coefficients increase in absolute value, as well as the adjusted R-squared. The results indicate that Spain has been characterized by a polarisation pattern in employment growth from 1994 to 2008.

The phenomenon of job polarisation is also robust to the use of the median instead of the mean.

Table 4.2: Regressions for Job Polarisation (ln)

	Dependent Variable	
	Ln change in employment share	
	1994-2000	1994-2008
	(1)	(2)
(ln) mean hourly wage 1994	-8.17***	-8.88***
	(2.12)	(2.31)
Sq. (ln) mean hourly wage 1994	1.56***	1.73***
	(0.40)	(0.43)
N	109	126
Adj. R-square	0.10	0.12
F	7.81	8.84

Notes: Each job is weighted by the initial number of observations. Robust standard errors between parentheses, significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2008) and EES (1995).

Goos and Manning (2007) calculate the change in logarithms, therefore measuring a smoothed trend. To verify correct functional form of the equation, the relative change between 1994 and 2008 is computed. We estimate the next quadratic form:

$$\Delta \mathrm{E}_j = \beta_0 + \beta_1 \ln(\mathrm{w}_{j,\mathrm{t\text{-}1}}) + \beta_2 \ln(\mathrm{w}_{j,\mathrm{t\text{-}1}})^2 \tag{4.3}$$

where $\Delta \mathrm{E}_j$ is the change in employment share of job j between the initial and the final year considered, $\ln(\mathrm{w}_{j,\mathrm{t\text{-}1}})$ is the logarithm of the mean wage of job j in t-1, and $\ln(\mathrm{w}_{j,\mathrm{t\text{-}1}})^2$ is the square of the initial mean wage.

In Table 4.3, panel (1) and (2), coefficients have the expected sign and are larger in magnitude when moving to the longest period, as it happens with the adjusted R-squared. However, as expected, results are not as significant as in the previous scenario.

Job polarisation is analysed by defining job wage percentile.[15] In this particular case,

[15]This methodology has been applied by Autor and Dorn (2013).

smoothing regressions are displayed rather than the actual data point (the previous case). Therefore, changes in employment share are plotted against the percentile of the initial wage distribution. A perfect U-shaped curve is clearly detected and shown in Figure 4.2. The main advantage of this method is that the biggest increases and losses are observable. For Spain, the biggest losses are between the 20th and the 40th percentile of the initial mean wage distribution. Overall, the shape of employment changes in the EPA data updates other studies with Spanish data and suggests that job polarisation is a robust phenomenon in Spain.

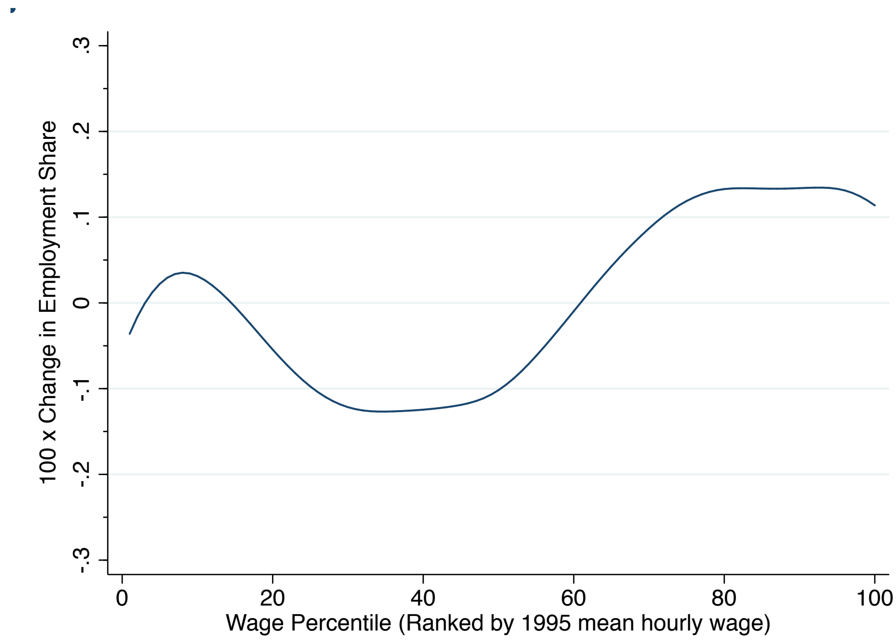
Table 4.3: Regressions for Job Polarisation

	Dependent Variable	
	Change in employment share	
	1994-2000	1994-2008
	(1)	(2)
(ln) mean hourly wage 1994	-2.03	-4.61
	(0.87)	(1.96)
Sq. (ln) mean hourly wage 1994	0.42*	0.98*
	(0.16)	(0.37)
N	156	160
Adj. R-square	0.06	0.07
F	6.49	7.92

Notes: Each job is weighted by the initial number of observations. Robust standard errors between parentheses, significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2008) and EES (1995).

Three robustness tests for the results presented above are implemented to ensure the validity of the results. First, the results are subjected to sensitivity testing with respects to the choice of the reference year. The 2000 EES and 2006 EES years were selected. Second, jobs are ranked by median rather than mean wage. Third and finally, the impact of an alternative definition of jobs is evaluated. In this case, a job is defined by two-digit ISCO (following Anghel et al. 2014) and by two-digit ISCO and two-digit NACE, Rev. 1.1 (as Fernández-Macías 2012). In all three cases, graphs result are invariant, the characteristic U-shaped curve is detected in the evolution of employment shares (look at the Appendix D for Figure D1, Figure D2, and Figure D3). Using the database, the employment changes in Spain between 1994 and 2010 are found to be consistent with the polarisation phenomenon, where employment growth occurs for bottom- and top-paid jobs, while decreases for middle-paid jobs.

Figure 4.2: Smoothed changes in Employment by wage percentile (1994,2008)



Notes: The figure plots ln changes in employment share by 1995 job skill percentile rank using a locally weighted smoothing regression (bandwidth 0.75 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of a job's mean ln wage in the 1995 Structure of Earnings Survey .
Sources: Author's analysis from the EPA (1994, 2008) and EES (1995).

4.4.2 The evolution of wages

In this section, and after studying the evolution of employment, the evolution of remuneration of jobs is investigated. In our analysis, wage polarisation is understood in the following way: first jobs are ranked according to their mean hourly wage in the first year. The change in wages is measured in each job between the first and the last year of our period of study. If the mean wage of jobs is found to be growing at the top and bottom of the wage ranking in the first year, while the mean wage of jobs in the middle of the ranking is decreasing, this phenomenon is defined as wage polarisation.

It is expected that the evolution of employment and the evolution of pay rules matches. As a consequence, to predict changes in wages, the same quadratic model is used to detect the U-shaped evolution of employment shares (Kampelmann and Rycx, 2011). Therefore, to examine wage polarisation, the following model is estimated:

$$\Delta \ln(\mathrm{w}_j) = \beta_0 + \beta_1 \ln(\mathrm{w}_{j,\text{t-1}}) + \beta_2 \ln(\mathrm{w}_{j,\text{t-1}})^2 \tag{4.4}$$

where $\Delta \ln(\mathrm{w}_j)$ is the change in the ln mean wage of job j between the initial year and the last year considered, $\ln(\mathrm{w}_{j,\text{t-1}})$ is the logarithm of the mean wage of job j in t-1, and $\ln(\mathrm{w}_{j,\text{t-1}})^2$ is the square of the initial mean wage.

Table 4.4 reports the OLS results. In this analysis, the number of individuals within a job in 1994 weights the initial number of observations in each job. The coefficients have the expected sign, but are not significant. It can be concluded that there is no evidence of wage polarisation for the sample period 1994-2008.

Finally, the changes in employment share are evaluated to match changes in pay rule. To do so, the correlation coefficient is computed between the two variables (ρ=0.09). The coefficient is positive but weak. Contrary to the existing literature in the US (Autor and Dorn, 2013) and Germany (Kampelmann and Rycx, 2011), the results suggest that the relationship between changes in employment share and changes in pay rules is almost zero in Spain.

Table 4.4: OLS regression for wage polarisation analysis

	Dependent Variable
	Change in (ln) mean wage 1995-2006
	(1)
(ln) mean hourly wage 1995	-0.70*
	(0.25)
Sq. (ln) mean hourly wage 1995	0.13
	(0.05)
N	160
Adj. R-square	0.07
F	7.06

Notes: The initial number of observations weights each job. Robust standard errors between parentheses, significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the ESS (1995, 2002, and 2006.)

4.5 Task-based analysis

4.5.1 Employment changes and tasks intensities

Thus far, it has been shown that there is a hollowing out of the employment distribution in Spain, while there is no evidence of wages following the same pattern. In order to better interpret the previous results, a task-based approach is used. Information on the activities carried out by workers on their jobs is used, where each worker performs different tasks with different intensities. Therefore, each job is not defined by one single task, but it can be classified as with a predominant task. To proceed with the analysis, further information concerning the nature of tasks performed by workers is gathered. Differently from Anghel et al. (2014) and Goos et al. (2014) who based their analysis on US data, an alternative database based on European data where Spain is included in is utilised. Data on the tasks workers perform on their jobs comes from the European Working Survey, as explained in Section 4.3.

The analysis is conducted by presenting the correlation among task measures and the education attainment at the two-digit ISCO-88 level. As observed in Table 4.5, the pairwise correlation between the abstract dimension and the routine measure is negative, while is positive with the manual task and the education variable. The RTI is negatively correlated with the abstract dimension and positively correlated with the routine and manual task. The education measure is positive correlated with the abstract dimension, while is negative with the routine and manual content, which is in line with results reported by Green (2012). However, these results differ in the methods of calculation since this study computed the correlation at the occupational level while Green (2012) explored the correlation between tasks measures and education at the individual level.[16]

Table 4.5: Correlation among the task measures and the education variable

	Abstract	Routine	Manual	RTI	Education
	(1)	(2)	(3)	(4)	(5)
Abstract	1				
Routine	-0.735	1			
Manual	0.452	0.541	1		
RTI	-0.789	0.868	0.739	1	
Education	0.739	-0.730	-0.775	-0.879	1

Notes: Correlations are computed at two-digit occupation.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and EWCS (2000).

Table 4.6 reports changes in employment share by major occupational groups (two-digit ISCO-88 level) and are ranked in ascending order by their mean wage in 1995. The mean level of education in 1994 (column 2) is also included. Occupations are classified in three major groups following the criteria from Autor and Dorn (2013): the first six occupations at the low part of the employment distribution are defined as bottom occupations, the next eight occupations as middle occupations, and the top nine occupations are

[16]Whereas Green (2012)reports the required education of the job, we use worker's actual highest education.

labelled as top occupations. The groups include 6, 8, and 7 occupations respectively.[17] These groups represent the theoretical classification of the RBTC model with services and elementary occupations at the bottom of the occupational distribution, productive and administrative occupations being in the middle, and professional and managerial at the top of the top of the occupational distribution.

To illustrate the richness data at the occupational level, Table 4.7, columns 2 to 5 present the average values of the task measures. Matching Table 4.6 with Table 4.7, a complete picture of the task content can be formed, which determined job polarisation in Spain. In line with expectations, the RTI values are higher among clerical work, repetitive production, and monitoring. Managers and professionals instead score among the lowest.

Analysing the bottom group occupation, results indicate that half of the occupations are growing in employment share, while the other half are losing employment share. The occupations that experience the most significant employment growth represent a mixture of elementary occupations such as "Sales and services elementary occupations" (ISCO 91), and services such as "Personal and protective services workers" (ISCO 51). All these occupations score higher in the manual than in the routine dimension. This is in line with the prevailing RBTC theory, low-skilled jobs rely on manual tasks, therefore are not affect by the introduction of technology.

Concerning the middle occupations, "Office clerks" (ISCO 41) and "Metal, machinery, and related trades workers" (ISCO 72) are those that register the highest employment losses, scoring higher in the routine dimension than in the manual measure. Moreover, "Drivers and mobile plant operators" (ISCO 83) has the highest score in RTI.

[17] Fernández-Macías (2012) criticises this classification arguing that a division in even groups would not lead to job polarisation in Europe. Our results remain invariant to this alternative classification. We still observe the polarisation pattern with middle-occupations exhibiting relative declining shares with respect to the top and the bottom.

Table 4.6: Occupations, mean wage and education

Occupation	ISCO-88	Mean wage 1995	Mean level education	Employment share
		(1)	(2)	(3)
	Bottom occupations			
Labourers in mining construction, and manufacturing	93	7.21	1.22	-0.92
Sales and services elementary occupations	91	8.03	1.18	1.26
Other craft and related trades workers	74	8.17	1.18	-2.36
Personal and protective services workers	51	8.44	1.51	1.89
Models, salespersons and demonstrators	52	9.50	1.47	-0.28
Extraction and building trades workers	71	9.65	1.23	1.60
	Middle occupations			
Drivers and mobile-plant operators	83	10.10	1.20	-1.92
Machine operators and assemblers	82	10.27	1.29	-1.18
Precision, handicraft, printing and related trades worker	73	10.33	1.48	-0.69
Customer services clerks	42	10.96	2.26	0.31
Metal, machinery and related trades workers	72	12.77	1.49	-2.35
Office clerks	41	13.19	2.33	-3.28
Life science and health associate professionals	32	14.34	2.94	0.30
Stationary plant and machine operators	81	15.33	1.45	-0.17
	Top occupations			
Physical and engineering science associate professionals	31	18.44	2.66	1.01
Other associate professionals	34	18.94	2.39	4.10
Other professionals	24	21.68	3.88	0.28
Life science and health professionals	22	22.33	3.91	0.17
Physical, mathematical and engineering science profession	21	24.30	3.92	1.02
Teaching professionals	23	25.90	3.89	0.68
Corporate managers	12	33.10	2.64	0.53

Notes: Occupations are ranked in ascending order by the mean hourly wage in 1995; column 2 reports the mean of the educational attainment in 1994, based on for-vales variable (elementary, basic, medium, high), column 3 shows the percentage point in employment share over the period 1994-2008.
Sources: Author's analysis from the the EPA (1994, 2008) and ESS (1995).

Table 4.7: Tasks measures by occupations

Occupation	ISCO-88	Abstract	Routine	Manual	RTI
		(1)	(2)	(3)	(4)
	Bottom occupations				
Labourers in mining construction, and manufacturing	93	0.61	0.65	0.81	-0.16
Sales and services elementary occupations	91	0.55	0.59	0.65	-0.36
Other craft and related trades workers	74	0.60	0.77	0.78	0.00
Personal and protective services workers	51	0.64	0.62	0.69	-0.41
Models, salespersons and demonstrators	52	0.52	0.62	0.48	-0.57
	Middle occupations				
Extraction and building trades workers	71	0.65	0.53	0.80	-0.43
Drivers and mobile plant operators	83	0.42	0.57	0.60	-0.20
Machine operators and assemblers	82	0.61	0.62	0.70	-0.34
Precision, handicraft, printing, and trades workers	73	0.65	0.62	0.70	-0.41
Customer service clerks	42	0.54	0.75	0.37	-0.66
Metal, machinery and related trades workers	72	0.65	0.57	0.80	-0.34
Office clerks	41	0.53	0.63	0.35	-0.87
Life science and health associate professionals	32	0.74	0.42	0.52	-1.22
Stationary-plant and related operators	81	0.58	0.52	0.76	-0.37
	Top occupations				
Physical and engineering science associate professionals	31	0.62	0.56	0.52	-0.75
Other associate professionals	34	0.67	0.46	0.30	-1.59
Other professionals	24	0.77	0.35	0.26	-2.12
Life science and health professionals	22	0.74	0.50	0.59	-0.91
Physical, mathematical and engineering science profession	21	0.75	0.39	0.34	-1.75
Teaching professionals	23	0.79	0.39	0.38	-1.67
Corporate managers	12	0.72	0.43	0.33	-1.63

Notes: Occupations are ranked in ascending order by the mean hourly wage in 1995. Column 1 to 4 reported normalised tasks measures in 2000 ranging [0.1].
Sources: Author's analysis from the EPA (1994, 2000, 2008), ESS(1995) and EWCS (2000).

Finally, within the group of the highest paying occupations, "Other associate professionals" (ISCO 34) and "Other professionals" (ISCO 24) are those that experienced the most significant employment growth. Consistent with the ALM model, these seven occupations score higher on the abstract dimension than on the manual task. These occupations demand tasks such as flexibility, problem solving, creativity and complex communication. Therefore, the likelihood of technology to substitute for workers in carrying out these tasks is very limited.

To verify previous results, changes in employment shares are regressed between 1994-2008 and the initial level of routine task index for each occupation. Table 4.8 —column 1, shows the stacked period, while column 2 and column 3 single decade estimators. As expected, a negative relationship is found between the two variables: higher routine task intensity leads to larger declines in employment occupations. As the RTI is bigger in the middle than at the two extremes of the employment distribution, this table suggests that the RTI explains the hollowing out of the employment distribution.

Table 4.8: OLS regression of changes in employment share and the initial level of routine intensity

	Dependent variable		
	Change in employment share		
	1994-2008	1994-2000	2000-2008
	(1)	(2)	(3)
RTI	-0.536***	-0.186***	-0.198***
	(0.158)	(0.068)	(0.069)
R^2	0.17	0.12	0.11
N	160	160	160

Notes: The regression includes a constant. Robust standard errors between brackets, significance levels ***p<0.01; **p<0.05; *p<0.10. The dependent variable is measured using two-digit ISCO and one-digit NACE, Rev. 1.1.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and EWCS (2000).

4.5.2 Task intensities over time

Understanding the evolution of tasks measures across time allow further analysis of job polarisation. The composition of tasks constitutes a vital piece of information to test the routinization hypothesis. Changes in the task structure of the labour market are analysed to determine if task structure relies on the changes within occupations (i.e., the intensive margin) or between occupations (i.e., the extensive margin). The EWCS allows decomposition of changes in importance, if the four tasks groups into changes in the intensive and extensive margin.

Table 4.9 presents the importance of the tasks in 1994 and 2008, as well as reports the results of the shift-share analysis. The change decomposition of tasks of each occupation is as follows:

$$\Delta \mathrm{T}_k = \sum_j \Delta \mathrm{E}_j \gamma_{jk} + \sum_j \Delta \gamma_{jk} \mathrm{E}_j \tag{4.5}$$

where $\Delta \mathrm{T}_k$ and $\Delta \mathrm{E}_j$ are the change in importance of tasks k and the change in employment in occupation j between 1994 and 2008, and γ_{jk} represents the importance of task k in occupation j. Finally, $\Delta\gamma_{jk}$ is the change in the share of task k in occupations and E_j is the average share of occupation j. The first term on the right-hand-side equation is the extensive margin, i.e., the task importance is held constant (and represents the average task importance across the two years), and time variation relies on changes across occupations. The second term is the intensive margin where occupational employment is held constant while the importance of tasks within occupations is allowed over time.

Table 4.9 compares the importance of the four tasks groups in 1994 and 2008 and the change between 1994 and 2008. Results indicate that manual tasks become less important in the Spanish economy, while abstract and routine task are increasing their magnitude. The RTI is almost zero. In the last two columns, the decomposition effect is divided into changes within occupations ("the intensive margin") and changes between occupations ("the extensive margin"). The increasing importance of the routine tasks occurs at the extensive margin, whereas abstract task increased its importance due to changes at the extensive margin. Therefore, while the routine task is increasing because routine occupations are now more routinized, the abstract task is increasing because occupations with a lower level of abstract tasks are now demanding it. The decreasing importance of manual tasks seems to rely mainly on the extensive margin. In other words, manual task lose employment due to decreasing tasks importance within jobs.

Table 4.9: Tasks shifts, intensive and extensive margin

	Abstract	Rotuine	Manual	RTI
	(1)	(2)	(3)	(4)
Importance 1994	62.38	55.61	55.63	-0.77
Importance 2008	63.81	59.22	52.14	-0.81
Change	1.43	3.61	-3.50	-0.05
Extensive Margin	1.00	-1.42	-0.79	-0.05
Intensive Margin	0.43	5.03	-2.71	0.00

Sources: Author's analysis from the EPA (1994, 2008) and EWCS (1995, 2010).

4.6 Technological change and tasks

The ALM model predicts that technology substitutes for labour in routine tasks while complements it in non-routine abstract tasks. No assumption is made for non-routine manual tasks. Therefore, the effect that computers have on tasks inputs needs to be investigated. Following Green (2012), a pseudo-panel is created, but the analysis differs as the routine task is not combined with the manual task, therefore evaluation is done on the routine index itself.

Testing the computerisation hypothesis, with the following regression model:

$$\bar{T}_{mtj} = \beta \bar{C}_{jt} + \sum_{t=1}^{T-1} \theta_t + \gamma_j + \epsilon_{jt} \tag{4.6}$$

where $\bar{T}_{mtj}$ is the task measure in either: (1) abstract, (2) routine, and (3) manual tasks at the job level j at time t. The main regressor of interest, $\bar{C}_{jt}$ is the variable capturing computer intensity in job j at time t (see Appendix E for further details on how is derived). The specification includes a set of year effects (θ_t), and a set of occupation effects (γ_j). Time fixed effects are included to control for omitted variables that vary across time, but not varying across occupations. Occupations fixed effects control for omitted variables which are not constant across occupations but evolve over time.

Table 4.10 presents results of the fixed effects regressions of the initial abstract task (column 1), routine task (column 2), and manual task (column 3), and the initial level of computer use for each job. As expected, the results are in line with the ALM model: on the one hand technology is significant and negative related with routine tasks. On the other hand, a positive effect between computer use and abstract task is found: workers in managerial, professionals and creative occupations are complements with computers. Regarding manual tasks, where the ALM does not predict neither substitution nor complementary effects, a negative relationship between manual task and computer use is found. However, the manual coefficient is lower than the routine coefficient, suggesting that the computer's substitution is higher among routine tasks.

Table 4.10: Impact of computer on adoption on task measures

	Dependent Variable		
	Abstract	Routine	Manual
	(1)	(2)	(3)
Computer use	0.124**	-0.23***	-0.17*
	(0.04)	(0.06)	(0.08)
N	252	252	252
R^2	0.87	0.94	0.74
F (Years dummy)	7.68	4.90	3.12

Notes: Fixed-effect estimates at the two-digit ISCO and one-digit NACE, Rev. 1.1 and weighted by the cell size. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and EWCS (2000).

In Table 4.11, the process is repeated but this time workers in bottom-paid occupations are excluded from the analysis for two reasons.[18] First, routine is defined as monotony procedures; therefore, respondents in the survey could mislead the concept and understood repetitive tasks. Second, the ALM does not predict any effect in bottom-paid occupations. As observed from Table 4.11, after excluding bottom-paid workers, manual task is not significant. At the same time, comparing the routine estimators, in the second case, the estimator is lower but still significant. It can be concluded that the negative association between routine and computer is just for middle-skilled workers.

[18]We exclude from the analysis bottom-paid occupations, those are: ISCO-51, ISCO-52, ISCO-71, ISCO-74, ISCO-91, ISCO-93.

Table 4.11: Impact of computer on adoption on task measures

	Dependent Variable	
	Routine	Manual
	(1)	(2)
Computer use	-0.18**	-0.07
	(0.07)	(0.08)
N	193	193
R^2	0.91	0.74
F (Years dummy)	3.68	0.80

Notes: Fixed-effect estimates at the two-digit ISCO and one-digit NACE, Rev. 1.1 and weighted by the cell size. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and EWCS (2000).

4.7 Occupational mobility of middle-paid workers

The analysis has provided empirical evidence of the negative impact of computerisation on routine workers, and therefore their displacement. In this section, the analysis is completed by switching the focus to occupational mobility of middle-paid workers.

The model proposed by Autor and Dorn (2013) provides a framework in which continuously falling price of technology induces low-skilled routine workers to reallocate from routine to manual tasks, at the bottom of the employment distribution. Therefore, first, it is expected that routine workers become more mobile over time, and second, the subsequent reallocation of routine workers at the bottom of the employment distribution.

The main drawback of the EWCS is the lack of information on past jobs. To overcome this problem, the main source of data is merged with an additional database: the European Community Household Panel (ECHP). The ECPH is a longitudinal survey of the employment circumstances on the European population covered from 1994 to 2001. At each interval, information on job characteristics and working condition is provided. Among other details, it includes information on activity and employment status, job characteristics, earnings, and education. For the analysis, individuals that are not in both years of the analysis are excluded, obtaining 4,308 workers between 1994 and 1997, and 2,924 for the period 1997-2000.

Table 4.12 presents the occupational change by educational group. In order to control for education, a three-level education variable ranging from 1 (low-education) to 3 (high-education) is created, having as a result three types of workers: low-, middle-, and high-skilled workers. The percentage of workers having the same educational attainment and changing occupation is then computed. The results are divided into two periods: 1994-1997 are reported in column 1, and 1997-2000 in column 2. Column 3 contains mobility over time. In line with the RBTC model, middle-skilled workers are shown to become more mobile over time (5.53), against low-skilled (4.67) and high-skilled workers (2.44).

Table 4.12: Occupational change by educational group

	Occupational change		
Education	1994-1997	1997-2000	Mobility
	(1)	(2)	(3)
Low	7.11	11.78	4.67
Medium	9.15	14.68	5.53
High	6.38	8.82	2.44
N	4,308	2,924	

Notes: The table shows the percentage of workers that change occupation among those with the same educational attainment.
Sources: Author's analysis from the EPA and ECHP.

After showing that middle-skilled workers become more mobile over time, middle-paid workers are analysed to determine if they moved towards bottom- or top-paid occupations. Following the model of Autor and Dorn (2013), it is expected that an increasing probability of middle-workers reallocate towards bottom-paid occupations, under the assumption that their relative comparative advantage is higher in manual than abstract tasks. To further understand the changes occurring, unemployment and inactivity could be analysed as in Schmidpeter and Winter-Ebner (2016). This would determine if it middle-workers end up outside the labour market. However, due to data limitation we only analyse upward and downward mobility.

To do so, the transition probability matrix is estimated, where each cell corresponds to the transition process of being in one job and move to another given by:

$$\mathrm{p}_{ij} = \Pr(\mathrm{X}_t = j | \mathrm{X}_t = i) \tag{4.7}$$

The probability from equation (7) can be computed as expressed in equation (8)

$$\mathrm{p}_{ij} = N_{ij} / \sum_{j=1}^{n} N_{ij} \tag{4.8}$$

where N_{ij} is the total number of workers changing from job i to job j (the cell counts) and $\sum_{j=1}^{n} N_{ij}$ is the total number of workers in the same job (the row counts).

To obtain a larger period, the analysis is completed with the use of the Survey of Income and Living Conditions (SILC). After applying all the restrictions to the final database, the exit probability for each category of workers is compared; bottom, middle, and top across each decade.

In Table 4.13, each cell corresponds to the transition probability from one occupation to another one in three different periods: from 1994 to 1997, from 1997 to 2000 and from 2005 to 2008. Three important remarks can be derived from this Table. First, middle-paid workers have the highest probability levels of mobility. As shown in Table 4.12, middle-paid workers have the lowest probability of remain in the same occupation: 0.71 against 0.75 and 0.83 in the first period, 0.69 against 0.80 and 0.79 in the second period, and finally 0.67 against 0.84 and 0.91 in the last period. These findings are in line with the ALM model: middle-paid workers are more affected by the introduction of technology and therefore are more mobile.

Second, the probability of being in the same occupation decreased for middle-paid occupations (from 0.71 to 0.67) while the probability of being in the same occupation increased for bottom- and top-paid occupations (from 0.75 to 0.80 for low occupations, and from 0.83 to 0.91 for high occupations).

Third, middle-paid workers are more likely to move up the occupational ladder. The percentage of middle-paid worker reallocating towards the top of the distribution is 0.17 against 0.12 in the first period, 0.21 against 0.10 in the second period, and 0.23 against 0.10 in the final period. Moreover, the probability of middle-paid workers to shift into top-paid occupation increases over time: from 0.17 to 0.23. Therefore, contrary to expectations, workers did not predominantly move towards bottom-paid occupations.

Table 4.13: Occupational transitions

		Occupation in 1997			
		Bottom	Midde	Top	Total
Occupation in 1994	Bottom	0.75	0.15	0.10	1
	Middle	0.12	0.71	0.17	1
	Top	0.06	0.11	0.83	1
		Occupation in 2000			
		Bottom	Middle	Top	Total
Occupation in 1997	Bottom	0.80	0.12	0.08	1
	Middle	0.10	0.69	0.21	1
	Top	0.09	0.12	0.79	1
		Occupation in 2008			
		Bottom	Middle	Top	Total
Occupation in 2005	Bottom	0.84	0.11	0.07	1
	Middle	0.10	0.67	0.23	1
	Top	0.03	0.06	0.91	1

Notes: Each cell corresponds to the transition probability form one state to another. Occupations are grouped into bottom, middle and top-paid.
Sources: Author's analysis from the EPA, ECHP, and SILC.

Our results suggest that there is a reallocation of middle-skilled workers. However, these workers did not move towards bottom-paid occupations. Overall more work needs to be done to understand the expansion at the lower and upper tail of the employment distribution, as the explanation based on the displacement of middle-workers is not fully satisfied. The last results raise doubts on the leading role of technology indicating that more needs to be done to understand the main determinants behind job polarisation.

Importantly, it has to be considered that since the 1990s, the demographic composition of the labour force in Spain has changed dramatically, mainly reflecting a rapid educational upgrading and migration surges. These two forces could play an important role in explaining the two tails of the employment distribution.

While during the first part of the 1980s, Spain was particularly behind other OECD countries, since then, Spain is under a process of educational expansion, where the share of workers with tertiary education increased, and the share of workers without secondary education decreased (Oesch and Rodríguez Menés, 2011). This could lead to an increase at the upper part of the employment distribution.

Regarding migration, it has increased sharply since the 1990s as argued by Muñoz de Bustillo and Antón (2012) and much more than in other European countries like Germany or Switzerland. Moreover, Oesch and Rodríguez Menés (2011) partially explain the increase in bottom-paid occupation in Spain from 1991 to 2008 by the job growth among migrants.

4.8 Conclusions

This chapter provides new insights into the debate on labour market polarisation in Spain. Different from previous studies, this study relies on European data only to measure the job content of occupations. Through the analysis, it is shown graphically and empirically that employment in Spain has polarised between 1994 and 2008. However, there is no evidence of a similar trend in wages unlike previous findings from the US. The sample suggests that jobs in top- and bottom-paid occupations increased, while employment shares decreased in the middle of the distribution.

To evaluate the ALM model, the method of analysis follows the previous literature on the task-based perspective analysing the task content of occupations. As the theory predicts, it is found that top-paid occupations and bottom-paid occupations increased the most, being the former classified in abstract tasks and the latter in manual tasks. Moreover, middle-paid occupations have lost significantly in employment share and can be classified as routine tasks. Similarly, changes in employment shares are found to negatively relate to the initial level of routine intensity index.

To enrich the analysis and to gain a better understanding empirically, a pseudo-panel was created to evaluate the association between computer use and routine task. A negative impact of computerisation on manual and routine tasks is found, and a positive effect on abstract tasks. This suggests that bottom-paid and middle-paid occupations are substitutes for computer use. By excluding from the analysis bottom-paid occupations, for which there is not a clear prediction from a theoretical point of view, the results are more significant. This means that the negative association found is associated with middle-paid occupations.

Finally, the analysis focused on the progressive substitution of technology for labour in routine tasks, and how this contributed to the employment growth at the bottom part of the occupational distribution. By merging the main database with the SILC, the analysis exploited questions on past jobs. In line as the model predicts, it was found that workers in middle-paid occupations become more mobile over time. However, contrary to expectations, workers did not predominantly move towards bottom-paid occupations. This finding suggests that more need to be than to understand the main determinants which explain the expansion of bottom-paid occupations and top-paid occupations.

5. Job polarisation and the Spanish local labour market

5.1 Introduction

A consensus has emerged among labour economists that there is an increase in both "good" and "bad" jobs relative to "middling jobs", a fact first introduced by Wright and Dwyer (2003) and later corroborated by Goos and Manning (2007). One of the key findings is the U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. Goos and Manning (2007) have termed this phenomenon as *job polarisation* basing their discussion on UK data. This fact is later corroborated in other developed countries such as the US (Autor and Dorn, 2013; Autor et al., 2006) and Germany (Dustmann et al., 2009; Kampelmann and Rycx, 2011; Spitz-Oener, 2006). However, results are mixed for Spain (Anghel et al., 2014; Muñoz de Bustillo and Antón, 2015; Oesch and Rodríguez Menés, 2011).

The economic literature highlights the role of technology as one of the main determinants of job polarisation. Goos and Manning (2007) explain job polarisation through the routine biased technical change hypothesis (RBTC): driven by persistently cheaper computerisation, technology replaces human labour in routine tasks, ceteris paribus. Since non-routine tasks are located at the low and high end of the occupational distribution, and routine tasks in the middle, the RBTC predicts two effects: 1) there is an employment decline in the middle of the occupational distribution, and 2) there is an employment growth at the bottom and top of the occupational distribution. Hence, for these authors, the polarisation effect of recent technical change is explained by the RBTC.

The RBTC model fits well with the evidence provided so far (Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014). However, this prominent theory is not able to explain three new empirical facts in the US during the 2000s. First, a decrease of the employment share in high-skilled occupations (Autor, 2015; Beaudry et al., 2016) where the supply of graduates grew faster than the demand of high-skilled jobs. Second, low-skilled jobs are growing more than middle- and high-skilled jobs. Job growth is therefore concentrated at the bottom of the employment distribution (Beaudry et al., 2016).[1] Finally, Beaudry et al. (2016) show little evidence of wage porlarisation in the US. It has also not been found in other countries, such as Canada (Green and Sand, 2015), the UK (Salvatori, 2015), and Spain (Sebastian, 2017). In light of the available evidence, it is clear that the relationship between technology and labour is more complex than the one assumed by the RBTC literature.

Alongside technological changes, change in the labour force supply constitutes another determinant of job polarisation advanced in the literature. Oesch and Rodríguez Menés (2011) highlight its importance as the driving force affecting occupational change to some extent. Their study graphically shows two new ideas: first, the increase at the bottom is partially explained by migrants. Second, the increase at the top reflects a

[1] Wage polarisation is defined as follows: if we rank all occupations according to their mean wage at date t-1, then wage polarisation between t-1 and t means that the mean wage of occupations situated in the middle of the ranking has decreased relative to occupations at the top and bottom of the wage ranking in t-1.

rapid educational upgrading. This chapter casts some doubts on the role of technology as the main driver behind occupational changes and suggests that supply-side changes are likely to be important in order to understand the phenomenon.

On the policy side, the phenomenon of job polarisation raises two significant issues in terms of job quality and occupational mobility. Firstly, the shrinking of middle jobs has consequences in the possibilities of moving up of low-skilled workers. Secondly, middle-paid workers are more likely to be reallocated in bottom-paid jobs. Therefore, for policy makers and governments it is important to understand the main determinants of job polarisation; this information will help them design economic policies that best promote sustainable growth.

Focusing on the case of Spain, this work contributes to the existing literature on polarisation in Spain by analysing novel evidence at the level of local labour markets inspired by the analysis of Autor and Dorn (2013). To the best of our knowledge we are the first ones exploring this issue outside the US. Therefore, using the Spanish Labour Force Survey and O*Net, we exploit geographical variation across Spanish provinces in their specialisation in the routine-intensive employment share, to identify the effect between technology and employment changes.

The study also contributes to the wider literature on job polarisation since we take into account other determinants beyond technology. In this case, and as pointed out by Muñoz de Bustillo and Antón (2012) and by Sebastian and Harrison (2017), two main factors have changed the Spanish labour market: the increase of migrants and increase in graduates. For migrants, in 1994 they represented only 0.62 per cent of total employment, whereas fourteen years later, the proportion has climbed up to almost 13 per cent. The increase of graduates has shifted from 21 per cent to 33 per cent of total employment from 1994 to 2008 respectively. Therefore we aim to disentangle the effect of technology and the role of supply changes in shaping the structure of employment in Spain between 1994 and 2008.

Our empirical findings are not completely in line with the predictions of Author's and Dorn model (2013). In line with them, we show that Spanish provinces with initially higher degree of routine task exhibit larger declines in middle-paid occupations and its subsequent displacement to bottom-paid occupations. However, no technological effect is found at the high-paid occupations where the graduate share and the high-skilled migrants share are the main drivers in explaining the growth at the top of the employment distribution

Evidence on the long-run effects of demographic factors is then presented. At the bottom of the occupational distribution, a higher local graduate share has a negative effect on employment growth. At the top part of the occupational distribution, high-skilled migrant concentrations are positively associated with the growth of employment. Regarding the concentration of graduates, it has a different effect depending on the decade: during the 1990s is negative and, during the 2000s, is positive. This is due to the possible catch-up in the first decade: provinces with initial lower human capital increase more than provinces with high initial human capital.

In the last part, because of potential endogeneity, we construct an instrumental variable based on the activity sector (industrial information) across Spanish provinces in the year 1977, almost two decades before the boom of computerisation in the workplace. Although the instruments are not strong, the findings obtained do not significantly differ from those of the baseline analysis.

Overall, this chapter provides new evidence on the main drivers behind job polarisation. On the one hand, technology seems to be behind the decrease in middle-skilled workers and its subsequent reallocation at the lower part of the employment distribution. On the other hand, technology does not play any role in explaining the growth at the top of the employment distribution. Graduate and high-skilled migrants supply changes are the main determinants behind the increase at the upper part of the employment distribution.

The chapter is organised as follow: Section 5.2 presents an overview of the relevant literature relating to job polarisation and local labour markets. In Section 5.3, we describe the data, the definition of local labour markets, the routine task intensity index, and the routine intensity measure. Section 5.4 presents initial evidence on job polarisation by occupation, demographic groups, and by Spanish provinces. Section 5.5 discusses the empirical specification and the identification strategy. Section 5.6 reports results from the empirical analysis. In Section 5.7 we perform a sensitivity analysis and several robustness checks. Section 5.8 summarizes the main findings of the work.

5.2 Literature review

In the ALM (2007) model, firms substitute routine tasks for technology, a process driven by the falling price in computers, while complement abstract tasks. Manual tasks are not directly affected by technology.

Autor and Dorn (2013) build on the RBTC model and present a general equilibrium model for routine replacement. In their economy there are two sectors which produce “goods” and “services” using computer capital, and three labour task inputs: Abstract, Routine, and Manual. The good production function uses abstract and routine labour while the service production function uses only manual labour. They assume that computer capital is a relative complement for abstract tasks and a relative substitute for routine tasks. In their model, there are two types of workers: high-skilled and low-skilled workers. High-skilled workers have a comparative advantage in abstract tasks, while low-skilled workers have a comparative advantage in routine and manual tasks. The main driver of the model is the exogenous falling price in computers. The basic implications in equilibrium are: 1) technological progress replaces low-skilled workers in routine occupations, and 2) since middle-workers have a comparative advantage in manual occupations; a greater reallocation at the bottom of the occupational distribution is expected.

The RBTC model has been empirically proven in the UK (Akcomak et al., 2013; Goos and Manning, 2007), Germany (Kampelmann and Rycx, 2011), Portugal (Fonseca et al., 2016), and Spain (Sebastian, 2017). These studies conclude that the RBTC hypothesis provides a convincing explanation for the role that technology plays in shaping the structure of labour market.

A more recent paper by Sebastian and Harrison (2017) complements the previous studies in two ways: first, job polarisation is studied through a shift-share analysis presenting changes within and between skills groups. Second, they study to which extent compositional changes could explain changes in the employment distribution. Results suggest that the growth at the top of the employment distribution is explained by the increase in the number of graduates.

As far as our understanding goes, no Spanish study has tried to test alternative hypotheses of job polarisation, i.e., the increasing supply share of graduates and migrants, the gaining of the population, or the growing offshorability of job tasks. This chapter aims at understanding the effect of technology on employment and at the same time provides evidence on the role of labour supply. To the best of our knowledge, this is the first paper proving a complete view on the determinants affecting the employment distribution using the Spanish local labour markets.

5.3 Data source and measurements

This section is concerned with a description of the data sets as well as the construction of the Routine Task Index. The main data set is the Spanish Labour Force Survey (*Encuesta de Población Activa* EPA, in Spanish) for the years 1994 to 2008, providing a representative sample of the Spanish workforce. We exclude the 2008-2014 years because of substantial changes in the ISCO code (from ISCO-88 to ISCO-08). In addition, we boost the sample size by pooling together 1994, 2000 and 2008 waves. The EPA is a continuous household survey of the employment circumstances of the Spanish population. It is conducted by the Statistical National Institute (*Instituto Nacional de Estadística*, INE). The EPA has been running on a quarterly basis from 1964 to 1968, it then became biannually from 1969 to 1974, and finally quarterly again from 1975 onwards. Each quarter covers 65,000 individuals, making up about 0.2 per cent of the Spanish population. In order to avoid problems with seasonality, we only retain the second quarter of each relevant year. Sampling weights adjusted for responses are used through the analysis.

We restrict the analysis to employees in paid work (i.e., employees and self-employed), aged between 16 and 64 in Spain. Occupations in the EPA are classified using the Spanish Classification Code (CNO-94). We recode occupations according to the International Standard Classification of Occupations (ISCO-88). Occupations are defined at the two-digit level. We exclude from our analysis workers associated with armed forces (ISCO 01), legislators and senior officials (ISCO 11), and agricultural occupations (ISCO 61 and ISCO 92). Employment in these occupations represents a small share of the total working population.[2]

The EPA does not include information on wages. To overcome this problem, we integrate our main source with the Structure of Earnings Survey (in Spanish *Encuesta de Estructura Salarial*, ESS). The ESS provides information on employee's wages and occupations. The survey has been carried out three times during the period of analysis (1995, 2002, and 2006). Throughout our analysis, we use the 1995 survey results, rather than the 2002 or the 2006, as our results remain invariant and is the closest to our starting period of analysis, 1994.[3][4] Average hourly wages are computed by first converting annual data into weekly income and then dividing by the weekly working hours (including overtime).

Our study needs time-consistent definitions of local labour areas. The area study, by Autor and Dorn (2013), interprets local labour markets as US commuting zones. The EPA does not include commuting zones; as such we choose 50 provinces as our econometric unit of analysis. Ceuta and Melilla are excluded from the analysis.

In order to properly measure the impact of technology on local labour markets, the assumption of low or null mobility of workers between provinces as a result of the effect of technological change must hold. If there were internal migration of workers, this would disperse the effect of technology exposure across the Spanish economy and undermine the effect. In Spain, the results are clear. Using Labour Force Survey data, Bentolila and Dolado (1990) show little evidence of any significant trend in regional mobility during the period 1960 to 1990. More recently, Gonzalez and Ortega (2011) find a very week

[2]Results remain invariant with the exclusion of those occupations. There results are available upon request.

[3]There results are available upon request.

[4]The high value of the Spearman correlation coefficients (0.92 between ESS1995 and ESS2002, 0.96 between ESS1995 and ESS2006, and 0.98 between ESS2002 and ESS2006) suggest that the wage rank is remarkably stable over time.

correlation between Spanish-born mobility and immigrant inflows at the level of local areas between 2001 and 2006. We can argue that the assumption that labour markets are regional in scope is a reasonable one.

5.3.1 The Routine Task Intensity (RTI) and the Routine Employment Share (RSH)

In order to investigate the effect that technological exposure has on local labour markets, we need information on routine task activities within provinces. Following Autor and Dorn (2013), we measure routine task activities with the Routine Task Intensity (RTI) index at the occupational level from an additional source, O*Net.[5] This index combines the routine, abstract, and manual task content of occupations, to create a summary measure, measuring the importance of routine tasks by removing measures of abstract and manual tasks. The index is calculated as follows:

$$RTI_k = \ln T^R_{k,1994} - \ln T^A_{k,1994} - \ln T^M_{k,1994} = \ln \frac{T^R_{k,1994}}{T^A_{k,1994} T^M_{k,1994}} \tag{5.1}$$

where $\ln T^R_{k,1994}$, $\ln T^A_{k,1994}$, and $\ln T^M_{k,1994}$ are the routine, abstract, and manual task abilities for each occupation k in the sample base year, 1994.

To contextualise the RTI, we derive our RTI at the occupational level from O*Net. This source is provided by the US Department of Labor. In O*Net, analysts at the Department of Labor assign scores to each task according to standardised guidelines, to describe their importance within each occupation.[6] Therefore, O*Net is a primary source of occupational information, providing data on key attributes and characteristics

[5] We use the framework by Autor and Dorn (2013) because they create the RTI. Other frameworks are Fernández-Macías and Hurley (2016), Fernández-Macías and Bisello (2017), and Matthes et al. (2014).

[6] We use version 11.0 of the survey, available at: http://www.onet.org

of occupations. O*Net data is collected for 812 occupations based on the Standard Occupation Classification (SOC2000). We convert SOC2000 codes into International Standard Classification of Occupations (ISCO-88) using a crosswalk made available by the Cambridge Social Interaction and Stratification Scale (CAMSIS) project.[7]

We follow the literature as close as possible by selecting components from O*Net which resemble those selected by Autor and Dorn (2013). We retain responses on "Harm-hand steadiness" and "Manual dexterity" for the manual aspect, on "GED math", and "Administration and management" for the abstract tasks, and on "Finger dexterity" and "Customer and personal services" for the routine dimension. After mapped into our ISCO-88 classification, we then normalized the RTI to have zero mean and unit standard deviation.

Table 5.1 presents the abstract, routine, manual, and RTI by Spanish region. It should be noted that Spain contains 52 provinces that are organised in 17 regions. For simplicity reasons we present the information at the regional level and not at the province level. The percentage of routine task intensity varies from 1.36 to -1.97, Galicia being the highest in routine task intensity and Madrid being the lowest. The difference between both is obvious: Madrid region has by far the largest city in Spain, it is a flourishing region with corporate headquarters, IT companies, multinationals, whereas Galicia is structurally weak. Another important difference is that while Madrid region has the most important city in Spain with 3.5 million of citizens (Madrid city), the biggest city in Galicia is Vigo with just 250 thousand citizens.

[7]Available at: http://www.cardiff.ac.uk/socsi/CAMSIS/occunits/us00toisco88v2.sps

Table 5.1: Task measures and RTI index by region

Region	Abstract index	Routine index	Manual index	RTI
	(1)	(2)	(3)	(4)
Galicia	0.38	0.44	0.33	1.36
Extremadura	0.38	0.43	0.33	1.23
Andalusia	0.39	0.44	0.33	1.09
Principality of Asturias	0.38	0.42	0.32	0.75
Cantabria	0.39	0.43	0.32	0.55
Castile and Leon	0.38	0.42	0.32	0.53
Aragon	0.38	0.42	0.32	0.43
Castile-La Mancha	0.38	0.42	0.32	0.36
Region of Murcia	0.38	0.42	0.32	0.33
Balearic Islands	0.39	0.42	0.32	0.23
Canary Islands	0.39	0.42	0.32	0.08
Valencian Community	0.39	0.41	0.31	-0.40
Catalonia	0.39	0.40	0.31	-0.77
Basque Country	0.40	0.41	0.31	-0.89
La Rioja	0.38	0.39	0.30	-1.19
Navarre	0.39	0.39	0.29	-1.72
Madrid	0.40	0.39	0.29	-1.97

Notes: Regions are ordered in descending order by the RTI.
Sources: Author's analysis from the EPA (1994) and O*Net.

To measure the RTI we rely on O*Net (look at Appendix B for construction of the indices). Therefore we measure the task content of occupations from a US survey. In Section 5.7, we further corroborate this results exploiting the task content of occupations from a European survey data, the European Working Condition Survey (EWCS). Differently from O*Net, the EWCS is a workers' survey data and it is administered by the European Foundation for the Improvement of Living and Working Conditions (Eurofound) and has become an established source of information about working conditions and the quality of work and employment. With six waves (one every five years) having been implemented since 1990, it enables monitoring of long-term trends in working conditions in Europe. At each wave, information on employment status, working time arrangements, work organisation, learning and training, and work-life balance among others is collected. In this research we focus on the second wave (1995). More information on the items selected is found in Section 5.7.

In order to measure the Routine Employment Share (RSH) within province we follow Autor and Dorn (2013), and we take take two more steps. First, using the RTI we classify as routine-intensity occupations those in the highest employment-weighted third share of RTI in 1994. Table 5.2 reports the 24 two-digit occupations, ranked in descending order by the RTI values. It also presents the employment distribution in 1994 and the cumulative distribution. Lastly, occupations that are considered routine-intensive occupations are indicated: "Other craft and related trades workers" (ISCO 74), "Machinery operators and assemblers" (ISCO 82), "Precision, handicraft, printing, and trades workers" (ISCO 73), "Metal, machinery, and related trades workers" (ISCO 72), and "Extraction and building trade workers" (ISCO 71).

Second, we compute for each province j, a routine employment share (RSH), calculated as:

$$RSH_{pt} = (\sum_{k=1}^{k} L_{pkt} * 1[RTI_k > RTI^{66}])(\sum_{k=1}^{k} L_{pkt})^{(-1)} \tag{5.2}$$

where L_{pkt} is employment in occupation k in province p at time t, $1[.]$ is a indicator function taking value of one if it is routine intensity. In other words, it is the routine employment share divided by employment share. The mean of RSH is 0.23 in 1994, and the interquartile (Iqr, henceforth) is 7 percentage points (RSH^{p25}=0.163 and RSH^{p75}=0.303). Accordingly, Table 5.3 shows the 1994 RSH by region ranked from low to high values where a higher RSH indicates a higher initial routine concentration.

Table 5.2: Task measures and RTI index by occupation

Occupation	ISCO-88	RTI	1994	Cumulative	Top 33 per cent
		(1)	(2)	(3)	(4)
Other craft and related trades workers	74	1.63	4.40	4.40	X
Machine operators and assemblers	82	1.34	4.67	9.07	X
Precision, handicraft, printing and related trades worker	73	1.02	1.17	10.24	X
Metal, machinery and related trades workers	72	0.89	7.26	17.49	X
Extraction and building trades workers	71	0.89	8.89	26.38	X
Drivers and mobile-plant operators	83	0.83	6.69	33.07	
Stationary-plant and related operators	81	0.82	1.25	34.32	
Labourers in mining construction, and manufacturing	93	0.76	5.48	39.80	
Sales and services elementary occupations	91	0.36	9.34	49.14	
Physical and engineering science associate professionals	31	0.26	1.73	50.87	
Models, salespersons and demonstrators	52	0.21	6.19	57.06	
Personal and protective services workers	51	0.14	10.02	67.08	
Life science and health associate professionals	32	-0.02	0.60	67.69	
Life science and health professionals	22	-0.18	2.62	70.30	
Office clerks	41	-0.38	8.03	78.33	
Customer services clerks	42	-0.68	4.94	83.27	
Physical, mathematical and engineering science profession	21	-0.95	1.80	85.06	
Other associate professionals	34	-1.12	5.27	90.34	
Other professionals	24	-1.19	0.48	90.81	
Corporate managers	12	-1.24	2.07	92.88	
Business associate professionals	33	-1.33	0.15	93.03	
Teaching professionals	23	-2.05	6.97	100.00	

Sources: Author's analysis from the EPA (1994) and O*Net.

Table 5.3: RSH by region

Region	RSH
Canary Islands	0.14
Andalusia	0.19
Galicia	0.19
Extremadura	0.20
Principality of Asturias	0.20
Balearic Islands	0.21
Cantabria	0.22
Castile and León	0.24
Region of Murcia	0.24
Aragon	0.25
Catalonia	0.26
Castile-La Mancha	0.26
Basque Country	0.27
Valencian Community	0.27
Madrid	0.28
La Rioja	0.32
Navarre	0.33

Notes: Regions are ordered in ascending order by the RSH.
Sources: Author's analysis from the EPA (1994) and O*Net.

5.4 Initial evidence of job polarisation

5.4.1 By occupational groups

We start our analysis by documenting the evolution of employment changes between 1994 and 2008. First, we compute employment shares for each job and their changes over time.[8] Second, we rank jobs according to their 1995 mean hourly wage.[9] Finally, we aggregate them into five equally sized groups containing almost the same percentage of employment in the initial year.[10] In Figure 5.1, we show the changes in employment share from 1994 to 2008 by job wage quintile. The figure shows a clear U-shaped curve

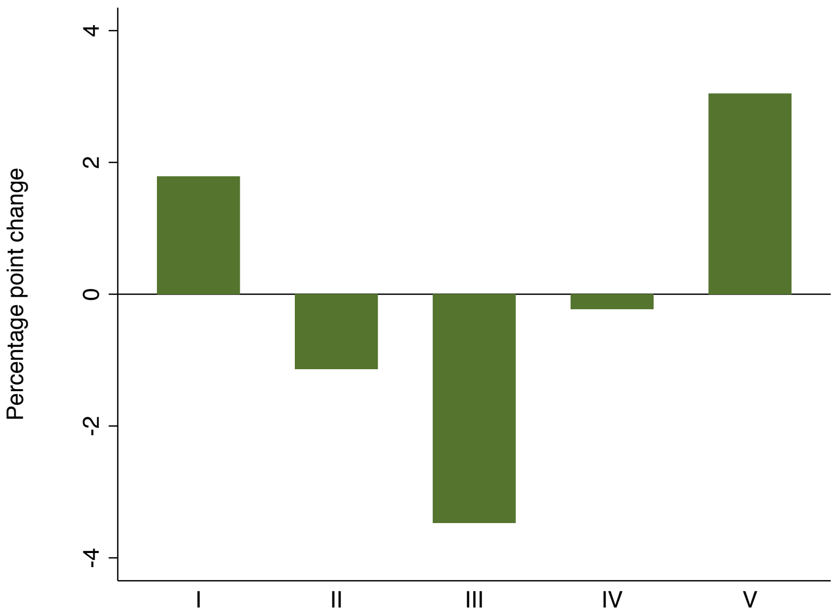
[8]In this occasion jobs are defined as the combination between two-digit occupation (ISCO-88) and one-digit industry (CNAE-93).

[9]Results remain invariant if we use the median.

[10]Jobs are defined as inseparable units therefore it is not possible to create groups that contain exactly the same percentage of employment.

of job polarisation: there is an increasing employment share at the bottom and top of the wage distribution (low and high-skilled jobs) and a decline in the employment share at the middle of the wage distribution (middle-skilled jobs). Figure 5.1 reveals a similar pattern as found by Anghel et al. (2014) and Sebastian (2017) for Spain, which is different from the results reported by Fernández-Macías (2012) and Muñoz de Bustillo and Antón (2015).

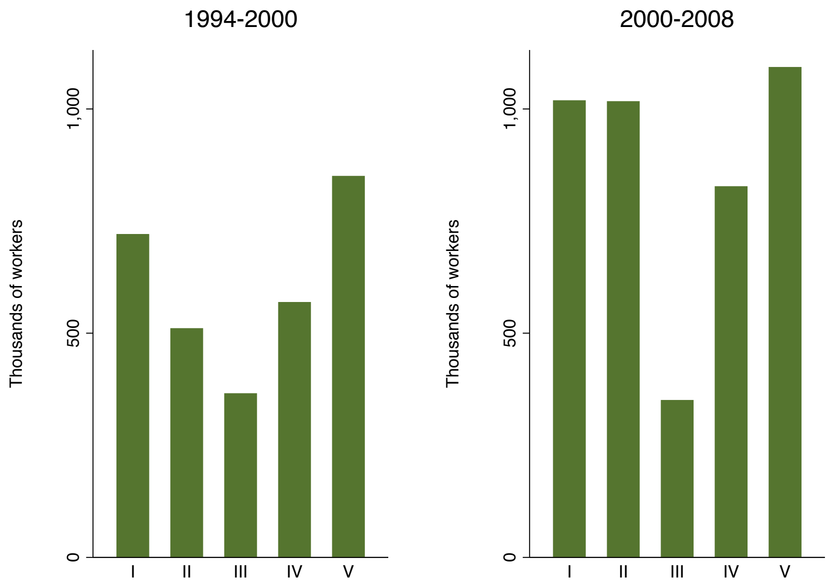
Figure 5.1: Evolution of employment changes between 1994 and 2010 by wage quintile



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on medan wages in 1995.
Sources: Author's analysis from the EPA (1994, 2008) and ESS (1995).

In Figure 5.2, we plot the percentage point change in employment share in each decade (1994-2000 and 2000-2008), ranked by hourly mean wage. Both scenarios are characterised by polarisation in employment growth. However, in the first decade there is a decline in the middle employment share of middle-skilled jobs (second, third and fourth quintiles), whereas in the second decade, just the third quintile decreased in the middle of the distribution. This pattern in the second decade is explained by the role of the construction during the first two years of the crisis (2007 and 2008).

Figure 5.2: Evolution of employment changes by time periods



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and ESS (1995).

To provide a more in depth analysis of these effects, we further analyse at the ISCO-88 two-digit level. Table 5.4 presents the major occupational groups ranked by their initial hourly mean wage (column 1), the level of employment during the period 1994 and 2008 (column 2 to 4), and the percentage point change in their employment between 1994 and 2008 (column 5). Drawing on Goos et al. (2014) we classify occupations into three groups which we label bottom, middle, and top-paid occupations. We again observe the job polarisation phenomenon among occupations: middling occupations are the ones with the higher decline (-8.56pp) compared to the bottom and top-paid occupations (-1.78pp and +10.35pp, respectively). Among the bottom-paid occupations, two out of six have a growing employment share. This group is driven by a mix effect: on the one hand service workers experience a significant positive employment growth (+3.49pp), while on the other hand, handicraft and printing workers exhibit a negative employment growth (-2.65pp). Within the middle-paid occupations, clerks (-3.33pp), metal, machinery and related workers (-2.66pp), and assemblers (+1.60pp) are those that experience the most significant employment losses. Concerning the group of top-paid occupations, those gaining more employment share between 1994 and 2008 are legal, social and related associate professionals (+4.32pp), and teaching professionals (+1.83pp).

To focus on the relevance RTI has in understanding job polarisation, Table 5.5 reports the average values of task occupations as well as the RTI in 1994. The middle-paid occupations have the highest positive values of RTI, therefore consistent with job polarisation. Occupations at the bottom are positive, occupations at the middle are either positive or negative, while occupations at the top score higher on the abstract measure and show negative values in RTI.

From Table 5.5 we classify these occupations into three major groups: routine, manual, and abstract occupations. First, the occupations with the highest RTI are defined as *routine-intensive occupations* (RI), as explained in Section 5.3 (occupational categories in bold). Second, we define the occupations in the top as *non routine abstract* (NRA). Finally, the remaining occupations in the bottom and middle category are defined as *non routine manual* (NRM).

One important question is whether the polarisation trend occurs in the manufacturing industry. For this purpose, we disentangle Table 5.4 by two sectors: manufacturing and non-manufacturing. Table 5.6 shows that job polarisation happens in both sectors: middle-paid occupations exhibit the highest declining shares with respect to the bottom and the top. One important difference is the manufacturing sector in the bottom is declining by 3.31 points, whereas the non-manufacturing sector is increasing by 0.21.

Table 5.4: Occupation, mean wage and RTI

Occupation	Code	Wage	1994	2000	2008	2008-1994	RTI
		(1)	(2)	(3)	(4)	(5)	(6)
Bottom occupations							
Labourers in mining, construction, manufacturing and transport	93	7.22	5.48	5.95	3.66	-1.82	0.76
Sales and services elementary occupations	91	8.04	9.34	8.46	10.06	0.71	0.36
Other craft and related trades workers	**74***	8.17	4.40	3.05	1.75	-2.65	1.63
Personal and protective services workers	51	8.45	10.02	10.45	13.51	3.49	0.14
Models, salespersons and demonstrators	52	9.50	6.19	5.77	5.88	-0.31	0.21
Extraction and building trades workers	**71***	9.65	8.89	9.57	7.68	-1.20	0.89
Middle occupations							
Drivers and mobile-plant operators	83	10.11	6.69	5.99	5.61	-1.07	0.83
Machine operators and assemblers	**82***	10.28	4.67	5.15	3.07	-1.60	1.34
Precision, handicraft, printing, and trades workers	**73***	10.33	1.17	0.79	0.40	-0.77	1.02
Customer services clerks	42	10.97	4.94	4.83	5.50	0.57	-0.68
Metal, machinery and related trades workers	**72***	12.78	7.26	5.91	4.59	-2.66	0.89
Office clerks	41	13.20	8.03	6.36	4.70	-3.33	-0.38
Teaching associate professionals	33	14.08	0.15	0.17	0.33	0.18	-1.33
Life science and health associate professionals	32	14.35	0.60	0.68	1.05	0.45	-0.02
Stationary plant and machine operators	81	15.34	1.25	0.97	0.92	-0.33	0.82
Top occupations							
Physical and engineering science associate professionals	31	18.44	1.73	2.16	3.11	1.38	0.26
Other associate professionals	34	18.95	5.27	8.04	9.59	4.32	-1.12
Other professionals	24	21.68	0.48	0.70	0.93	0.46	-1.19
Life science and health professionals	22	22.34	2.62	2.81	3.14	0.52	-0.18
Physical, mathematical and engineering science profession	21	24.31	1.80	2.28	3.14	1.34	-0.95
Teaching professionals	23	25.91	6.97	7.58	8.80	1.83	-2.05
Corporate managers	12	33.11	2.07	2.33	2.58	0.51	-1.24

Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Table 5.5: Task measures and RTI index by occupation

Occupation	Code	Group		Abstract index	Routine index	Manual index	RTI
			(1)	(2)	(3)	(4)	
Bottom occupations							
Labourers in mining, construction,and manufacturing	93	NRM	0.34	0.48	0.38	0.76	
Sales and services elementary occupations	91	NRM	0.30	0.38	0.30	0.36	
Other craft and related trades workers	**74***	RI	0.24	0.60	0.45	1.63	
Personal and protective services workers	51	NRM	0.33	0.33	0.32	0.14	
Models, salespersons and demonstrators	52	NRM	0.34	0.40	0.29	0.21	
Extraction and building trades workers	**71***	RI	0.35	0.50	0.42	0.89	
Middle occupations							
Drivers and mobile-plant operators	83	NRM	0.30	0.45	0.37	0.83	
Machine operators and assemblers	**82***	RI	0.29	0.58	0.44	1.34	
Precision, handicraft, printing and related trades worker	**73***	RI	0.35	0.52	0.45	1.02	
Customer services clerks	42	NRM	0.40	0.28	0.23	-0.68	
Metal, machinery and related trades workers	**72***	RI	0.40	0.53	0.45	0.89	
Office clerks	41	NRM	0.40	0.35	0.24	-0.38	
Teaching associate professionals	33	NRM	0.32	0.41	0.07	-1.33	
Life science and health associate professionals	32	NRM	0.45	0.33	0.38	-0.02	
Stationary plant and machine operators	81	NRM	0.38	0.53	0.41	0.82	
Top occupations							
Physical and engineering science associate professionals	31	NRA	0.45	0.41	0.39	0.26	
Other associate professionals	34	NRA	0.47	0.29	0.18	-1.12	
Other professionals	24	NRA	0.47	0.32	0.15	-1.19	
Life science and health professionals	22	NRA	0.57	0.36	0.38	-0.18	
Physical, mathematical and engineering science profession	21	NRA	0.62	0.39	0.20	-0.95	
Teaching professionals	23	NRA	0.52	0.30	0.09	-2.05	
Corporate managers	12	NRA	0.59	0.30	0.20	-1.24	

Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.
Sources: Author's analysis from the EPA (1994) and O*Net.

Table 5.6: Task measures and RTI index by industry

		Manufacturing				Non manufacturing			
Occupation	Code	1994	2000	2008	2008-1994	1994	2000	2008	2008-1994
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bottom occupations									
Labourers in mining construction, and manufacturing	93	8.89	8.99	5.93	-2.96	4.47	5.14	4.29	-0.18
Sales and services elementary occupations	91	1.49	0.94	0.87	-0.62	11.67	10.46	11.30	-0.37
Other craft and related trades workers	74	16.22	14.28	14.23	-1.99	1.01	0.73	0.42	-0.59
Personal and protective services workers	51	0.55	0.24	0.38	-0.17	12.83	13.17	14.19	1.36
Models, salespersons and demonstrators	52	1.02	0.93	1.05	0.03	7.73	7.06	6.86	-0.87
Extraction and building trades workers	71	4.46	5.07	6.85	2.39	10.20	10.76	11.06	0.86
Middle occupations									
Drivers and mobile-plant operators	83	3.57	3.43	4.44	0.87	7.61	6.68	6.02	-1.59
Machine operators and assemblers	82	18.73	22.69	18.68	-0.05	0.50	0.49	0.51	0.01
Precision, handicraft, printing and related trades worker	73	4.27	3.27	2.40	-1.87	0.25	0.13	0.09	-0.15
Customer services clerks	42	1.59	1.70	1.75	0.16	5.93	5.66	5.93	0.01
Metal, machinery, and related trades workers	72	15.83	11.79	10.26	-5.57	4.60	3.68	3.07	-1.53
Office clerks	41	6.60	5.13	4.90	-1.70	8.45	6.69	4.72	-3.73
Teaching associate professionals	33	0.19	0.22	0.33	0.14	0.19	0.22	0.33	0.14
Life science and health associate professionals	32	0.20	0.38	0.52	0.32	0.72	0.76	0.98	0.26
Stationary-plant and related operators	81	4.22	4.07	5.62	1.41	0.37	0.15	0.18	-0.19
Top occupations									
Physical and engineering science associate professionals	31	2.43	3.34	3.87	1.45	1.52	1.84	2.51	0.99
Other associate professionals	34	4.16	6.57	8.71	4.55	5.60	8.43	9.52	3.91
Other professionals	24	0.06	0.11	0.14	0.08	0.60	0.85	0.88	0.29
Life science and health professionals	22	0.28	0.29	0.42	0.14	3.31	3.48	3.25	-0.06
Physical, mathematical and engineering science profession	21	2.01	2.11	3.46	1.45	1.73	2.32	2.70	0.97
Teaching professionals	23	0.40	1.21	1.40	1.00	8.91	9.28	8.87	-0.04
Corporate managers	12	3.02	3.47	4.11	1.09	1.79	2.02	2.31	0.52

Notes: Occupations are ranked by ascending order by the mean hourly wage in 1995. Occupations in bold and with asteristic are those defined as routine-intensity.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Specifically, the manufacturing sector occupational categories losing the most are "Metal, machinery, and related trades worker" (ISCO 72), and "Handicraft and printing workers" (ISCO 74); in the non-manufacturing sector, it is "General and keyboard clerks" (ISCO 41). This result aligns with previous results from Autor et al. (2015), where they find job polarisation across economic sectors.

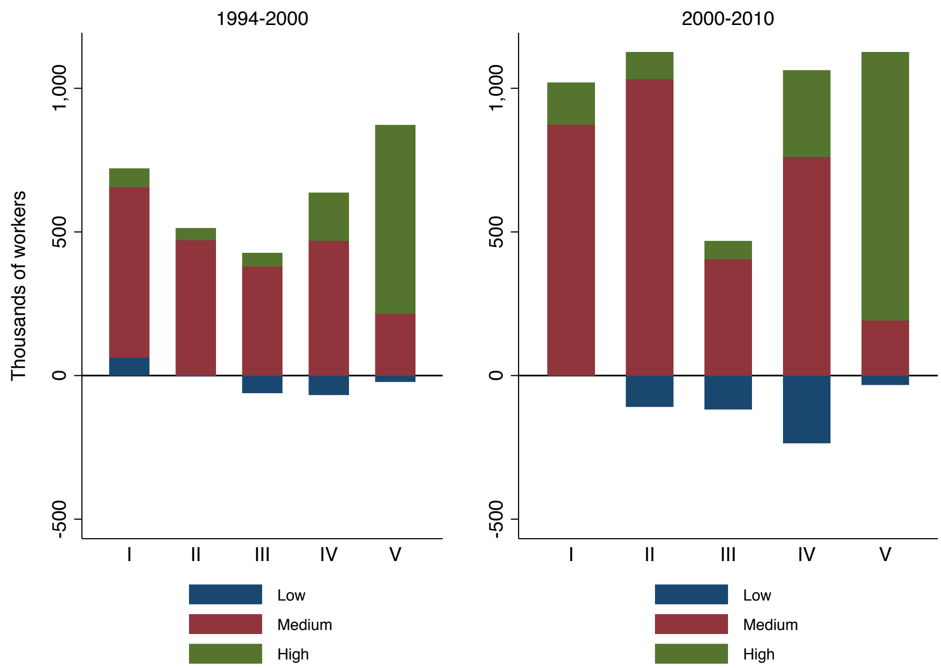
5.4.2 By demographic groups

We proceed with our analysis by examining changes in demographic groups, measured by educational qualification, migration status, and type of industry. Figure 5.3 plots changes in total employment in each decade from 1994 to 2008 by occupation wage quintiles. Graduates are represented by individuals with a university degree. Non-graduates are divided in two: low (primary and secondary education) and medium (upper secondary and post-secondary, non-tertiary education).[11]

Figure 5.3 shows that the low educated workers are losing employment in the middle of the wage distribution. Moreover, medium- and highly educated workers are gaining employment along the whole distribution, but medium educated workers have gained at the bottom whereas high educated at the top of the wage distribution. We further use number of years of education instead of using the categorical variable consisting in the highest level of educational attainment reached by workers. Results are robust to this alternative specification.

[11] The usual ISCED division into low, medium and high is adopted where low is equivalent to ISCED 0-2 (i.e., primary and lower secondary education), medium is given by ISCED 3-4 (i.e., upper secondary and post-secondary non-tertiary education) and high is ISCED 5-7 (i.e., tertiary education).

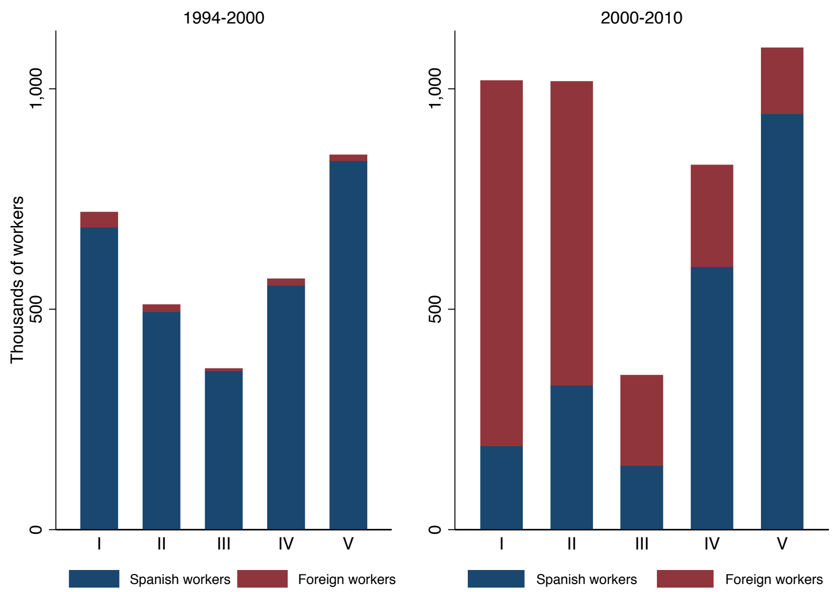
Figure 5.3: Evolution of employment changes by educational qualification and decade



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.3 shows absolute net employment change in job quintiles (in thousands of workers) by educational classification.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

To understand how migration status relates to job polarisation, in Figure 5.4 the employment distribution is broken into Spanish workers and foreigners. One observation is that the employment distribution of native employees is polarized in both periods but in larger magnitude in the first period. When we look at migrants, we observe an increase of foreign workers in bottom-paid occupations. Two thirds of the growth of jobs of the first quintile are taken by the immigrant workforce. These figures explain how, in a very short period of time, there was a radical change in the labour landscape in certain jobs such as hotels, catering or household services. Often these jobs were taken by workers with higher qualifications, giving way to a specific problem of over-education.

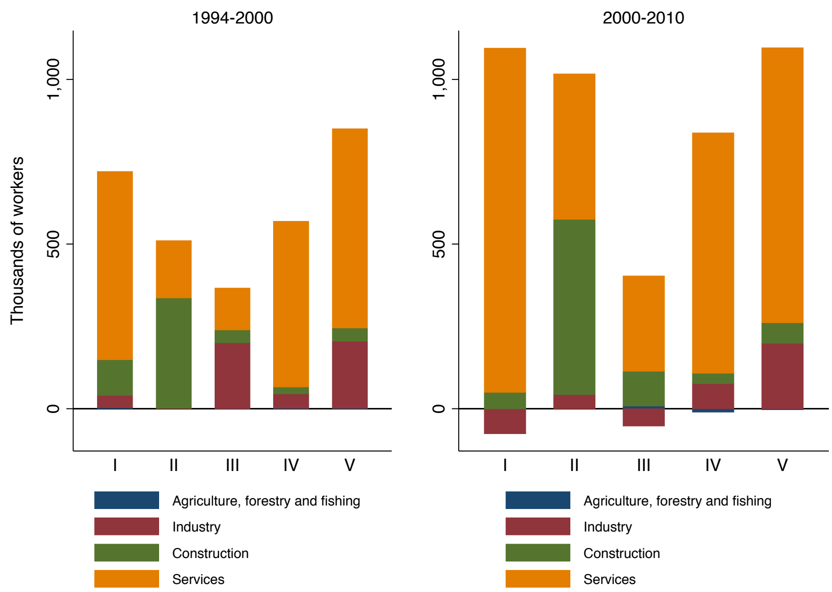
Figure 5.4: Evolution of employment changes by migration status and decade



Notes:Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.4 shows absolute net employment change in job quintiles (in thousands of workers) by Spanish workers (blue) and foreign workers (red).
Sources: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

Analysing by industry, Figure 5.5 shows changes in thousands of workers by type of industry. In order to do so, we use a classification of sector of activity comprising a manageable number of categories: agriculture, industry, construction, and services. Figure 5.5 reproduces the absolute changes in employment by quintile and sector of activity. Focusing on the main patterns, the following factors can be highlighted: first, services contribute in all quintiles, with a larger presence at the two extremes of the distribution. Moreover, the contribution of services outweights that of agriculture, industry, and construction. Second, the growth of construction is located, most of it, in the second quintile. Third, in the second decade, the destruction of employment is explained by the industry.

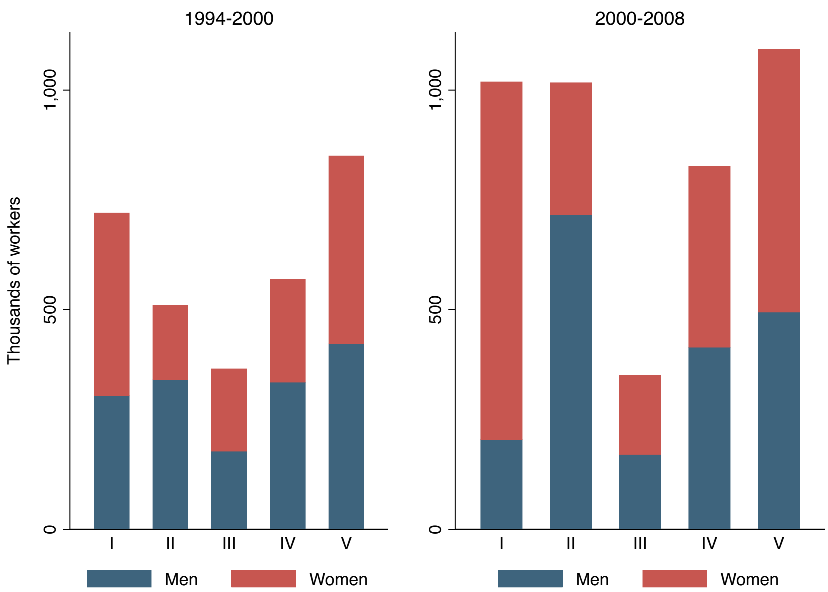
Figure 5.5: Evolution of employment changes by type of industry and decade



Notes: Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.5 shows absolute net employment change in job quintiles (in thousands of workers) by type of industry.
Sources: Author's analysis from the EPA (1994, 2008) and ESS (1995).

To complete the initial analysis, in Figure 5.6 we replicate the analysis by gender. Our findings are in line with previous figures. There are several highlights found in the chart: first, overall the gender perspective does not change the conclusion presented in relation to the nature of employment distribution. Both men and women have an employment distribution that fits with the polarisation phenomenon: losing employment in the middle of the wage distribution while gaining at the extremes. Second, within this general shared pattern, the employment change of women during both decades is more intensively polarizing. Third, the lack of growth of female employment in the second quintile. This "anomaly" is explained by the role of construction in this segment of the job distribution, a male dominated industry.

Figure 5.6: Evolution of employment changes by gender and decade



Notes:Jobs wage quintiles are based on two-digit occupation and one-digit industry and on mean wages in 1995. Figure 5.4 shows absolute net employment change in job quintiles (in thousands of workers) by gender.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and ESS(1995).

5.4.3 By labour market area

Table 5.7 presents descriptive statistics of the sample for a number of measures. This includes the routine employment share in local labour markets (RSH), the relative graduate share (GradSH), the migrant population share (MigSh), and the manufacturing population share (ManfSH) in 1994, 2000, and 2008.

As one can expect, the employment share in routine-intensity occupations decreases by 4 percentage points in two decades (from 1994 to 2008). Similarly, the relative share of manufacturing looses 2 percentage points in the period under study. On the contrary, the relative share of graduates and relative share of migrants increases over time. In the case of relative share of graduates grows in 6 percentage points in each decade, almost doubling between 1994 and 2008. The relative share of migrants increases during both decades and has accelerated during the second decade (+0.1pp), being almost explained by the increased in high-skilled migrants.

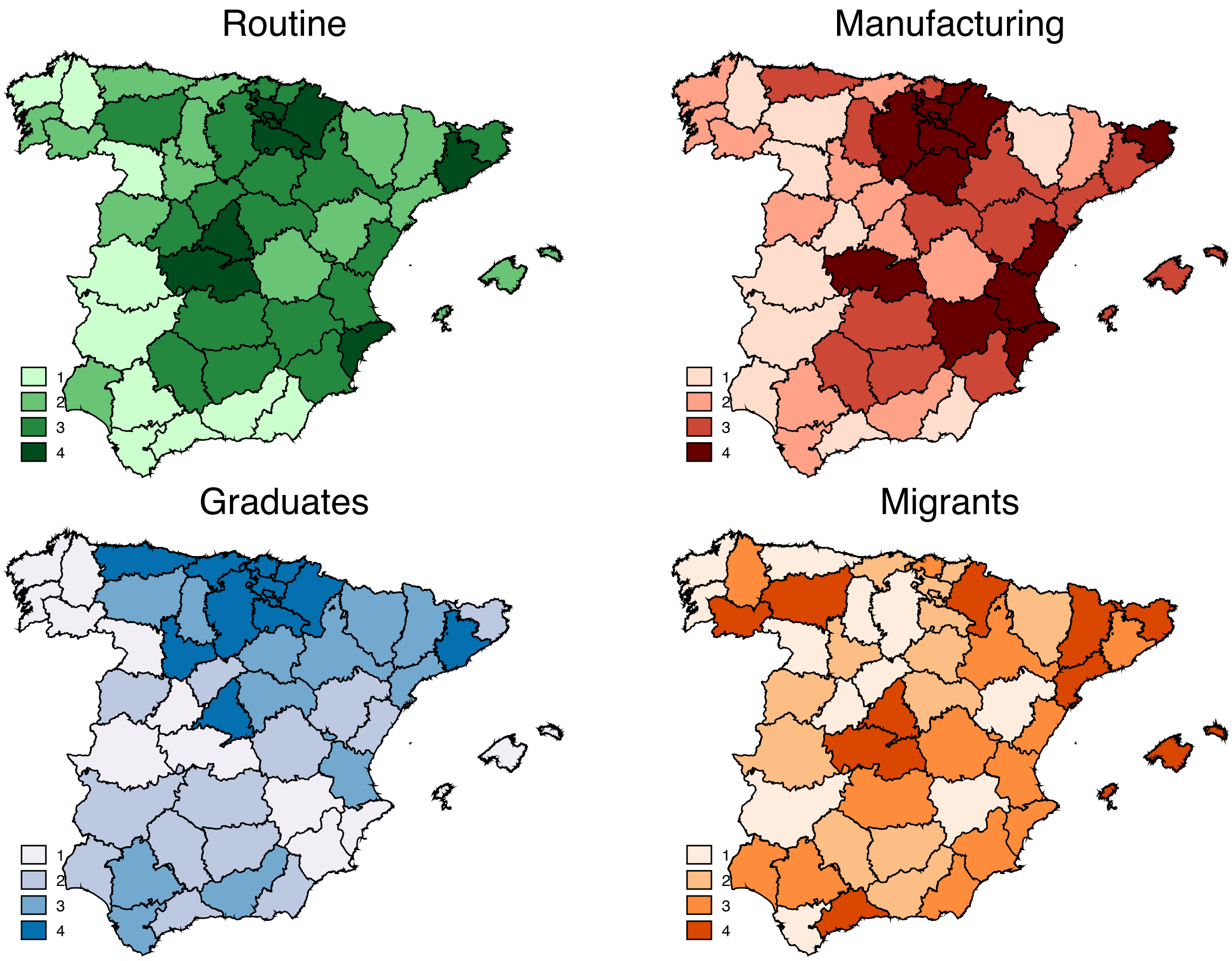
Table 5.7: Summary statistics

	1994			2000			2008		
	Mean	Std. Dev	Iqr	Mean	Std. Dev	Iqr	Mean	Std. Dev	Iqr
RSH	0.233	0.050	0.070	0.213	0.047	0.061	0.190	0.030	0.033
GradSH	0.193	0.052	0.060	0.255	0.056	0.064	0.316	0.068	0.086
MigSH	0.004	0.004	0.004	0.009	0.010	0.010	0.109	0.070	0.113
HigMigSH	0.001	0.001	0.002	0.003	0.003	0.002	0.022	0.018	0.023
LowMigSH	0.003	0.003	0.002	0.006	0.007	0.007	0.087	0.055	0.094
ManufSh	0.143	0.058	0.082	0.131	0.055	0.076	0.119	0.038	0.051

Sources: Author's analysis from the EPA(1994, 2000, 2008).

In the light of the above findings, Figure 5.7 shows the graphical distribution of routine, manufacturing, graduates, and migrants across Spanish province in 1994. Several important insights are revealed; first, higher levels in routine and manufacturing are concentrated in the same provinces, i.e., Navarra, La Rioja, and Basque country. Two exceptions to this rule are Madrid and Barcelona where they are more intense in routine employment than manufacturing specialization. Second, the two provinces with higher levels of graduates shares are Madrid and Barcelona, provinces that are typically specialised towards professionals, scientific and technical activities. Moreover, graduates share is more concentrated in the north with high presence in Asturias, Cantabria, Basque Country, Navarra, and La Rioja. Third, migrants working share are instead more spread geographically, with high concentration in the Mediterranean area.

Figure 5.7: Graphical distribution of routine, manufacturing, graduates and migrants employment share in 1994



Notes: We include the same number of provinces inside each group. As we have 50 provinces, our groups are uneven: the first group includes 12 provinces, the second group 13 provinces, the third group 13 provinces, and the fourth group 12 provinces.
Sources: Author's analysis from the EPA (1994, 2008).

5.5 Model specification

Until now, the descriptive statistics in Table 5.1 to Table 5.7, and Figure 5.1 through Figure 5.7 showed preliminary evidence of the displacement of labour on routine tasks, leading to a polarized employment distribution.

To test more rigorously the effect that technology has on labour and exploiting our regional database, we follow the Routine Biased Technical Change (RBTC) hypothesis. RBTC predicts that recent technological change is biased towards replacing labour in routine tasks (tasks that require methodological repetition, therefore being easier to automate). This progressive substitution of technology leads to two different effects depending on workers' relative comparative advantage: first, technology fosters workers who have a relative advantage in abstract tasks, expecting therefore a growth in high-skill occupations. Second, since technology substitutes routine workers with a comparative advantage in low-skill tasks (rather than in high-skilled tasks), we expect a greater reallocation of workers in jobs with routine tasks in non-manual occupations.

In the local labour market, we expect that provinces that initially have higher routine employment share, experience two different effects: first, a higher relative employment decline in routine occupations; second, a higher relative employment increase in manual (low-skilled workers) and abstract (high-skilled workers).

To test this hypothesis, we build on Autor and Dorn (2013) to analyse variation across the Spanish local market. We use the following model:

$$\Delta \mathrm{Y}_{pct} = \alpha_t + \beta_1 \mathrm{RSH}_{pt-1} + \beta_4 \mathrm{X}'_{pt-1} + \gamma_c + \delta_t + \epsilon_{pct} \tag{5.3}$$

where $\Delta \mathrm{Y}_{pct}$ is the change in local employment shares in (1) routine, (2) manual, and (3) abstract occupations, in province p located in region c, between the initial year and the final year considered (1994-2008). The RSH_{pt-1} is the variable capturing the initial local employment share of routine occupations in province p (see Section 3.1 for further details on how is derived). In order to control for potential shifts in local supply and demand, a vector of covariates is included (X'_{jt-1}). This includes information on the local initial relative shares of graduates and migrants, and the local initial share of manufacturing employment. To be more precise, the latter variable tries to capture the international import competition. To control for region-specific time trends, we include a dummy for regions in Spain (NUTS-2). The stacked regression also includes a dummy for time periods to account for changes over time.

5.6 Results and discussion

5.6.1 Changes in routine employment occupations

The first test is to identify whether historically routine intensive provinces have larger declines in routine occupations. We estimate equation (3) by ordinary least squares (OLS). Table 5.8 displays the estimates of the OLS regression model in routine occupations (panel a), graduates (panel b), and non-graduates (panel c). Table 5.8 also shows the estimates for time periods and for the stacked specification.

Table 5.8 (panel a) confirms that provinces with higher levels of routine employment shares, experience a higher decline in routine occupations. Single decades estimates are positive but only significant in the second decade, suggesting that the magnitude of this effect increases over time. The OLS estimates in panel (a) column (1) point out a decrease of 1.06 percentage points for provinces starting at the 75^{th} percentile more than those at the 25^{th} percentile of the routine employment distribution. The sign of this coefficient is the same as the findings in the US but the coefficient is lower. Autor and Dorn (2013) show that US commuting zones with a routine employment share at the 75^{th} percentile in 1990, decreased 1.8 percentage points more than a US commuting zone at the 25^{th} percentile during the first decade.

We continue our analysis by dividing the population between graduate workers (panel

b) and non-graduate workers (panel c). Two main remarks can be made: first, for graduate workers, the RSH estimates are not significant and negative, describing job polarisation as a non-graduate phenomenon. Second, for non-graduate workers, the RSH estimates are significant, positive, and the effect increases over time.

Table 5.8: Changes in routine occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: all			
RSH_{pt-1}	-0.106	-0.439*	-0.537*
	(0.171)	(0.222)	(0.289)
R^2	0.016	0.119	0.188
Panel B: graduates			
RSH_{pt-1}	-0.347	-0.738	-0.456
	(1.293)	(0.454)	(1.177)
R^2	0.305	0.155	0.115
Panel C: non-graduates			
RSH_{pt-1}	-0.269*	-0.411**	-0.676**
	(0.136)	(0.194)	(0.280)
R^2	0.099	0.131	0.138
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

The next stage of the analysis investigates the role of potential shifts in demand and supply in non-graduate workers. In Table 5.9 column 1-3, the econometric specification comprises the routine employment share, the relative local graduate share, and the relative local migrant share. In columns 4-6, we include the initial share of manufacturing.

Looking at column 1-3, our results indicate that the initial level of routine is significant and the magnitude is the same as the previous case. The inclusion of the initial graduate share and the initial migrant concentrations do not affect our results. The initial human capital has a negative effect on employment changes in non-graduate workers, being higher in the second decade. Therefore, higher levels of human capital experience a higher decline in the middle of the employment distribution for non-graduate workers. Differently from graduates, the initial relative share of migrants appears not significant in the first period and the stacked period. However, it is significant in the second decade. This predicts that provinces with initially higher migrant share experience a higher rise in routine occupations.

For columns 4-6, the initial share of manufacturing employment is included. It should be noted that the correlation between the main regressor of interest (RSH) and the initial share of manufacturing is high (0.48). When all the controls are added, the initial routine share is significant and increases its magnitude. The control variables are not significant in the first decade and the specification with stacked periods. However, during the 2000s, the initial migrant concentration has a positive effect and the initial share of manufacturing has a negative effect on employment changes in non-graduate workers.

Considering the effect of technology in routine occupations, provinces with initially higher specialization in routine-intensive occupations experience larger declines in non-graduate routine-intensive occupations.

Table 5.9: Changes in routine occupations: non graduates

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	-0.301**	-0.314*	-0.616***	-0.196*	-0.841**	-1.225***
	(0.131)	(1.165)	(0.045)	(0.099)	(0.391)	(2.02)
$GradSh_{pt-1}$	-0.134**	-0.176*	-0.306**	-0.034	0.053	0.026
	(0.060)	(.103)	(.142)	(0.083)	(.075)	(0.129)
$MigSh_{pt-1}$	0.063	0.244**	0.248	-0.189	0.189*	0.165
	(0.677)	(0.116)	(0.157)	(0.571)	(0.098)	(0.126)
$ManufSh_{pt-1}$				-0.370	-0.852***	-1.030
				(0.333)	(0.290)	(0.747)
R^2	0.185	0.233	0.237	0.297	0.555	0.529
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

5.6.2 Changes in manual employment occupations

In analysing changes in manual jobs, we expect that low-skilled workers reallocate from routine to manual tasks at the bottom of the employment distribution. This follows Autor and Dorn (2013) framework. The assumption behind the previous idea is that low-skilled workers comparative advantage is higher in low-skilled than in high-skilled tasks.

The results contained in Table 5.10 confirm this hypothesis. It displays the estimates of the regression model for all the workers (panel a), graduates (panel b), and non-graduates (panel c). OLS results point out a significant and positive effect of technological exposure on non-graduates in every decade as well as stacked periods. Therefore, provinces with initially higher routine tasks have a larger increase in non-graduate, manual occupations.

Table 5.10: Changes in manual occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: all			
RSH_{pt-1}	0.243	0.296	0.554
	(0.237)	(0.193)	(0.433)
R^2	0.084	0.143	0.128
Panel B: graduates			
RSH_{pt-1}	1.227	0.726	2.075
	(0.742)	(0.843)	(1.558)
R^2	0.221	0.162	0.165
Panel C: non-graduates			
RSH_{pt-1}	0.146*	0.255*	0.409**
	(0.079)	(0.133)	(0.180)
R^2	0.134	0.156	0.167
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Table 5.11 shows the results of the analysis on the reallocation of non-graduate workers in manual occupations. Again, we include the initial relative labour supply shares of graduates and low-skilled migrants (column 1-3) and the initial local share of manufacturing (column 3-6).

With respect to the initial labour supply share (column 1-3), the RSH coefficients are significant and positive. Therefore, the main results still hold when the control variables are plugged-in. Looking at the initial share of graduates, the results are significant, meaning that provinces with higher graduate share in the first year are negatively associated with employment changes in non-graduate manual occupations during the whole period. Therefore, the higher the graduate shares, the larger the decline in non-graduate manual occupations. However, no effect is found using the initial relative share of migrants.

In the last columns (4-6), the initial share of manufacturing employment is conditioned. Three observations can be done. First, the point estimate on the RSH variable remains significant. Second, the initial share of human capital is negatively associated with employment changes in manual occupations. Third, the initial share of migrants and the initial share of manufacturing do not have any effect.

Table 5.11: Changes in manual occupations: non graduates

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	0.102*	0.212**	0.208**	0.283**	0.131**	0.179**
	(0.118)	(0.095)	(0.099)	(0.109)	(0.057)	(0.068)
$GradSh_{pt-1}$	-0.211**	-0.167***	-0.372***	-0.153	-0.232***	-0.378***
	(0.094)	(0.044)	(0.113)	(0.105)	(0.052)	(0.132)
$MigSh_{pt-1}$	-1.227	0.128	-1.159	-1.319	0.235	-1.150
	-1.104	(0.592)	-1.501	-1.092	(0.582)	-1.533
$ManufSh_{p,t-1}$				-0.207	0.229*	0.0206
				(0.141)	(0.120)	(0.114)
R^2	0.456	0.388	0.567	0.488	0.449	0.567

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

Overall, the econometric analysis provides evidence for the displacement of middle-workers from routine occupations to manual occupations. Our results clearly suggest that provinces with initial higher level of routine task specialisation predict higher changes in manual occupations at the bottom of the distribution. Moreover, the initial number of graduate shares is significant and negatively associated to changes with non-graduates employment changes at the bottom of the occupational distribution. This finding differs from the result obtained by Autor and Dorn (2013) for the US.

5.6.3 Change in abstract employment occupations

So far we have showed the decline of employment share for non-graduate routine job workers and its next reallocation at the low part of the employment distribution. To finish the puzzle, we need to study employment changes in abstract occupations at the upper part of the occupational distribution. As explained in Section 5.5, due to a complementarity effect between high-skilled workers and technology, the model predicts an increased level of employment share for graduate abstract task workers.

Table 5.12: Changes in abstract occupations

	1994—2000	2000—2008	1994—2008
	(1)	(2)	(3)
Panel A: all			
RSH_{pt-1}	0.165	0.129	0.165
	(0.106)	(0.088)	(0.106)
R^2	0.037	0.193	0.194
Panel B: graduates			
RSH_{pt-1}	0.001	2.897	3.226*
	(0.625)	(1.828)	(1.897)
R^2	0.062	0.155	0.158
Panel C: non-graduates			
RSH_{pt-1}	0.405	0.709	1.102
	(0.345)	(0.556)	(0.782)
R^2	0.099	0.221	0.227
N	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

In Table 5.12, we investigate the effect that technology has at the top of the employment distribution. Table 5.12 presents changes in abstract occupations for the total number of workers (panel a), graduate workers (panel b), and non-graduate workers (panel c). One expectation can be formulated from the model: a positive effect of technological exposure on employment in abstract occupations. However, the initial relative share of routine labour is not statistically significant in any of our three scenarios. Therefore, we can conclude that technological change has not caused an upward shift of the marginal high-skilled workers.

Because of the absence of technological effect, the focus of the analysis shifts to the role of labour supply and demand shifter in increasing of graduate employment in top occupations. The results of the analysis are presented in Table 5.13.

Table 5.13 includes the initial local routine employment, the initial share of graduate concentrations, and the initial share of high-skilled migrants. The initial relative share of graduates is significant and negatively associated with high-educated workers changes in the first decade, while it is significant and positively associated with this variable during the second decade. The explanation behind this is a general education catch-up across areas during the first decade. Provinces with a larger proportion of worker with university degrees experiences the smallest increases in education, while in the 2000s, initial local graduate share has a positive effect on changes in graduate abstract occupations. For migrant share, the initial local high-skilled migration is significant and has a positive effect on changes in graduate abstract occupations. Provinces with higher high-skilled migration share have a larger increase in abstract occupations. Our intuition is that this variable is capturing the expanding process of the European Union.

In column 4-6, the full set of explanatory variables is included, incorporating the initial share of manufacturing employment. The introduction of initial share of manufacturing employment does not alter our results. The findings are also in line with the predicted outcomes of Autor and Dorn's (2013) model.

To summarise, technology exposure (the initial routine share) does not play any role in explaining changes in graduate abstract occupations. An important observation different from Autor and Dorn (2013) is that the initial share of graduates and migrants are positively related to changes in graduate abstract occupations.

Table 5.13: Changes in abstract occupations: graduates

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
RSH_{pt-1}	0.114	0.127	0.240	0.668	0.074	0.663
	(0.315)	(0.179)	(0.393)	(0.720)	(0.380)	-1.022
$GradSh_{pt-1}$	-0.317**	0.205**	-0.112	-0.193**	0.233**	0.0315
	(0.124)	(0.101)	(0.214)	(0.093)	(0.112)	(0.302)
$MigSh_{pt-1}$	0.407**	0.609***	1.017***	0.401**	0.637***	1.010***
	(0.172)	(0.176)	(0.318)	(0.190)	(0.173)	(0.341)
$ManufSh_{pt-1}$				-0.558	-0.107	-0.645
				(0.590)	(0.231)	(0.798)
R^2	0.226	0.367	0.489	0.293	0.427	0.519

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and O*Net.

5.7 Extensions and robustness checks

5.7.1 Potential endogeneity

The measurement of the causal effect of technology on local labour markets could require one identification assumption which is discussed in the literature. The assumption of OLS estimates is that the variation of routine occupation shares (RSH) is exogenous and is not driven by time-varying local specific unobservable. In what follows, we discuss this problem.

In order to understand the previous problem, a simplified version of equation (3) is used to replace the main regressor of interest:

$$\mathrm{RSH}_{pt-1} = RSH^*_p + \upsilon_{pt-1} \tag{5.4}$$

Replacing now (5.4) in (5.3), the latter equation can be rewritten as:

$$\Delta \mathrm{Y}_{pct} = \alpha^{'}_t + \beta^{'}_1 \mathrm{RSH}^*_p + \beta^{'}_2 \upsilon_{pt-1} + \epsilon^{'}_{pt} \tag{5.5}$$

where RSH^*_p represents the long-run quasi-fixed component of industrial structure which in our model determines provinces' routine occupation shares. Additionally, υ_{pt-1} stands for unobservables. In other words, time-varying attributes that affect at the same time changes in employment share ($\Delta \mathrm{Y}_{pt}$) and local routine occupation shares (RSH). If that is the case, we will obtain biased OLS estimates in equation (5.3). There are two possibilities:

(1) If $\beta^{'}_2 > \beta^{'}_1$ and Var $(\upsilon_1) > 0$ in equation (5), OLS estimates of β_1 in equation (5.3) will be upward biased.

(2) If $\beta^{'}_2 < \beta^{'}_1$ and Var $(\upsilon_1) > 0$ in equation (5), OLS estimates of β_1 in equation (5.3) will be downward biased.

To address this endogeneity problem, we construct an instrumental variable for the routine employment share levels based on the Autor and Dorn's (2013) instrument. It consists of exploiting historical local industry information to remove the long-run quasi-fixed component of the routine occupation share. The instrument is constructed as follows:

$$\mathrm{RSH}_p^{IV} = \sum \mathrm{E}_{i,p,1977} * \mathrm{R}_{i,-p,1977} \tag{5.6}$$

where $\mathrm{E}_{i,p,1977}$ is the employment share in industry i in province p, and $\mathrm{R}_{i,-p,1977}$ is the routine occupation employment share in industry i in all the Spanish provinces except p.

This measure is an appropriate instrumental variable for RSH: we expect that past industrial information is correlated with the long-run component and uncorrelated with current economic shocks. Therefore, we can obtain an exogenous measure for the routine employment share.

In Table 5.14, we estimate equation (6) by two-stage least squares (2SLS) regression model. Panel (a) displays the changes in routine occupations, panel (b) shows the changes in manual occupations, and panel (c) indicates the changes in abstract occupations. Table 5.14 reports as well the the Kleibergen-Papp F-statistics from each of the first-stage regression.[12]

As can be seen from Table 5.14, the initial routine employment share coefficient for the routine, manual, and abstract do not differ from the main analysis. However, the Kleibergen-Papp F-statistics is below the rule of thumb threshold of 10 proposed as by Staiger and Stock (1997). Although the instrument is not strong, the results are in line with those of the baseline analysis.

[12]Look at Appendix F for the first stage.

Table 5.14: Changes in occupations

	1994—2008
Panel A: Routine occupations	
RSH_{pt-1}	-0.406**
	(0.192)
Panel B: Manual Occuparions	
RSH_{pt-1}	-0.505*
	(0.286)
Panel C: Abstract occupations	
RSH_{pt-1}	-0.094
	(0.104)
First stage	
F-K test	6.990
N	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1977, 1994, 2000, 2008) and O*Net.

5.7.2 Contemporaneous labour supply changes

To explore the effect of the technology, the model must control for contemporaneous labour supply changes. The analysis addresses this by including the relative growth of graduates and migrants. Table 5.15 reports the estimates from OLS for the routine (panel a), manual (panel b), and abstract (panel c) specifications. It contains information on single decades and stacked periods.

Looking now to non-graduates routine occupations (panel a), results are in line with the main analysis: the decline at the middle part of the employment distribution is explained by technology exposure.

Panel b displays changes in manual occupations. The initial relative share of routine is positive related with changes in manual occupations. It suggests that the growth at the bottom part of employment distribution is explaining by technological exposure, confirming previous results. However, OLS results show a more substantial relevance of labour of labour supply changes: initial local graduates' concentrations are significantly related to manual occupations and this association grows over time.

Finally, panel c reports changes in graduate abstract employment. Different from what we found previously, OLS results suggest a significant positive effect of technology exposure on graduate workers. As in the main analysis, findings indicate that the initial graduates and high-skilled migrant share are positively correlated with changes in abstract occupations, and therefore, explain top employment growth.

Table 5.15: Conditional on local labour supply

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
RSH_{pt-1}	-0.269*	-0.411**	-0.676**	-0.269*	-0.415**	-0.689**
	(0.137)	(0.194)	(0.281)	(0.137)	(0.195)	(0.278)
$GradSh_{pt-1}$				-0.067	-0.243*	-0.301***
				(0.0577)	(0.131)	(0.112)
$MigSh_{pt-1}$				0.0137	0.00750	0.0213
				(0.0110)	(0.0198)	(0.0189)
Panel B. Non-graduate manual occupations						
RSH_{pt-1}	0.146	0.255*	0.409	0.138	0.256***	0.398**
	(0.238)	(0.135)	(0.341)	(0.154)	(0.078)	(0.161)
$GradSh_{pt-1}$			-0.365**	-0.312***	-0.675***	
				(0.136)	(0.037)	(0.153)
$MigSh_{pt-1}$			-0.019	-0.005	-0.025	
				(0.013)	(0.010)	(0.015)
Panel C. Graduate abstract occupations						
RSH_{pt-1}	0.405	0.709	1.102	0.378	0.671*	1.108*
	(0.345)	(0.556)	(0.782)	(0.354)	(0.375)	(0.635)
$GradSh_{pt-1}$			0.0184	0.727**	0.719	
				(0.217)	(0.313)	(0.493)
$MigSh_{pt-1}$				0.052*	0.002	0.057
				(0.026)	(0.049)	(0.064)
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1994, 2000, 2008) and O*Net.

5.7.3 Alternative database: EWCS

Until now, and following previous research, the study relied on O*Net to measure the RTI index. To test whether the results are robust to the use of this database (designed for the US), the same analysis is performed using the European Working Condition Survey (EWCS) dataset. One advantage is that assumptions on task composition between the US and Spain can be relaxed, the EWCS collects information on the latter country. However, there is no perfect correspondence between the two datasets, we selected those items that are similar in both databases (see Appendix G for more detailed).

Table 5.16 reports OLS and 2SLS estimates using the EWCS. Following Autor and Dorn (2013) as close as possible, we construct a measure of task intensity at the occupational level. For the abstract tasks, responses on “learning new things”, “solving unforeseen problems”, and “assessing yourself the quality of your job” are retained. For the manual tasks, we selected questions on “physical strength” (e.g., carrying or moving heavy loads), “skill or accuracy in using fingers/hands” (e.g., repetitive hand or finger movements), and “physical stamina” (e.g., painful positions at work). For routine tasks, we opt for routine activities they performed within their job: “does your main job involve (1) dealing with people, (2) repetitive tasks, (3) dealing with customers”. The items for manual and routine tasks are on a 7-point scale ranging from 1 (“all of the time”) to 7 (“never”). These variables in Likert scale are then normalized to range from 0 to 1. After collapsing each index at the ISCO-88 two-digit level, weighting each observation for the Spanish sampling weight, we merge the EWCS index to the EU LFS. The results obtained employing this database are very similar to the ones reported above, both in terms of statistical significance and size of the coefficients.

Table 5.16: Finding using EWCS

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
RSH_{pt-1}	-0.0676	-0.264*	-0.316*	-0.176	-0.240*	-0.416**
	(0.108)	(0.155)	(0.181)	(0.136)	(0.134)	(0.204)
$GradSh_{pt-1}$				-0.164**	-0.216*	-0.373**
				(0.0704)	(0.109)	(0.155)
$MigSh_{pt-1}$				0.043	0.273**	0.312
				(0.083)	(0.127)	(0.187)
Panel B. Non-graduate manual occupations						
RSH_{pt-1}	0.344	0.341***	0.691*	0.065	0.232**	0.304*
	(0.238)	(0.135)	(0.341)	(0.154)	(0.078)	(0.161)
$GradSh_{pt-1}$				-0.204**	-0.130**	-0.328***
				(0.097)	(0.052)	(0.120)
$MigSh_{pt-1}$				-0.019	-0.005	-0.025
				(0.013)	(0.010)	(0.015)
Panel C. Graduate abstract occupations						
OLS						
RSH_{pt-1}	0.144	1.016*	1.156	0.0414	0.212	0.171
	(0.374)	(0.579)	(0.882)	(0.296)	(0.188)	(0.341)
$GradSh_{pt-1}$				-0.324***	0.177	-0.148
				(0.117)	(0.115)	(0.215)
$MigSh_{pt-1}$				0.450**	0.596***	1.047***
				(0.183)	(0.179)	(0.329)
N	50	50	100	50	50	100

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and EWCS (2000, 2005, 2010, 2015).

5.7.4 Alternative definition of RSH

The overall analysis indicates that in Spanish provinces with higher routine specialization experience declines in routine occupations and larger increases in manual occupations. Nevertheless, the routine task specialisation is not able to explain the increases in high-skilled occupations. The initial graduate share and the initial high-skilled migrants are the main drivers of the employment growth at the top of the employment distribution.

One limitation is that the study relies on Autor and Dorn's measure to define the local routine share employment (RSH). However, the 30 per cent top of routine-intensive occupations of the RTI index may not be that restrictive. To test this, we re-construct the technology exposure measure using the top 40 per cent. Table 5.17 reports the estimates obtained by the new definition. In line with the baseline results, the estimates on the alternative routine share measures are similar in magnitude to the baseline, although they are less precisely estimated. We confirm the results presented above.

Table 5.17: Robustness check: top employment-weighted 40 per cent

	1994 2000	2000 2008	1994 2008	1994 2000	2000 2008	1994 2008
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-graduates routine occupations						
OLS						
RSH_{pt-1}	-0.206	-0.431**	-0.639*	-0.298*	-0.400*	-0.713*
	(0.172)	(0.199)	(0.330)	(0.174)	(0.209)	(0.348)
$GradSh_{pt-1}$				-0.258**	-0.336*	-0.591
				(0.123)	(0.171)	(0.261)*
$MigSh_{pt-1}$				-0.018	0.268*	0.240
				(0.080)	(0.136)	(0.162)
Panel B. Non-graduate manual occupations						
OLS						
RSH_{pt-1}	0.193	0.291**	0.229**	0.022	0.235*	0.142
	(0.254)	(0.122)	(0.107)	(0.116)	(0.119)	(0.158)
$GradSh_{pt-1}$				-0.386**	-0.248***	-0.624***
				(0.143)	(0.085)	(0.185)
$MigSh_{pt-1}$				-0.146	0.044	-0.109
				(0.151)	(0.081)	(0.208)
Panel C. Graduate abstract occupations						
OLS						
RSH_{pt-1}	0.405	0.709	1.102	0.125	0.271	0.395
	(0.345)	(0.556)	(0.782)	(0.362)	(0.189)	(0.464)
$GradSh_{pt-1}$				-0.512**	0.399*	-0.113
				(0.229)	(0.203)	(0.403)
$MigSh_{pt-1}$				0.509**	0.719**	1.228**
				(0.245)	(0.273)	(0.481)

Notes: All models include an intercept and region dummies. The stacked regression includes a time period dummy. Standard errors clustered at the province level are showed in parentheses in the stacked regression. Robust standard errors are used for single-period regressions. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1994, 2000, 2008) and O*Net.

5.8 Conclusion

During the last two decades, the employment structure of many developed economies has undergone substantial changes. On the supply side, many economies experience the simultaneous effects of an ageing and more feminine labour force, as well as increasing supplies of higher-education and foreign workers. On the demand side, economists have paid attention to employment effects of technological change and trade. This chapter contributes to this literature by examining the relationship between technological progress and employment polarisation in Spain exploiting the spatial variation of technological exposure at the local labour market.

We find that provinces with initial higher level of routine task adopted technology faster and witnessed a larger reallocation of routine employment at the bottom of the employment distribution. However, technology does not have any effect at the top of the employment distribution, countering Autor and Dorn's (2013) predictions. Our econometric analysis highlights the importance of supply side factors in order to understand the main drivers behind the growth at the upper part of the employment distribution. Concretely, initial high-skilled migrants concentrations and initial local graduates' concentrations show larger increases at the top part of the employment distribution.

In the last section we further cope with the potential endogeneity of the share of routine work within territories, we assess the robustness of OLS analysis employing the historical pattern of specialisation in each province as an instrumental variable. Results are in line with the OLS.

One important observation can be made from the study. While employment in Spain experienced a polarising trend at the occupational level between 1994 and 2008, technology is far from being represented as the only explanation for this phenomenon. As we can see from our analysis, there is a strong importance of demographic factors on employment changes. The dramatic changes in graduate labour supply affect the downward shift of middle-skilled workers as well as the increase in graduate abstract occupations. While the economic literature highlights the role of technology as the main determinant behind job polarisation, this chapter highlights that understanding the main drivers behind job polarisation is more difficult than expected. Much remains to be understood specially when making predictions on the future of jobs.

6. The effect of immigration on natives' task specialization. The case of Germany

6.1 Introduction

The potential negative effects of immigration on the labour market outcomes of native workers is one of the major concerns of researchers and policy makers alike. While the theoretical aspects of the possible effects of immigration on the receiving economies' labour markets are well understood (Dustmann et al., 2008), in reality, the effects are contingent on a number of factors, from the skills of migrants, those of the native workers and the institutional context, to the measures governments and firms enact in response to immigration. This multiplicity of factors might explain why the existing empirical studies (with estimates in the hundreds as per Longhi et al., 2008) have found often confusing and contradictory effects.

This chapter attempts to advance the existing literature by taking a more refined look at the effect of immigration on labour markets. Specifically, we investigate whether natives, as a response to increased migration, tend to specialize in communication-intensive occupations, where they arguably have a comparative advantage due to language proficiency.[1] We define migrants as foreign-born individuals and look specifically at the lower educated migrant group, as their contribution to the economy is usually more controversial and oftentimes thought to be negative (see Dustmann and Glitz, 2011, for a comprehensive literature overview on lower educational attainment of migrant workers). We follow the methodology developed by Peri and Sparber (2009) for the US. This methodology addresses concerns that responses to immigration to a certain region from native workers (through inter-regional mobility) and from firms (through changes in production and output mix), diffuse the costs and benefits across the entire country (Bansak et al., 2015). Moreover, it zooms in on skills cells in order to avoid complementarities and substitutabilities that cancel each other out (idem). The methodology also considers the often imperfect substitutability between native and migrant workers within a particular skill cell.

We conduct our analysis for Germany, a country that has received increasingly high numbers of immigrants over the past few decades (see Bauer et al., 2005, for more detailed information on immigration to Germany). Given that the wage structure in Germany is more rigid, that employment protection legislation is rather high and that unions still play a relatively large role in the wage-setting process (Pischke and Velling, 1997), we expect immigration to have a more significant effect on natives' employment than in the US context. We find that an increase in the share of low-skilled migrants is indeed associated with an increase in the share of natives specializing in communication-intensive occupations, and our results are in line with studies conducted for the US (Peri and

[1] Aldashev et al. (2009) document that language proficiency significantly increases employment probability and occupational choice for immigrants to Germany. Dustmann et al. (2010) show that employment rate and wage differentials in Germany and the UK are larger for immigrants from non-OECD countries.

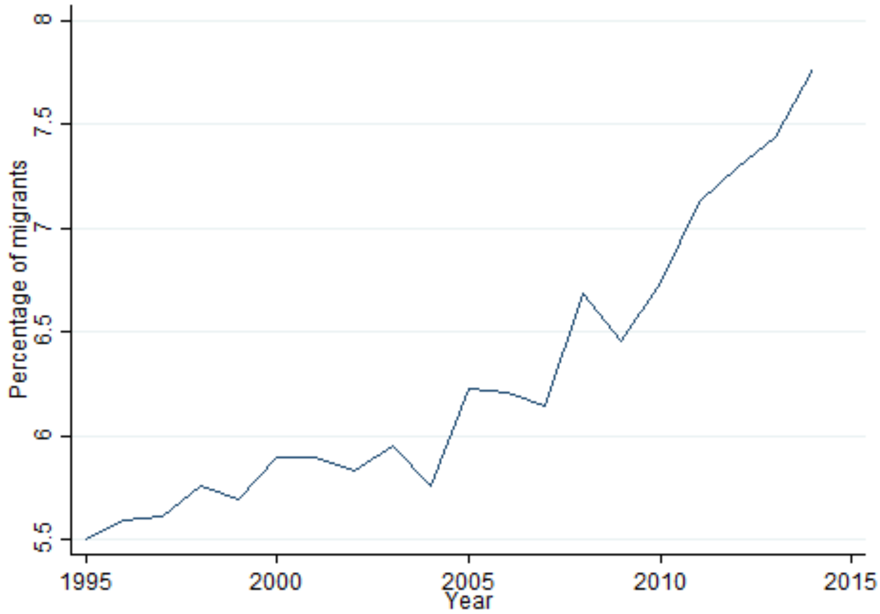
Sparber, 2009) and Spain (Amuedo-Dorantes and De la Rica, 2011).

The rest of the chapter is divided as follows. Section 6.2 provides an overview of the recent immigration trends to Germany, while section 6.3 reviews the existing literature on the effects of immigration on the labour market. Section 6.4 presents the data employed in the analysis and corresponding descriptive statistics. It also looks at the intensity of tasks by occupational group following the methodology employed by Peri and Sparber (2009). Section 6.5 presents the model and the results of our empirical analysis. Section 6.6 provides an alternative analysis using the PIAAC and EWCS datasets, to test the robustness of our results, while in Section 6.7 we conclude the research and provide a discussion on the implications of our findings.

6.2 Recent immigration trends to Germany

Net immigration flows to Germany have increased substantially since 1995, with a sharp increase being observed from 2010 onwards (Figure 6.1). The most recent increase can be attributed to the significant numbers of refugees coming from conflict-affected countries such as Syria, Iraq or Afghanistan. Significant growth can also be observed after the first enlargement round of the EU in 2004 and the second enlargement round in 2007, with a small decline during the Great Recession, in 2009.

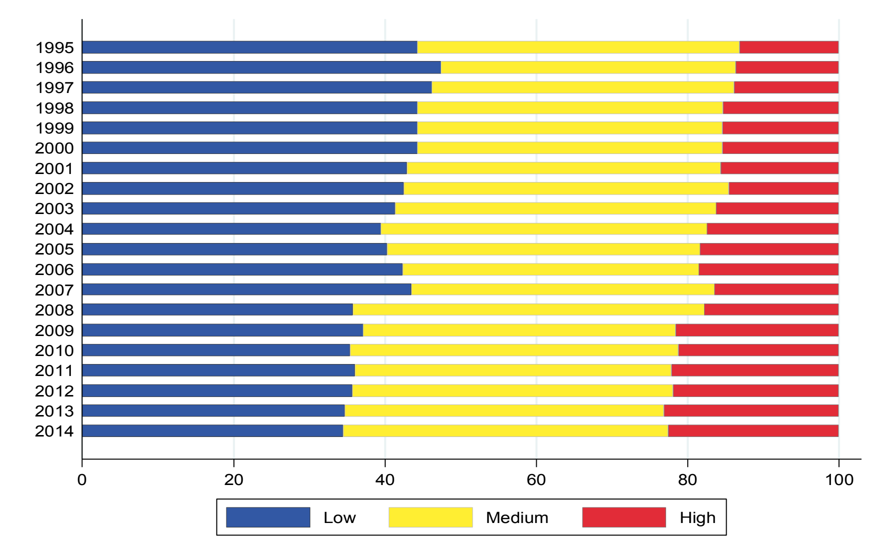
Figure 6.1: The evolution of the share of migrants in Germany's working age population



Notes: Percentage of migrants in working age population 16-65.
Sources: Author's analysis from the German Labour Force Survey (DE-LFS) (1995-2014).

In terms of the skill composition of the migrants in Germany (Figure 6.2), there seems to be a small shift from low-skilled to high skilled immigration during the period analysed. If in 1995, the share of highly skilled migrants was only 13 per cent while the share of low-skilled migrants 44 per cent, by 2014, 23 per cent of the migrant population was now highly skilled, with 34 per cent being low-skilled (a transfer of almost 10 per cent). The share of medium skilled migrants seems to have been more or less constant over the same time period.

Figure 6.2: Share of migrants by educational level, 1995-2014



Notes: Educational attainment coded into three values: high, medium and low-educated (skilled). The derived categorical variable for education takes value of 1 for low-educated (ISCED 0-2; i.e., primary and lower secondary education), 2 for medium (ISCED 3-4; i.e., upper secondary and post-secondary nontertiary education) and 3 for high (ISCED 5-7; i.e., tertiary education).
Sources: Author's analysis from the DE-LFS (1995-2014).

In light of the above observation, the information from Figure 6.3, which compares the share of migrants by broad occupational group, between 1995 and 2011, becomes even more interesting. To begin with, despite the fact that the share of low-skilled migrants in the total migrant population decreases overall in the past two decades, the share of migrants in elementary occupations increases substantially over the same time period. Moreover, compared to other occupational groups, migrants in Germany seem to be disproportionally found in lower skilled occupations, such as elementary and service and sale workers, pointing to a substantial skill mismatch.

Clerical occupations also register a significant increase in the share of hired migrants over the period analysed, as well as skilled agricultural and fishery workers, which more than doubled between 1995 and 2011. Highly skilled job categories such as professionals, associate professionals or managers increase only incrementally, despite a significant

Figure 6.3: Share of migrants by occupation

Notes: ISCO-88 occupations at one-digit level.
Sources: Author's analysis from the DE-LFS (1995-2011).

increase in the share of highly skilled migrants.

The picture changes significantly, however, if we look only at recent migrants (i.e., migrants with less than five years in Germany) (Figure 6.4). Whereas in 1999, most recent migrants would be employed in elementary occupations by a high margin, in 2011, migrant employment was more or less divided between professional, trades and machine operations occupations (the baseline period changes to 1999 due to data availability). Interestingly, while the overall share of migrants in Figure 3 pointed to a decrease in trade occupations between 1995 and 2011, the share among recent migrants is significantly larger. Recent migrants, thus, seem to be relatively better matched with their level of education, since there seems to be more or less an equal distribution between types of occupations.

Figure 6.4: Share of recent migrants (less than 5 years) by occupation

Notes: ISCO-88 occupations at one-digit level. Recent migrants are defined as those with at most five years of residence in Germany.
Sources: Author's analysis from the DE-LFS (1999-2011).

6.3 Literature review

6.3.1 The effect of immigration on labour markets

The impact of immigration on the hosts country's labour market depends critically on the skills of migrants, the skills of the native workers, and the characteristics of the host economy, including its institutions (Angrist and Kugler, 2003; Ruhs and Vargas-Silva, 2015). We should also distinguish between immediate and delayed effects, since in time the labour market can adjust to immigration.

The immediate effects are shaped significantly by the extent to which the skills migrants possess are substitutes or complements to the skills of the native workers (Borjas, 1995). If the skills of the migrants and natives are substitutes, the laws of supply and demand imply that an increase in immigration could results in increased competition for jobs and a decline in wages (Borjas, 2003). The extent to which the decrease in wages will in turn lead to a rise in unemployment depends on the native's willingness to accept the lower wages. Alternatively, complementarity between the skills of migrants and natives could lead to increased productivity and subsequent increases in wages for native workers.

The existing, rather vast literature, however, seems to contradict the neoclassical model —immigration has been found to have little or no effect on wages and employment. As Borjas (2003) points out, the measured impact of immigration on natives fluctuates significantly from study to study, but seems to be clustering around zero.

One explanation for the limited evidence of a negative effect of immigration on native worker's employment and wages may have to do with the underlying assumptions of the models employed. For instance, a great number of empirical studies use the spatial correlation method, which examines the relation between the share of immigrants and the labour market outcomes of native workers in a particular region. Examples include Dustmann et al. (2005) in the UK, Card (2005) in the US or Addison and Worswick (2002) in Australia, which find little or no evidence that immigration has an effect on employment or wages at the aggregate level. Yet, one of the major weaknesses of the spatial correlation method is its assumption that the effects of immigration are not offset by the internal migration of native workers (Bansak et al., 2015). If native outflows are larger than migrant inflows, then the effects of immigration would be indeed underestimated.

The skills cell approach, which implies that that the national labour market is divided by skill groups (education-age or experience cells), was developed as a way to overcome this particular issue of internal mobility of native workers as a response to immigration. Examples of studies using the method include the seminal work of Borjas (2003) for the

US, or more recently Card and Peri (2016) for the same country.[2] However, this approach depends on the assumption that immigrants and natives are perfect substitutes within pre-defined skill categories, which does not hold if immigrants considerably downgrade after arrival, as shown by Dustmann et al. (2013) in their analysis for Britain, or if natives change their skills in response to immigration.

Ottaviano and Peri (2008, 2011) build on this previous body of work and tackle the issue of perfect substitutability between native and migrant workers, an assumption many of the previous models take for granted. They argue that migrant and native workers with the same educational background can differ in their skills, leading them to different task specialisations. This in turn means that migrants and natives compete for different jobs and occupations, therefore the effect of migration on the native labour market should be minimal, if at all.

Peri and Sparber (2009) complement and extend the analysis of Ottaviano and Peri (2008, 2011) by focusing on workers without a college education in the US. Their principal contribution is the use of the "task biased technological change" framework to argue that the way in which occupations are affected by the arrival of migrants depends to a large extent on the comparative advantage of the tasks they perform, rather than on their educational level. They predict a progressive substitution of migrants for native labour in physical tasks. On the one hand, less educated migrant workers have a comparative advantage in occupations demanding physical tasks, mainly because of limited language proficiency. On the other hand, less educated native workers will reallocate to complex tasks under the assumption that their relative comparative advantage is higher in "communication tasks" than in "physical tasks". They empirically show that less educated

[2] As far as our understanding goes there is no research of this type for Germany

recent migrants specialise in physical occupations, while less educated native workers respond to the influx of migrants by increasing their supply of complex tasks.[3]

Amuedo-Dorantes and De la Rica (2011) build on the Peri and Sparber (2009) model by adding a gender dimension and looking at the case of Spain. The authors provide evidence that native men (women) reallocate to occupations with complex content in response to an increase in male (female) migration.

To the best of our knowledge, theirs is the only one study using this model to show the effect of migration on natives' task allocation. The present chapter builds on this existing literature and it advances it by looking at the case of Germany, a country with a significantly different labour market structure and dynamic than either Spain or the US.

6.3.2 The effect of immigration on the German labour market

A number of studies have looked specifically at the German context. Investigating geographical substitution effects between immigrants and natives across local labour markets in Germany, Pischke and Velling (1997) find little effects for displacement due to immigration. They conclude that the small or no effects of immigration previously observed in Germany cannot be explained by a reallocation of natives to other geographical areas. Similarly, using administrative data for the period 1987-2001 and a labour-market equilibrium model, D´ Amuri et al. (2010) find that the substantial immigration of the 1990s had very little adverse effects on native wages and on their employment levels. Glitz (2012) finds evidence of adverse employment effects but no detrimental effects on wages. Winkelmann and Zimmermann (1993) and New and Zimmermann (1994) find

[3] Similarly, Ottaviano et al. (2013) document that occupations characterized by low cognitive intensity, low communication intensity, high manual intensity and low overall complexity have a larger share of hours worked by immigrants.

that immigration has negatively affected the unemployment rate and wages of the native population, with some industries being hit harder than others. What is more, New and Zimmermann (1994) distinguish between white collar and blue collar jobs and find that the effect is negative only for blue collar, a finding that points to the importance of distinguishing between skilled and unskilled workers. More recently, Brücker et al. (2014) find that in the short term, wages are significantly affected in Germany, however, in the long term, under the empirically supported assumption that capital stocks adjust to shocks in labour supply, immigration does not affect wages. They also find that, since the elasticity of substitution between migrants and the native population is relatively low, the impact of immigration on both wages and employment is higher.

6.4 Data and descriptive statistics

We base our analysis on data derived from the German Labour Force Survey (DE-LFS) and explore the period between 2002 and 2014, for which information at the regional level is available. The DE-LFS is carried out as part of the annual micro-census, which is based on the "micro-census law" (Eurostat, 2009). The survey has been carried out since 1957 in the old West-Germany, and since 1991 in the new Bundesländer and East-Berlin. Quarterly data has been available from 2005 onwards, when the survey has been organised as a continuous survey covering all weeks of the year. The survey includes information on country of birth, on which we base our conceptualization of a migrant. Hence, we define migrants as those individuals who are foreign-born. We drop from our analysis long-term foreign-born workers (i.e., those with five of more years in Germany), as they are more likely to have acquired German proficiency and other human capital skills of natives.[4]

[4]Our results are robust to the inclusion of all the migrants.

Additionally, since we are most interested in analysing the effect that low-skilled migrants have on low-skilled natives task specialization, we restrict the data to only this educational group. We exploit information on the highest qualification achieved.[5] Moreover, since we look at the effect on task specialization, we confine our sample to only those natives and migrants which are either employed or self-employed, thus the working population. We use the NUTS1 regional disaggregation as available in the LFS, for a total of 16 regions.

Table 6.1 displays some descriptive statistics of low-skilled migrants and natives. Both groups seem to share similar characteristics, in terms of the average age in the sample or the share of younger adults (less than or 42 years old). The most substantial difference appears with regards to the share of women in the low-skilled bracket, which represents more than half for the native population, while almost 44 per cent for immigrants.

Table 6.1: Characteristics of low-skilled migrants and natives, low-skilled only

Characteristics	Natives	Immigrants
	(1)	(2)
Average age	37.1	39.8
Female (per cent)	51.3	43.5
Less than or equal to 42 years old (per cent)	61.9	62.9
Total number of observations	206,208	49,800

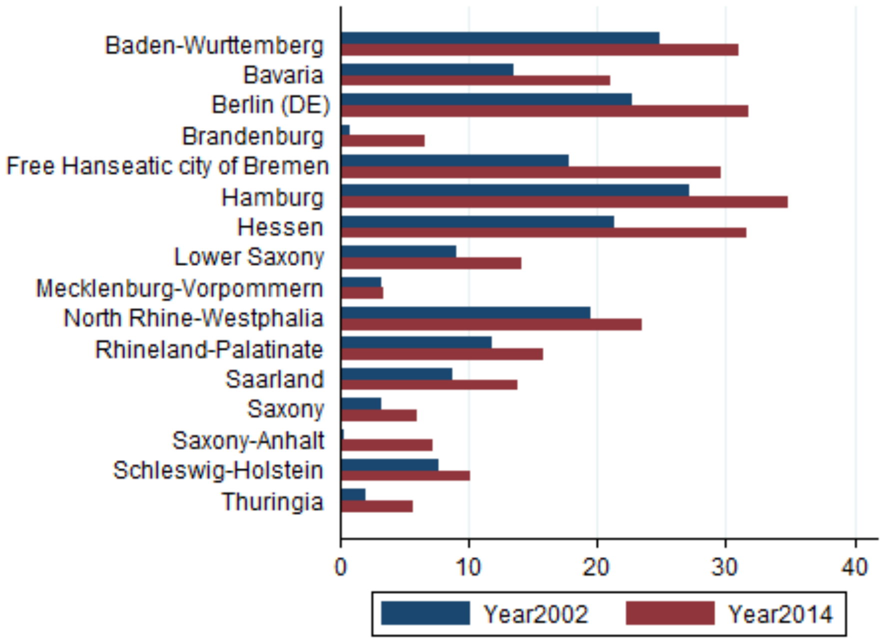
Notes: Workers (employed or self-employed) between 17 and 67.
Sources: Author's analysis from the DE-LFS.

Figure 6.5 looks at the change in the geographical distribution of less educated migrants across German regions. Although all regions register increases in the share of less educated migrants over the analysed period, the magnitude of the increase differs significantly. While regions such as Hamburg, Berlin, Hessen or Baden-Wurttemberg exhibit large shares for both time periods, regions such as Brandenburg or Saxony-Anhalt register differences between the two, with a significant upsurge from one period to the

[5] We use the variable hatlevel to measure the highest level of education.

other.

Figure 6.5: Share of less educated migrants, by region



Sources: Author's analysis from the DE-LFS (2002-2014).

6.4.1 Task-intensity variables

In order to investigate the effects of migrants on natives' task specialisation, we need information on the activities performed by workers on the job. Unless otherwise noted, and like previous studies on migration and task-specialisation, we rely on the US Department of Labor's O*Net abilities survey to derive data on job tasks requirements.[6] Hence, we work under the assumption that task composition is the same in the US and in Germany. This database makes our results easily comparable with other studies.

Applying the O*Net survey to our data poses some challenges. Mainly, the O*Net codify 812 occupations based on 2000 standard code (SOC) which we had to convert into ISCO-88, as we only have the occupations in ISCO. Therefore we convert occupa-

[6] We use version 11.0 of the survey. It is available at: http://www.onetcenter.org/

tional codes from SOC into ISCO using the crosswalk made available by the Center for Longitudinal Studies in the UK.[7] We aggregate the 812 occupations into 67 ISCO codes (three-digit level), and then into 25 ISCO codes (two-digit level).

We merge the O*Net abilities data with the German Labour Force Survey (DE-LFS) by occupation using the ISCO codes. In order to show the importance of each particular ability in Germany, we properly weight each occupation's ability raw scores. To facilitate the interpretation of our results, we transform the ability scores into percentages. This is done by dividing each weighted ability score by the maximum score of the ability in question in other occupation. As such, each final ability score ranges between 0 and 1, and is indicative of the relative importance of that particular task in the occupation at hand —as opposed to its importance in other occupations.

In order to establish the task content of each job's measures, we use the same framework as Peri and Sparber (2009). Their classification is based on a two-dimensional typology: manual as opposed to communication. We define manual skills using the following abilities: [1] dexterity ("Limb, hand, and finger dexterity", "Body coordination and flexibility", and "Strength"), [2] coordination ("Multilimb coordination" and "Gross body coordination"), and [3] strength (static and dynamic). Interactive skills include measures of oral and written expression and comprehension.

Table 6.2 presents the manual and the interactive tasks values, together with their ratio, for each of the two-digit ISCO-88 occupations included in the analysis. This aggregation offers a clear interpretation of task's content of the occupations. As one would expect, high-skilled occupations, "Corporate managers" (ISCO 12), "Physical, mathematical and engineering science profession" (ISCO 21) and "Life science and health

[7] Available at: http://www.cls.ioe.ac.uk

professionals" (ISCO 22) are those ones having the greatest level of interactive tasks and a smaller content of manual tasks. At the other end of the spectrum, low-skilled occupations such as "Agricultural, fishery and related labourers" (ISCO 92), "Metal, machinery and related trades workers" (ISCO 72) among others have high levels of manual tasks and a smaller content of interactive tasks. As a result, the values of C/M are lowest among craft and trade workers, and in operative and elementary occupations. Managers and professionals score instead among the highest.

Table 6.2: Task intensities by occupation

Occupations (ISCO-88 code)	M	C	M/C
	(1)	(2)	(3)
12 Corporate managers	0.35	0.83	0.43
13 General managers	0.38	0.72	0.53
21 Physical, mathematical and engineering science profession	0.29	0.82	0.35
22 Life science and health professionals	0.55	0.81	0.67
23 Teaching professionals	0.36	0.73	0.49
24 Other professionals	0.21	0.77	0.28
31 Physical and engineering science associate professionals	0.53	0.73	0.73
32 Life science and health associate professionals	0.63	0.72	0.87
33 Teaching associate professionals	0.28	0.61	0.47
34 Other associate professionals	0.27	0.71	0.38
41 Office clerks	0.27	0.65	0.42
42 Customer services clerks	0.36	0.60	0.59
51 Personal and protective services workers	0.64	0.56	1.13
52 Models, salespersons and demonstrators	0.56	0.58	0.97
61 Market-oriented skilled agricultural and fishery workers	0.87	0.46	1.86
71 Extraction and building trades workers	0.86	0.45	1.93
72 Metal, machinery and related trades workers	0.90	0.50	1.78
73 Precision, handicraft, printing and related trades worker	0.69	0.44	1.54
74 Other craft and related trades workers	0.79	0.43	1.83
81 Stationary-plant and related operators	0.79	0.49	1.62
82 Machine operators and assemblers	0.89	0.45	1.97
83 Drivers and mobile-plant operators	0.84	0.49	1.70
91 Sales and services elementary occupations	0.59	0.47	1.25
92 Agricultural, fishery and related labourers	0.98	0.31	3.18
93 Labourers in mining, construction, and manufacturing	0.80	0.45	1.74

Notes: Workers between 17 and 67 with little educational attainment (hatlevel=1). The manual (M) and communication (C) indices are derived averaging tasks measures and weighting with the DE-LFS.
Sources: Author's analysis from the DE-LFS (2002-2014).

We use the O*Net database, a US survey to measure the task content of occupations. In section 6.6, we test the robustness of these results by using the task content of occupations from two other sources of survey data: the European Working Condition Survey (EWCS) and the Programme for the International Assessment of Adult Competencies (PIAAC). Unlike the O*Net, the EWCS and PIAAC are workers' survey data. More information on the items selected is found in section 6.6.

6.5 The effect of immigration on the relative task supply of natives

6.5.1 Model specification

Thus far, we have provided preliminary evidence of the greater relative supply of manual tasks by migrants compared to native thorough the descriptive statistics in Table 6.1 and Table 6.3, along with Figure 6.1 through Figure 6.5. We now proceed to test whether less-skilled natives respond to increasing migration inflows by shifting onto job characterized by a lower manual to communication ratio.

To test the previous hypothesis we follow Peri and Sparber (2009). We collapse the data using data from 16 German regions from 2002 to 2014, and we estimate the next regression equation:

$$\ln[M_D/C_D]_{rt} = \alpha_r + \beta_t + \gamma(share_{foreign})_{rt} + \epsilon_{rt} \tag{6.1}$$

Where $\ln[M_D/C_D]_{rt}$ is the logarithmic average ratio of manual to communication supply at the regional (r)/year(t) level. We apply region fixed effects α_r to control for regional unobserved characteristics that might also affect task reallocation, and time fixed effects β_r to control for time-varying factors common to all regions.

Equation 6.1 examines the impact of the supply shock on the provision of relative manual tasks by less educated natives in the economy. If natives specialize in occupations requiring fewer manual, as opposed to interactive, tasks as the share of foreign-born workers increases, the coefficient γ should be negative and statistically different from zero.

Following Peri and Sparber (2009), we can go further and estimate whether the negative effect is due to a decrease in the native's supply of manual tasks or an increase in the natives supply of communication tasks. Therefore, we separately estimate equations Equation 6.2 and Equation 6.3:

$$\ln(M_D)_{rt} = \alpha_r + \beta_t + \gamma(share_{foreign})_{rt} + \epsilon_{rt} \tag{6.2}$$

$$\ln(C_D)_{rt} = \alpha_r + \beta_t + \gamma(share_{foreign})_{rt} + \epsilon_{rt} \tag{6.3}$$

When we measure the effect of migrants on native workers on local labour markets, the literature has defined two identification assumptions that must hold in order to estimate properly the previous equations. The first one concerns the inter mobility of native-born workers as a result of migrant-born workers flows. If there were internal migration of native-born workers, this would disperse the effect of migrant across the German economy and undermine the effect of it. The second issue deals with the potential endogeneity of foreign-born workers. We need to ensure that the variation of the share of less-educated foreign-born workers is exogenous and is driven by supply shifts (not by any unobserved employment opportunity). In the next two sections, we discuss more in depth these two problems.

Native-born mobility

Evidence on native-born mobility responses to migrant's inflows is mixed in the US. On the one hand, Frey (1995) and Borjas (2003) find evidence of an adverse effect of inmmigration on native internal mobility. On the other hand, Wright et al. (1997), Card (2001), and Card (2001) consider inter mobility of native-born workers an irrelevant issue. With regards to the UK, the results are clearer. Using the International Passenger Survey (IPS), Hatton and Tani (2005) show a negative correlation between net migration rate from abroad and inter-regional net migration rates. This relationship is however significant only for the southern regions. In a later paper, Wadsworth (2012) reexamined the relationship between immigration and interregional mobility. They show a weak correlation between UK-born mobility and immigrant inflows during the period 2004-2008.

As far as Germany is concerned, Pischke and Velling (1997) examined the impact of increased immigration on employment outcomes of natives in Germany at the local labour market.[8] Their analysis, which covers the period from 1985 to 1989, shows that there is little evidence for displacement effects due to immigration, and this is particularly true for unemployment rates. More recently, Glitz (2012) analyzes the specific issue of the impact of ethnic German immigration on the relative skill-specific employment and wage rates of the resident population in different geographic areas between 1996 and 2001. He finds evidence of adverse employment effects but no detrimental effects on average wages.

[8] It must be noted that Pischke and Velling (1997) use a more disaggregated level of regionalisation than us; therefore the internal mobility of German workers will be even less at a more aggregated level.

We can therefore argue that the assumption that labour markets are regional in scope is a reasonable one.

Endogeneity and measurement error

As previously stated, the endogeneity of migrants share could make our estimations inaccurate. Immigration does not take place in a vacuum, rather the decision of whether to migrate and where to migrate are made simultaneously. Therefore, characteristics which might explain the allocation of the migrant share across regions in Germany may also help explain the allocation of manual to communication tasks as migrants would migrate to areas which offer suitable or desirable employment opportunities. Many of these characteristics are unobservable, such as migrant abilities, risk aversion or labour demand conditions at regional level. This uncertainty makes it difficult to establish a causal relationship and tends to bias the estimations.

To address the potential endogeneity issue, we construct an instrumental variable for the share of low-educated migrant workers. We draw on Amuedo-Dorantes and De la Rica (2011) and use the share of low-educated long-term migrants —a group that was excluded from the analysis, as an instrument. The underlying assumption behind the choice of the instrument is that settlement patterns of previous migration cohorts are a main determinant of immigrants' location choices (Amuedo-Dorantes and De la Rica, 2011; Card, 2001; Ottaviano and Peri, 2011).

6.5.2 Results and discussion

The following section explores the relation between less-educated native workers and the corresponding less-educated migrants' task supply, across the 16 regions in Germany and across the 13 years under analysis. Namely, we investigate whether there has been a reallocation of native individuals to jobs characterized by a higher share of non-manual tasks, as a result of a rise in the share of migrants with similar skills.

Before moving on to the actual analysis, however, in a similar fashion to Peri and Sparber (2009) and Amuedo-Dorantes and De la Rica (2011), we control for a potentially spurious relationship between the immigration shock and natives' provision of manual to non-manual tasks. To do so we first regress each individual task supply on a number of personal characteristics, namely gender (female dummy), age (four age groups) and education level (dummy equal to 1 for a low level of education and 0 otherwise). We then obtain the "cleaned" residuals by subtracting the predicted task supply from the individual's observed task supply, which we use in the final regression analysis. Table 6.3 below displays the coefficients of the personal characteristics variables used in the "cleaning" procedure. The estimated coefficients seem to largely confirm our expectations —women generally tend to occupy jobs where communication skills are predominantly used while manual skills less so, a trend confirmed by a positive and a negative association, correspondingly. Age is negatively associated with manual-intensive tasks too, an intuitive find since manual tasks usually require more physical strength and vigour. Again not surprisingly, communication-intensive tasks are associated with higher levels of education, the effect being the strongest across all three indicators.

Table 6.3: Task supply "cleaned" of demographic effects

	Manual	Communication
	(1)	(2)
Female	-0.060***	0.027***
	(0.000)	(0.000)
Age	-0.002***	0.001***
	(0.000)	(0.000)
Low Education	0.059***	-0.077***
	(0.000)	(0.000)
Constant	0.256***	0.494***
	(0.000)	(0.000)
N	1,873,287	1,873,287

Notes: We use the "cleaned" residuals from the above regressions to compute the manual and communication task supply measures. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the DE-LFS (2002-2014).

Turning to our regression analysis, Table 6.4 below presents an ordinary least square and a weighted least square regressions including and excluding the region of Berlin, where the migrant share in the working population is substantially higher, which might lead to biased results. Standard errors are clustered by region. We find that an increase in the share of low-educated migrants has a negative effect on the manual and communications task content of the native workers. Specifically, a one percent increase in the relative supply of migrants is associated with between 0.8 and 1.4 percent decrease in the supply of manual versus communication tasks for the native population. Turning to the relative supply of manual and communication tasks for natives, our findings suggests that a one percent increase in the supply of migrants decreases the supply of natives' manual tasks by 0.6 to 1.1 percent, while it increases the supply of native's communication tasks between 0.2 to 0.3 percent.

When we exclude Berlin, an outlier which exhibits a relatively high share of migrants in the working population, the direction and magnitude of our effect seems to hold for both the ordinary and weighted least square equations. The OLS and WLS estimates are almost identical to those measuring the tasks content of occupations across all 16 regions: all coefficients have the expected sign and are statistically significant, suggesting that our results are not driven by the inclusion of outliers in the data.

As hypothesised above, the magnitude of the effects of immigration of natives' relative supply of tasks in Germany is substantially higher than in the case of the US (see Peri and Sparber, 2009), or the case of Spain (see Amuedo-Dorantes and De la Rica, 2011), the difference being largely due to variation across labour market systems.

Table 6.4: The effect of migration on the relative task supply of less-educated native workers, OLS and WLS

	Explanatory variable: share of low-educated migrant workers			
Dependent variable	OLS	WLS	OLS without Berlin	WLS without Berlin
	(1)	(2)	(3)	(4)
Ln(M/C)	-1.406**	-0.839***	-1.367**	-0.789***
	(0.546)	(0.227)	(0.548)	(0.220)
R^2	0.255	0.218	0.207	0.178
Ln(M)	-1.074**	-0.645***	-1.047**	-0.610***
	(0.415)	(0.161)	(0.413)	(0. 158)
R^2	0.152	0.160	0.123	0.116
Ln(C)	0.332**	0.194**	0.320*	0.178**
	(0.145)	(0.076)	(0.150)	(0.074)
R^2	0.137	0.120	0.119	0.109
Region and year fixed effects	Yes	Yes	Yes	Yes
Observations	208	208	195	195

Notes: Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Specifications (3) and (4) do not include Berlin. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis the DE-LFS (2002-2014).

To address any potential endogeneity between the relative supply of manual and communication tasks and variation in the share of migrants, we use an instrumental variable.

Specifically, we use the share of long-term low-educated migrants as an instrument.[9] Table 6.5 below reports the results of the IV regression against the results of the previous OLS regression, including the first-stage regression and the Kleibergen-Paap F-statistics. The results of the IV regression also point to a negative effect of an increase in the share of low-skilled migrants on the relative task allocation of natives. Thus, the effects hold true regardless of the methodology employed. Moreover, the F-statistics value is 28.9, above the Staiger and Stock's (1997) rule of thumb threshold value of 10. Furthermore, the magnitude of the effect becomes notably larger and the effect itself becomes significant at 99 per cent confidence interval when we introduce the instrument. Specifically, a one per cent increase in the relative supply of low-educated immigrants seems to lead to a 5 per cent decrease in the supply of manual versus communication-intensive tasks for the native population. Moreover, a one per cent increase in the relative supply of migrants seems to reduce the native's supply of manual-intensive tasks by 2 per cent and to increase the supply of communication-intensive tasks by 1 per cent. Again, the immigration effects in the case of Germany seem to be considerably larger than the ones found in the case of the US and Spain, a clear consequence of the more rigid nature of the labour market.

[9] See Appendix H ,Table H1, column 1, for the first stage regression.

Table 6.5: The effect of migration on the relative task supply of less-educated native workers, OLS and IV

Dependent variable	OLS	IV
	(1)	(2)
Ln(M/C)	-1.406**	-2.322***
	(0.546)	(0.431)
R^2	0.255	
Ln(M)	-1.074**	-1.812***
	(0.415)	(0.286)
R^2	0.152	
Ln(C)	0.332**	0.510***
	(0.145)	(0.161)
R^2	0.137	
First stage F-K test		28.919
Region and year fixed effects	Yes	Yes
Observations	208	199

Notes: Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the DE-LFS (2002-2014).

The analyses above explore the effect of an increase in the relative supply of the general population of immigrants, however, it seems rather intuitive to expect different effects when distinguishing between recent and long-term migrants. We define recent migrants as those who have been living in the country for less than 5 years. We expect that long-term migrants, by virtue of having lived in the destination country for longer time, accumulate more specific human capital and become comparable to native workers in terms of knowledge of the local language and the local labour market. From this perspective, long-term migrants become less complementary and more substitutes to the native population.[10]

However, because of the high collinearity between these two migrant groups, we cannot test empirically this effect; what we do instead, in a similar fashion to Amuedo-Dorantes

[10]The terms skill and education are interchangeable in our context.

and De la Rica (2011), is to explore the average relative supply of manual to communication tasks for natives, recent and long-term migrants (Table 6.6). As expected, recent migrants supply more manual relative to communication skills than long term migrants, while natives supply the least manual skills, or, conversely, the most communication skills.

Table 6.6: Average relative task supply for different groups of low-educated workers

Variable	Natives	All migrants	Recent migrants	Long-term migrants
	(1)	(2)	(3)	(4)
M/C	0.857	0.919	0.934	0.917
	(0.41)	(0.37)	(0.37)	(0.36)
Observations	203,093	49,627	4,801	44,826

Notes: Recent migrants are those with at most 5 years of residence in Germany. Only working individuals between 16 and 65 with little educational attainment (secondary and primary or less education) are considered. Standard deviations in parenthesis.
Sources: Author's analysis from the DE-LFS (2002-2014).

Indeed, the results in Table 6.7 seem to confirm our assumptions. Firstly, female migrants seem to exert no effect on the task supply of native females, confirming our hypotheses of substitutability. More interesting, however, is the fact that the situation changes when we consider only recent female migrants —they seem to have a negative effect on both the supply of manual versus communication skills of the native females and on the supply of manual skills. Again, no effect on the supply of communication skills of the native female workers. This is a most fascinating finding. If we interpret it correctly, then recent female migrants are not direct substitutes to native female workers because of potential language barriers; in time, however, they improve their language abilities and become substitutes for the native female workers, which is why we do not find an effect pointing to task reallocation. The same cannot be said about male migrants, which seem to be complementary to the native male workforce even after long-term residency; we find a significant, negative effect on the supply of skills for both long-term and recent migrants.

Table 6.7: The effect of all migrants and recent migrants on the relative task supply of less-educated native workers from a gender perspective, OLS and IV

Dependent variable	OLS	OLS recent	IV
	(1)	(2)	(3)
$\text{Ln}(M/C)_{Female}$	-0.391	-3.105**	-0.832**
	(0.463)	(1.131)	(0.361)
R^2	0.043	0.114	
$\text{Ln}(M)_{Female}$	-0.455	-2.150**	-0.896***
	(0.366)	(0.762)	(0.266)
R^2	0.049	0.105	
$\text{Ln}(C)_{Female}$	-0.065	0.954	-0.064
	(0. 166)	(0.559)	(0.125)
R^2	0.039	0.086	
$\text{Ln}(M/C)_{Male}$	-2.193***	-6.567***	-3.450***
	(0.681)	(1.367)	(0.951)
R^2	0.233	0.368	
$\text{Ln}(M)_{Male}$	-0.918***	-2.643***	-1.481***
	(0.290)	(0.592)	(0.133)
R^2	0.227	0.348	
$\text{LN}(C)_{Male}$	0.483***	1.546***	0.701***
	(0.145)	(0.264)	(0.082)
R^2	0.203	0.346	
First stage F-K test			28.919
Region and year fixed effects	Yes	Yes	
Observations	208	199	199

Notes: Each cell contains estimates from separate regressions and Ln(M/C) is calculated for each specific demographic group of natives. Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the DE-LFS (2002-2014).

6.6 Sensitivity analysis: EWCS and PIAAC tasks variables

The previous section has pointed to a negative relationship between the increase in the share of migrant workers and the relative task supply of the native workers. However, as already mentioned, we have used the O*Net data from the US to conduct our analysis, a major reason being the possibility to compare our results to other existing studies. We now conduct a sensitivity analysis to test the robustness of our findings using two alternative datasets: the European Working Condition Survey (EWCS) and the Programme for the International Assessment of Adult Competencies (PIAAC). One advantage of these datasets is the fact that we do not need to assume the same task composition between the US and Germany any longer, as both the EWCS and PIAAC collect information on the latter.[11] However, there is no perfect correspondence between the three datasets, therefore we have tried to select the items that most resemble each other.[12]

Table 6.8 reports OLS, WLS and IV estimates using the EWCS. In this case, we select the items on "skill in using hands or fingers" (e.g., repetitive hand or arm movements), "physical strength" (e.g., carrying or moving heavy loads), and "physical stamina" (e.g., tiring or painful positions) to represent manual skills, and "dealing directly with people who are not employees at your workplace" and "using internet / email for professional purposes" to represent communication skills. The results resemble the baseline model with regards to the significance and magnitude of the effect. The OLS estimates are almost identical to those obtained while using O*NET. When we instrument the share

[11]See Appendix B for more information on the construction of the indices.

[12]See Appendix I for a complete mapping between task variables in the three dataset.

of migrant workers, the results are statistically significant, still positive, the magnitude is higher but the Ln(C) is not significant. The main differences appear when using the weighted least square regressions: WLS estimators are not statistically significant and the magnitude is lower.[13]

Table 6.8: The effect of migration on the relative task supply of less-educated native workers, OLS, WLS and IV using EWCS

Dependent variable	OLS	WLS	IV
	(1)	(2)	(3)
Ln(M/C)	-1.089*	-0.135	-2.493**
	(0.549)	(0.376)	(0.963)
Ln(M)	-0.913**	-0.300***	-1.548
	(0.365)	(0.105)	(0.435)
Ln(C)	0.176*	0.235	0.909
	(0.437)	(0.134)	(0.569)
First stage			
F-K test			31.161
Region and year			
fixed effects	Yes	Yes	Yes
Observations	208	208	199

Notes: Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the DE-LFS (2002-2014) and EWCS (2005).

In Table 6.9 we repeat the same regressions, this time using the PIAAC dataset, after a suitable conversion of occupational codes.[14] In this case, we define manual skills using the following items: "how often does/did your job usually involve using skill or accuracy with your hands and fingers at your workplace?" and "how often does/did job usually involve working physically for a long period?". Communication skills are defined using the items "how often does/did job usually involve making speeches or presentations in front of five people or more?" and "how often does/did job usually involve selling a

[13]See Appendix H ,Table H1, column 2, for the first stage regression.

[14]ISCO-08 occupational codes in PIAAC were matched to the ISCO-88 classification using the cross-walk made by Harry Ganzeboom.

product or a service?" In this case, too, we find a negative effect of an increase of the migrants' share of the relative task supply of the natives, although the magnitude of the effects seems to be significantly higher. We therefore conclude that the results presented in the previous section are robust to the choice of the database, and using the EWCS or PIIAC does not significantly alter our results.[15]

Table 6.9: The effect of migration on the relative task supply of less-educated native workers, OLS, WLS and IV using PIAAC

Dependent variable	OLS	WLS	IV
	(1)	(2)	(3)
Ln(M/C)	-29.920**	-11.961	-6.7373**
	(12.105)	(7.785)	(1.223)
Ln(M)	-22.645**	-14.084***	-4.412***
	(8.934)	(3.521)	(0.609)
Ln(C)	4.829	-1.490	2.324***
	(6.821)	(5.399)	(1.828)
First stage			
F-K test			41.504
Region and year fixed effects	Yes	Yes	Yes
Observations	208	208	199

Notes: Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the DE-LFS (2002-2014) and PIAAC (2012).

6.7 Conclusions

There is now e heightened interest in migration-related research, hoping for findings that will guide immigration policies in receiving countries. This chapter aims to contribute to the existing literature and provide evidence for sound policy-making.

Using an approach developed by Peri and Sparber (2009), the chapter explores the effect of an increase in the relative supply of migrants on the natives' task reallocation.

[15]See Appendix H ,Table H1, column 3, for the first stage regression.

The hypothesis is that, as low-skilled migrants enter the labour market into predominantly manual-intensive occupations, natives will self-relocate to occupations which make use of their comparative advantage, namely communication skills. The chapter focuses on Germany, a country with an increasingly high immigrant population, and a relatively rigid labour market, which would imply a more significant effect on natives' task reallocation. Using the German Labour Force Survey (DE-LFS) and the O*Net database, our results show that an increase in the migrant share has a significant and negative effect on the native's relative task supply. The effect of immigration on natives' task reallocation in Germany is substantially higher than the effect found in the US and Spain. Moreover, the effect is significantly larger for recent and for male migrants, pointing to an assimilation effect taking place over time, and gendered effects. These particular findings confirm the consensus that the impacts of migration depend on the skills of migrants and their familiarization with the labour market.

The study contributes to our better understanding of the effect of immigration on the local labour market. Specifically, it helps explain why the literature has so far found so negligible effects of immigration on wages or employment rates. In this particular case, while immigration might lead to a wage decline for low-skilled migrants in manual-intensive tasks, the aggregate effect on wages will be small because it will be compensated by the skill and job upgrading of the displaced native workers. An important implication of our findings is that through adjustments in natives' task specialization and occupational upgrading, immigration may increase job mobility, improve the quality of job matches and contributing to increasing labour market efficiency (Amuedo-Dorantes and De la Rica, 2011).

Furthermore, our findings point to the importance of considering different group characteristics when investigating the impacts of immigrants' on natives' labour market outcomes. Particular attention should be paid to skill levels, gender differences and duration of stay in the host country, but other characteristics such as age should be accounted for too. It is essential to acknowledge that any type of labour market analysis, particularly when it involves migration, is bound to face a number of methodological limitations. Firstly, all evidence found on the effects of immigration on native's labour market outcomes is bound to be dependent on context and the time of the analysis, and our study is no exception. Secondly, as migrants often go to areas which are experiencing both economic growth and strong labour demand, immigration can be both a cause and consequence of changes in wages and employment, which makes it difficult to establish causality Ruhs and Vargas-Silva (2015). Thirdly, our study overlooks other responses to immigration as for instance, labour demand responses, changes in industry mix, choice of production technologies, as well as native labour supply, which when accounted for might make estimates of the wage impact of immigration to vary Bodvarsson and Van den Berg (2013). Last but not least, the outcomes of any study on the impacts of migration is highly dependent on the definition of "migrants".

7. Conclusions - Conclusiones

7.1 Conclusions

7.1.1 Final remarks

This dissertation has focused on the role of technology in shaping the outcomes of European labour markets, with particular emphasis on the Spanish case. Even though technological changes represent only one of the changes affecting modern societies, it alters not only the nature of the jobs created and destroyed, but also the content of the tasks workers perform. Although each of the individual chapters include its own section of conclusions highlighting its key findings, these final pages aim to present some overall conclusions that summarize not only the main implications of the work but also future lines of research linked to the impact of technological changes. This is a debate that goes back to the origins of contemporary Political Economy. This thesis has been an attempt to explore the role and impact of technology from an empirical point of view with a special focus on Europe and Spain.

Chapter 2 has represented a discussion of different theoretical frameworks aimed at explaining the impact of technology on the labour market. Technology has always been considered the main source of economic progress, but it has also generated substantial cultural anxiety. Discussion and research on how technology shapes the labour market have been crucial to understanding the phenomenon. During the 1980s the consensus view was that technological change had been skill-biased —that is that technological change was a complement of skilled labour, resulting in larger demand for high-skill workers relative to unskilled ones and leading to monotone employment and wage growth along the wage (skill) distribution (Berman et al., 1998; Bound and Johnson, 1992; Katz and Murphy, 1992; Machin and Van Reenen, 1998). This trend has been called skill-biased technical change (SBTC).

A recent wave of research has challenged the traditional SBTC hypothesis. This literature has illustrated that the diffusion of computer technology driven by declining prices has led to a different pattern, with employment growth concentrated on the tails of the occupational wage distribution. Some recent papers have linked this hollowing out of the employment distribution to the displacement of middle-skilled routine jobs. The argument has been the following: because of their substitutability with computer capital, routine tasks have been most affected by technological changes. Driven by real price declines, routine-biased technical change (RBTC) has predicted a reallocation of employment away from routine task-intensive occupations that are typically located in the middle of the wage distribution towards non-routine tasks that are located at both tails of the distribution, thereby inducing employment polarization. In contrast to the traditional SBTC hypothesis, the task-based framework especially has allowed for increases in low-skilled non-routine manual employment that is neither a substitute nor a complement to computer capital. This chapter contributes to the theoretical foundations on how technology has affected labour demand. We summarized the main theoretical frameworks and discussed why the RBTC has fit better with a recent phenomenon: the increase in employment shares both at the bottom and at the top of the wage distribution, combined with a decline in the middle. This phenomenon has been defined as *job polarization*.

After understanding why the RBTC has been a better fit with the empirical evidence provided so far, chapter 3 has focused on the discussion of how to measure the phenomenon. The interest of this chapter lies in the different data sources that we have explored. We have compared the existing databases —the EWCS, PIAAC, PDII, and O*Net— and have looked at their differences by comparing the task content of jobs at the European level. While the PIAAC, PDII, and O*Net have produced similar results, results from the EWCS have differed to some extent. We have calculated the Routine Task Intensity Index (RTI) measure and have found that the Northern countries have had the lowest RTI values while Eastern and Mediterranean countries have the highest RTI values. The latter countries will have to face the challenge of adapting to the changes implied by the transition to the digital economy.

The fourth chapter has aimed at analysing recent changes in the labour market structure at the job level in Spain. Using the Spanish Labour Force Survey (ES-LFS) and the European Working Condition Survey (EWCS), we have found that the evolution of the Spanish job structure is characterised by a U-shaped relationship between growth in employment share and job's percentile in the wage distribution. This phenomenon has been called *job polarisation* and, particularly, our analyses have suggested that these results are explained by the task content of jobs, supporting the so-called *routinisation hypothesis*. This chapter has also provided evidence of occupational mobility showing that middle-skilled workers have not predominately moved to low-skilled occupations. This last finding does not fit well the RBTC framework, leaving space for future research in understanding what factors other than routinisation might be driving this fact.

Chapter 5 has explored job polarisation in Spain and its main drivers. This chapter has exploited, for first time for this country, geographical variation in the exposure to technology, taking advantage of low mobility among Spanish provinces. Our identification strategy has exploited the fact that workers in Spain rarely move, so each province represents a relatively closed labour market and, at the same time, each province displays a different initial specialization in routine-intensive activities, which provides a measure of a differential exposure to automatisation. The results have been coherent with the ones obtained in the previous chapter, suggesting that in Spain, technology partially explains the decline of middle-paid workers, and its subsequent reallocation at the bottom part of the employment distribution. However —contrary to the US— technology has not explained the increase found at the top of the employment distribution. This has not only highlighted the quite likely major role of other factors —such as labour market institutions— but also has suggested a promising niche for future research.

The last chapter has employed the model presented in the two previous ones to assess the role of immigrant labour supply in the puzzle of the impact of technology in Europe, and how this force has interacted with the introduction of technologies replacing routine-intensive jobs. Exploring the case of Germany, we have studied the effect of an increase in the relative supply of migrant labour supply on natives' task reallocation. Our hypothesis, guided by previous literature, has been that as low-skilled migrants enter the labour market in predominantly manual-intensive occupations, natives self-relocate to positions which make use of their comparative advantage: communication skills. We have found that an increase in the share of migrant population is indeed negatively associated with the native population's relative supply of manual tasks. Moreover, recent migrants have seemed to supply more manual skills relative to communication skills than long-run migrants, while natives tend to supply less manual skills and more communication ones. As expected, the magnitude of the effect has been significantly higher for women.

Technology has always been part of our progress. However, at the same time, it has represented many challenges to societies, transforming economic and labour relations. Currently, there is grave concern whether technology is replacing large numbers of middle-class jobs. One of the most common considerations is that technological progress will cause widespread substitution of machines for labour, which in turn could lead to technological unemployment and a further increase in inequality. These concerns have recently regained prominence as pointed out by Brynjolfsson and McAfee in their book: *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. According to them: "Rapid and accelerating digitization is likely to bring economic rather than environmental disruption, stemming from the fact that as computers get more powerful, companies have less need for some kinds of workers. Technological progress is going to leave behind some people, perhaps even a lot of people, as it races ahead. As we will demonstrate, there is never been a better time to be a worker with special skills or the right education, because these people can use technology to create and capture value. However, there is never been a worse time to be a worker with only "ordinary" skills and abilities to offer, because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate." (Brynjolfsson and McAfee, 2014, p.11)

The link between technological progress and the increase in income inequality in present turbulent times is far from being clear and undisputed (Atkinson, 2015b; Autor, 2015; Eurofound, 2017; Jenkins et al., 2013; Mishel et al., 2013). In any case, the eventual existence of job polarisation in at least some countries could be a force contributing to create a more unequal society. As it is customary in economics, any forecast of the impact of technology in future should necessarily be taken with caution. In any case, it is worth commenting on several of the issues that can mark the future policy agenda.

First of all, the concerns on the effect of technical change on jobs are far from being new. Keynes himself commented not only on this phenomenon but also on the possibility of technological unemployment: “We are being afflicted with a new disease of which some readers may not have heard the name, but of which they will hear a great deal in the years to come —namely, technological unemployment” (Keynes, 1930). On one side, robots and computers can replace labour as long as, in the context of automatisation, the former has a comparative advantage over the latter. However, in this discussion, the extent of substitution of labour by machines has usually been overstated and the positive impact of technology on job creation, understated. Actually, on the other side, there are new jobs arising due to technological change and strong complementarities between automatisation and labour, leading to increases in productivity and earnings. Additionally, the aggregate impact of technology in the economy increases the demand for other goods and services produced by not only other sectors of activity but also those industries most exposed to technical change. A good example of this point is documented by Bessen (2015) regarding the introduction of automated teller machines (ATMs) and employment in banking. With the introduction of ATMs in 1970 and further quadrupling in the number of ATMs from 100,000 to 400,000 between 1995 and 2010, one might expect that the number of jobs as bank tellers would decrease. However, US bank teller employment actually rose modestly from 500,000 to approximately 550,000 over the 30-year period from 1980 to 2010. However, with the growth of ATMs, what are all of these tellers doing? Bessen (2015) explains that the bank tellers move from routine cash-handling tasks to a broader range of bank personnel involved in "relationship banking" such as salespersons, forging relationships with customers and introducing them to additional bank services like credit cards, loans, and investment products.

Finally, it is informative to bring to this final part of the dissertation the insightful comments of the last work of the recently deceased Anthony Atkinson (2015b), who highlight how the role of technology in augmenting income inequality has traditionally been over-emphasized. In this respect, Atkinson's view is slightly dissenting: he argues that technological change is not exogenous, and is not determined by god. On the contrary, technological change is determined by the economic and social system. As explained in his book, technological advances reflect decisions made by researchers, managers, investors, and governments, among others. These decisions have long-run implications for the wages and incomes of future generations (Atkinson and Stiglitz, 1969), and that is why public policy should play an important role in influencing the nature of technological change and hence the future direction of market outcomes. Lastly, even if the consequences of technology on income distribution are negative, that does not mean that an increase of inequality is an unavoidable outcome, but that we should rethink the role of some of well-known instruments for redistribution —such as progressive taxation or minimum wages— and reflect on the convenience of new tools, like basic citizen's income or guaranteed job programs. In any case, the first step in this challenging process of reshaping of Western societies begins by understanding the relationships between technology and the labour market, which has been the main objective of this PhD thesis.

7.2 Conclusiones

7.2.1 Observaciones finales

Esta tesis se ha centrado en entender el papel que juega la tecnología a la hora de explicar la evolución del merado laboral europeo, poniendo especial énfasis en el caso español. Aunque el cambio tecnológico representa sólo una pequeña parte de los cambios que afectan a las sociedades modernas, éste altera no sólo la naturaleza de los empleos creados y destruidos, sino también el contenido de las tareas que desempeñan los trabajadores. Aunque cada uno de los capítulo individuales de esta tesis incluye su propia sección de conclusiones, estas páginas finales pretenden presentar un mapa general que resume no sólo las principales ideas y limitaciones del trabajo, sino también las futuras líneas de investigación vinculadas al impacto del cambio tecnológico. Por tanto esta tesis ha retomado un debate que se inicia en los orígenes de la Economía Política contemporánea ya que se ha centrado en explicar el papel que juega la tecnología a la hora de modelar el mercado laboral europeo, y en particular, el mercado español.

El capítulo 2 ha resumido los diferentes marcos teóricos que han explicado el impacto de la tecnología en el mercado de trabajo. Desde siempre, la tecnología ha sido considerada la principal fuente de progreso económico, pero también ha generado una gran ansiedad cultural. En este debate entre progreso económico y ansiedad cultural, tanto la discusión, como la investigación, han sido cruciales para entender dicho fenómeno. Durante los años ochenta la opinión de consenso era que el cambio tecnológico estaba sesgado a favor del trabajo cualificado. En otras palabras, el cambio tecnológico era un complemento de mano de obra cualificada, dando lugar a una mayor demanda de trabajadores altamente cualificados en relación a los no cualificados, obteniendo una distribución de empleo (y salario) ascendente a lo largo distribución salarial (Berman et al., 1998; Bound and Johnson, 1992; Katz and Murphy, 1992; Machin and Van Reenen, 1998). Esta tendencia se explicó a través del sesgo que la tecnología tiene a favor del trabajo cualificado (en inglés, skill-biased technical change, por lo que llamaremos a esta hipótesis SBTC).

Sin embargo, una reciente ola de investigación ha desafiado la hipótesis central del SBTC. Esta literatura ha ilustrado que la difusión de la tecnología, impulsada por una caída en los precios, ha llevado a un patrón diferente: la concentración del crecimiento del empleo en ambas colas de la distribución salarial. Estos trabajos de investigación han relacionado el decrecimiento del empleo con el grado de rutina de dichos empleos. El argumento ha sido el siguiente: debido a la disminución de precios reales, el cambio tecnológico rutinario (en inglés, routine-biased technical change, por lo que llamaremos a esta hipótesis RBTC) ha predicho una reasignación del empleo de las ocupaciones rutinarias hacia ocupaciones no rutinarias. La principal diferencia con la hipótesis tradicional del SBTC es que la RBTC ha permitido un aumento en el empleo manual no rutinario de baja cualificación, siendo dicho empleo ni un sustituto ni un complemento al capital informático. En resumen, en este capítulo hemos explicado los marcos teóricos y discutido por qué el RBTC se ha ajustado mejor a un reciente fenómeno: el aumento de empleo tanto en la parte inferior como en la parte superior de la distribución salarial, combinado con un descenso en el medio de la distribución salarial. Este fenómeno que se ha definido como *porlarización del trabajo.*

Después de entender cómo la evidencia empírica se ajusta al RBTC, el capítulo 3 se ha centrado en la medición del fenómeno. El interés de este capítulo reside en las diferentes fuentes de datos que hemos explorado. De esta forma, y para examinar el contenido de las tareas de los puesto de trabajo a nivel europeo, hemos analizado las siguientes bases de datos: EWCS, PIAAC, PDII y O*Net. Los resultados han sido los siguientes: mientras que PIAAC, PDII, y O*Net han obtenido índices muy similares, los resultados de los EWCS han diferido en cierta medida. A su vez, en este capítulo hemos calculado el Índice de Intensidad de Tareas Rutinarias (en inglés, Routine Task Index, por lo que lo llamaremos RTI) para así poder explicar qué países tendrán que adaptarse a la nueva economía digital. Los índices más bajos los hemos encontrado en los países del norte, mientras que los índices más altos los han obtenido los países del este y del Mediterráneo. Gracias al RTI hemos podido concluir que son los últimos países mencionados los que tendrán que afrontar una mayor transición tecnológica.

El cuarto capítulo ha tenido como objetivo analizar los cambios en la estructura del mercado de trabajo a nivel laboral en España. A partir de la Encuesta Población Activa (EPA) y de la Encuesta Europea de Condiciones Laborales (en inglés, European Working Condition Survey, EWCS) hemos encontrado que la evolución de la estructura laboral española se caracteriza por una relación en forma de U entre el crecimiento de la participación laboral y el percentil del empleo salarial. Este fenómeno se ha denominado *polarización del trabajo.* En particular, nuestro análisis ha sugerido que estos resultados se explican por el tipo de tareas que se realizan en cada trabajo, apoyando la llamada *hipótesis de la rutina, RBTC.* En la parte final de este capítulo hemos proporcionado evidencia acerca de la movilidad ocupacional. De esta forma hemos mostrado que no son los trabajadores de cualificaciones medias (trabajadores que se encuentran en el centro de la distribución salarial) los que se han trasladado a ocupaciones poco cualificadas (ocupaciones en la parte inferior de la distribución salarial). Dicho hallazgo no encaja en el marco de la RBTC por lo que otros factores —tales como la educación, la migración o la incorporación de la mujer al mercado laboral— podrían estar impulsando dicho hecho.

El capítulo 5 ha explorado la polarización del empleo en España y sus principales determinantes. Este capítulo ha utilizado, por primera vez para este país, la variación geográfica en la exposición a la tecnología, aprovechando la baja movilidad de las provincias españolas. La estrategia de identificación ha explotado el hecho de que los trabajadores en España apenas se mueven, por lo que cada provincia representa un mercado de trabajo relativamente cerrado y, al mismo tiempo, cada provincia presenta una especialización inicial diferente en la intensidad rutinaria de cada ocupación. Los resultados han sido coherentes con los obtenidos en el capítulo anterior, lo que sugiere que en España, la tecnología explica el descenso de los trabajadores con salarios medios y su posterior reubicación en la parte inferior de la distribución del empleo. Sin embargo —contrariamente a los EE.UU.— la tecnología no ha explicado el aumento que se encuentra en la parte superior de la distribución del empleo. Esto no sólo ha puesto de manifiesto el probable papel de otros factores, como las instituciones del mercado de trabajo, sino que también ha sugerido un nicho prometedor para la investigación futura.

El último capítulo ha empleado el modelo presentado en los dos anteriores capítulos para determinar el papel que juega la oferta relativa de mano de obra migrante en el puzle del impacto tecnológico en Europa. En este caso, a diferencia de los dos previos capítulos, hemos analizado el caso de Alemania. Nuestra hipótesis, guiada por la literatura precedente, es que a medida que los migrantes poco cualificados entran al mercado de trabajo en ocupaciones predominantemente manuales, los nativos se recolocan en ocupaciones en las que aprovechan su ventaja comparativa: las tareas comunicativas. Hemos encontrado que un aumento en la proporción de la población migrante está de hecho negativamente asociada con la oferta relativa de la población nativa de tareas manuales. Los migrantes recién llegados (menos de 5 años en el nuevo país) parecen proporcionar más habilidades manuales en relación con las habilidades de comunicación que los migrantes de largo plazo. A su vez los nativos tienden a proporcionar menos habilidades manuales y más habilidades comunicativas. Como era de esperar, la magnitud del efecto ha sido significativamente mayor para las mujeres.

La tecnología siempre ha sido parte de nuestro progreso pero, al mismo tiempo, ha representado muchos retos para las sociedades, transformando las relaciones económicas y laborales. Actualmente, existe una gran preocupación sobre si la tecnología está reemplazando a un gran número de empleos de clase media. Una de las afirmaciones más comunes es que el progreso tecnológico sustituirá la mano de obra por máquinas, lo que a su vez podría conducir al desempleo tecnológico y a un mayor aumento de la desigualdad. Estas preocupaciones han sigo recogidas por Brynjolfsson y McAfee en su libro: *La segunda era de las máquinas: trabajo, progreso y prosperidad en un tiempo de brillantes tecnologías*. Según ellos: "La rápida y acelerada digitalización probablemente traerá perturbaciones económicas en lugar de ambientales, derivadas del hecho de que a medida que los ordenadores se hacen más poderosos, las empresas tienen menos necesidad de contratar algún tipo de trabajadores. El progreso tecnológico dejará atrás a algunas personas, tal vez incluso a mucha gente. Como demostraremos, nunca ha habido un mejor momento para ser un trabajador con habilidades especiales o con la educación adecuada, porque estas personas pueden usar la tecnología para crear y capturar valor. Sin embargo, nunca ha habido un momento peor para ofrecer habilidades "comunes", ya que los ordenadores, los robots y otras tecnologías digitales están adquiriendo estas habilidades y capacidades a un ritmo extraordinario." (Brynjolfsson and McAfee, 2014, p.11)

El vínculo entre el progreso tecnológico y el aumento de la desigualdad de los ingresos en estos tiempos está lejos de ser claro y es discutible (Atkinson, 2015b; Autor, 2015;

Eurofound, 2017; Jenkins et al., 2013; Mishel et al., 2013). En cualquier caso, la existencia eventual de la polarización del empleo en al menos algunos países podría significar una fuerza que contribuya a crear una sociedad más desigual. Como es costumbre en economía, cualquier proyección del impacto de la tecnología en el futuro debe tomarse necesariamente con precaución. En cualquier caso, vale la pena comentar varios de los temas que pueden marcar la futura agenda política.

En primer lugar, las preocupaciones sobre el efecto que la tecnología tiene en el empleo están lejos de ser nuevas. El propio Keynes comentó no sólo este fenómeno, sino también la posibilidad del desempleo tecnológico: "Estamos siendo afligidos por una nueva enfermedad de la que algunos lectores quizás no han oído el nombre, pero de la cuál se hablará en un futuro cercano, el desempleo tecnológico" (Keynes, 1930). Por un lado, los robots y los ordenadores pueden sustituir al trabajo, siempre y cuando, en el contexto de la automatización, el primero tenga una ventaja comparativa sobre el segundo. Sin embargo, en esta discusión, el alcance de la sustitución del trabajo por las máquinas ha sido magnificado, y el impacto positivo de la tecnología en la creación de empleo subestimado. Por otro lado, en realidad, hay nuevos puestos de trabajo que surgen debido al cambio tecnológico ya que hay una gran complementariedad entra la automatización y el empleo. Además, el impacto agregado de la tecnología en la economía aumenta la demanda de otros bienes y servicios producidos no sólo por otros sectores de actividad, sino también por las industrias más expuestas al cambio técnico. Un buen ejemplo de este punto está documentado por Bessen (2015), respecto a la introducción de cajeros automáticos y el empleo en la banca. En EE.UU los cajeros automáticos se introdujeron en 1970 y desde entonces su número se cuadruplicó pasando de 100.000 a 400.000 cajeros automáticos entre 1995 y 2010. Uno podría esperar que tras tal incremento, el número de empleos como cajeros disminuiría. Sin embargo, dichos empleos aumentaron modestamente de 500.000 a 550.000 en un período de 30 años. Bessen (2015) explica que los empleados que trabajan como cajeros pasaron de realizar tareas rutinarias a una gama más amplia de tareas tales como vendedores de servicios bancarios adicionales como tarjetas de crédito, préstamos y productos de inversión o nuevas formas de comunicación con el cliente.

Por último, es pertinente traer a esta parte de la tesis los comentarios de la última obra del recientemente fallecido Anthony Atkinson (2015b). En su obra se destaca cómo tradicionalmente se ha exagerado el papel que juega la tecnología en el aumento de la desigualdad. A este respecto, la opinión de Atkinson es ligeramente discrepante: argumenta que el cambio tecnológico no es exógeno, y no está determinado por dios. Por el contrario, el cambio tecnológico está determinado por el sistema económico y social en el que vivimos. Como se explica en su libro, los avances tecnológicos reflejan las decisiones tomadas por investigadores, gerentes, inversores y gobiernos, entre otros. Estas decisiones tienen repercusiones a largo plazo sobre los salarios y los ingresos de las generaciones futuras, por lo que las políticas públicas deben desempeñar un papel importante para influir en la naturaleza del cambio tecnológico y, por consiguiente, en la dirección futura de los resultados del mercado. Por último, aunque las consecuencias de la tecnología sobre la distribución del ingreso sean negativas, eso no significa que un aumento de la desigualdad sea un resultado inevitable, sino que debemos repensar el papel de algunos de los instrumentos bien conocidos de redistribución —como el impuesto progresivo o el salario mínimo— y reflexionar sobre la conveniencia de nuevas herramientas, como los ingresos básicos del ciudadano o programas de trabajo garantizado. En cualquier caso, el primer paso en este desafiante proceso de remodelación de las sociedades occidentales comienza por entender las relaciones entre la tecnología y el mercado de trabajo, y ese ha sido el principal objetivo de esta tesis doctoral.

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Appendix A: Description of the source

(Chapter 2)

1. The O*Net database

   The Occupational Information Network database (O*Net) is a comprehensive database of worker attributes and job characteristics. It has replaced the Dictionary of Occupational Titles (DOT) and provides additional information not available in the DOT. O*Net, which is a primary source of occupational information, is sponsored by the US Department of Labor/Employment and Training Administration (USDOL/ETA).

   O*Net contains a rich set of variables covering different domains, among them workers characteristics (e.g., abilities) and workers requirements (e.g., skills), occupational requirements (e.g., work activities), and occupation-specific information (e.g., tasks). O*Net data comes from three different sources: a randomly selected sample of job incumbents, occupational analysts and occupational experts. Most of the occupational information comes from standardized questionnaires completed by job incumbents while analysts only provide ratings for abilities and skills .

   The database, which is publicly available for download free of charge, is updated on a regularly scheduled basis. The current production release of the O*Net database is 20.1 (October 2015) contains data for 953 occupations. We select O*Net version 17.0 (released in 2012) for the analysis from 2011 onwards and O*Net version 11.0 (released in 2006) for the earliest periods. The variability over time of occupational measures in the two versions of O*Net, which is due to ongoing updates, is minimal. However, because O*Net has been implemented as a SOC (Standard Occupational Code)-based system, we can convert the six-digit 2010 SOC used in version 17.0 into four-digit ISCO-08 and the six-digit 2000 SOC used in version 11.0 into four-digit ISCO-88 , taking therefore into account changes in the ISCO occupational classification which occurred around 2012. Sometimes the O*Net occupational coding splits up several SOC occupations into multiple separate occupations: because we do not have employment data for these categories separately, we decide not to include them. Results would be very similar if we decided to take a simple mean of the importance measure for each task.

2. European Working Conditions Survey(EWCS)

The European Working Conditions Survey (EWCS) is provided by the European Foundation for the Improvement of Living and Working Conditions (Eurofound). This survey has become an important source of information about working conditions and the quality of work and employment since it enables monitoring of long-term trends in these topics in the case of Europe. That is possible because of the amount of waves (one every five years more or less, adding a total of 6 until the date) that have been implemented periodically since it was launched in 1990. The scope of the survey and the themes covered are extensive: working time arrangements, work-life balance, employment status, health and safety, work organisation, learning and training, physical and psychosocial risk factors, worker participation, earnings and financial security, work and health, etc.

3. Programme for the International Assessment of Adult Competencies (PIAAC)

   The Programme for the International Assessment of Adult Competencies (PIAAC) assesses the proficiency of adults in literacy, numeracy and problem solving skills. The survey is conducted in 33 countries. The first round of the first assessment programme was carried out during the period 2008 to 2013; the second round, between 2012 and 2016. Apart from measuring the key cognitive and workplace skills, the survey also collects information on demographic characteristics, qualification, work experience, training and use of the skills at work, at home and in the community. Evidence on the development of key aspects of human capital in different countries can assist policy makes to implement better informed education and social policies.

4. British Skill Survey (BSS)

   The main aim of the BBS is to provide an analysis of level and distribution of skills being used in British workplaces. The survey is conducted in 1997, 2001 and 2006. The three repeated cross-sections cover altogether 14,717 workers (mean and women), repectively 2,467 in 1997, 4,470 in 2001, and 7,780 in 2006. At each wave, information on job chatacteristics and working conditions are collected: these include details on the intensity of the tasks being performed, the degree of repetetition of the activities carried out and the computers or computerised equipment in the workplace.

5. Qualification and Career Survey

   The Qualification and Carrer Survey is a survey of employees carried out by the German Federal Institutr for Vocational Training (Bundeinstitut für Berufsbildung, BIBB) and the Research Institute of the Federal Employment Service (Institut für Arbeitsmark- und Berufsforschung, IAB). It includes six cross sections launched in 1979, 1985/86, 1991/92, 1998/99, 2006 and 2012, each covering about 30,000 individulas (men and women). All waves include measures of occupational skill requirements, the measure of technology (detailed information on the tools and machines used by employees at the workplace), and types and levels of respondent's formal education.

Appendix B: The construction of the indices

(Chapter 3, 4, 5, and 6)

The procedure we have followed for constructing the indices can be summarized in a number of steps:

1. Identification of variables: we first selected the variables that could match the elements in our model.

2. Normalization of variables to a 0-1 scale: in the original sources, the individual variables use different scales which are not directly comparable. Therefore, they had to be normalized before they could be aggregated. We opted for a normative rescaling to 0-1, with 0 representing the lowest possible intensity of performance of the task in question, and 1 the highest possible intensity.

3. Correlation analysis: once the variables related to an individual element in our model were normalized, we proceeded to analyse the correlations between them. In principle, different variables measuring the same underlying concept should be highly correlated, although there are situations in which they may legitimately not

be (for instance, when two variables measure two compensating aspects of the same underlying factor). Beside standard pairwise correlations, we computed Cronbach's Alpha to test the overall correlation of all the items used for computing a particular index, and a Principal Components Factor Analysis to evaluate the consistency of the variables and identify variables that did not fit our concept well.

4. Once we selected the variables to be combined into a single index, we proceeded to combine them, by simply averaging.[1] Unless we had a particular reason to do otherwise, all the variables used for a particular index received the same weight.

5. Finally, we proceeded to compute their average scores for all the occupation combinations at the two-digit level and one-digit level. When the data source included the information at the individual worker level, we computed also the standard deviation and number of workers in the sample, for later analysis.

6. Data from the European Union-Labour Force Survey (EU-LFS) on the level of employment in each job was added to the dataset holding the task indices. These employment figures were later used for weighting the indices.

[1]The results remained invariant if we use the first component of the principal component analysis

Appendix C: Methodology applied to measured job polarisation

(Chapter 4)

Our enquiry builds on a methodology first proposed by Joseph Stiglitz for the study of occupational change in the US, later refined by Wright and Dwyer (2003). Due to its simplicity, it is subsequently applied subsequently applied to British (Goos and Manning (2007)), German (Kampelmann and Rycx (2011)), Swedish (Adermon and Gustavsson (2015)) and European data (Goos et al. (2009, 2010, 2014), and Fernández-Macías (2012)). Three steps are usually followed.

In the first step, we define a job as a particular occupation in a particular industry. Therefore, jobs are classified into a matrix whereas the columns are economic sectors and the rows are occupations. Examples of these jobs would be managers in the agricultural sector or clerks in the construction industry. Throughout our investigation, we use two-digit International Standard Occupational Classification (ISCO88) code and one-digit industry codes from the Classification of Economic Activities in the European Community (NACE REV.1) as a measure of jobs. Individuals aged 18 to 66 are placed in cells, and weighted by the total population of each cell. Because many cells are empty, two filters are applied to the data. We first drop observations for which information on the job variable is missing. Second, we also drop Melilla and Ceuta geographical areas due to no accurate information, reducing the total number of jobs from 188 to 160 jobs.

In the next step, we compute jobs' real hourly wage by taking the ratio of the gross annual salary to the total number of hours actually worked. The salary figure includes extraordinary payments. We then rank jobs according to their mean wage in the first year.[2]

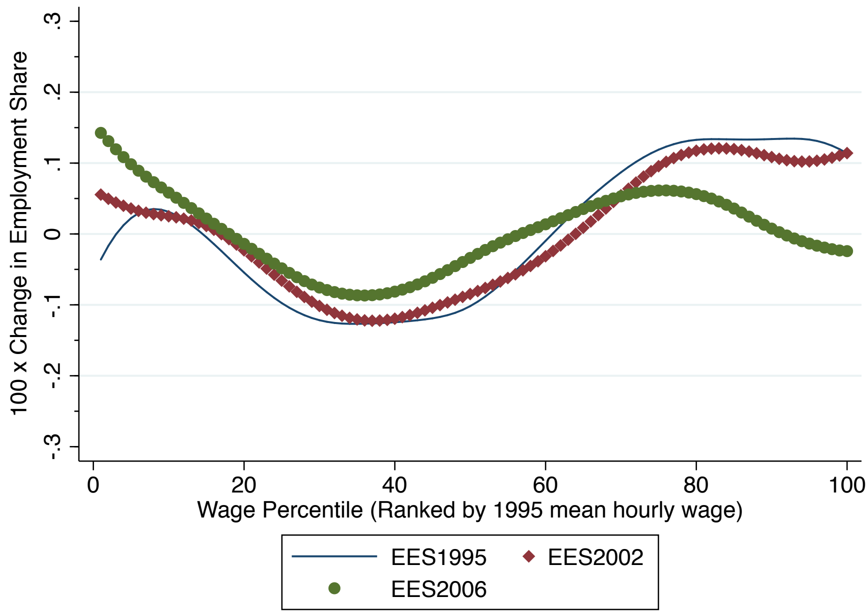
In the last step, we represent graphically the evolution of jobs in terms of their wages where there are three possibilities of representation: the actual point of jobs where we plot the percent change in employment share against the (ln) mean wage. In the second case, we display smoothing regressions rather than the actual data point.

[2]The shape of the graph does not change if median average are used for determining job quality.

Appendix D: Extra Figures

(Chapter 4)

Figure D1: Smoothed changes in employment in Spain (1994-2008), being jobs ranked in 1995, 2002 and 2006 by EES

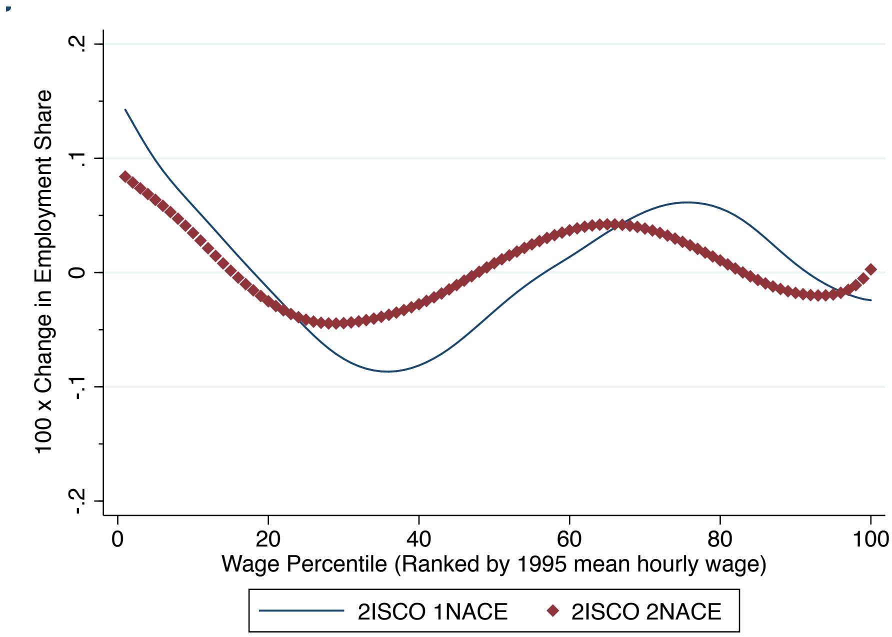


Notes: The figure plots a locally weighted non-parametric smoothing regression (bandwidth 0.75 with 100 observations). The jobs are defined at two-digit ISCO level and at one-digit NACE REV.1 level. For the period 1994-2008, jobs are ranked by the EES 1995, EES 2002, and EES 2006 mean wage.
Sources: Author's analysis from the EPA (1994, 2008) and EES (1995, 2002, 2006).

Figure D2: Smoothed changes in employment in Spain (1994-2008), jobs are ranked by 1995 mean and median wage percentile

Notes: The figure plots a locally weighted non-parametric smoothing regression (bandwidth 0.75 with 100 observations). The jobs are defined at two-digit ISCO level and at one-digit NACE REV.1 level. For the period 1994-2008, jobs are ranked by the 1995 ESS mean wage (blue line) and 1995ESS median wage (red line).
Sources: Author's analysis from the EPA (1994, 2008) and ESS (1995).

Figure D3: Smoothed changes in employment in Spain (1994-2008), jobs are ranked by wage percentile



Notes: The figure plots a locally weighted non-parametric smoothing regression (bandwidth 0.75 with 100 observations). The jobs are defined at two-digit ISCO level and at one-digit NACE REV.1 level (blue line) and at two-digit ISCO level and at two-digit NACE REV.1 level (red line). For the period 1994-2008, jobs are ranked by the EES 2006 media wage.
Sources: Author's analysis the EPA (1994, 2008) and ESS (2006).

Appendix E: Variables construction

(Chapter 4)

Wages. Our wage variable (hwage) is the gross hourly pay. For all the cases hwage was computed as gross usual weekly pay divided by usual hours and minutes worked per week, including usual overtime. Wages are measured in euro. We trim our data such that hourly wages lower than 1 and higher than 100 are excluded.

Occupations. We classify occupations according to the International Standard Classification of Occupations (ISCO-88) (see ILO, 1990). Occupations were originally classified according to the National Classification of Occupations (CNO-94). Codes are manually matched on the basis of the guidelines distributed by the Occupational Information Unit of the Office for National Statistics. This harmonisation allows researchers to compare occupations over time to make our results strictly comparable to other papers. ISCO-88 defines four levels of aggregation, consisting of 10 major groups (one-digit), 28 sub-Major groups (two-digits), 116 minor groups (three-digits) and 390 unit groups (four-digits).

Industry. I classify industry according to the Statistical Classification of Economic Activities in the European Commission (NACE, Rev. 1.1). Industry codes were originally classified according to the National Classification of Economic Activities (CNAE-93). Codes are manually matched on the basis of the guidelines distributed by Eurostat. This harmonisation allows researchers to compare occupations over time to make our results strictly comparable to other papers. NACE, Rev. 1.1 defines five levels of aggregation, consisting of 17 one-letter sections, 31 two-letter sub-sections, 60 two-digit main groups, 222 three-digit groups, and 513 four-digit sub-groups. NACE, Rev. 1.1 was in turn based on the International Standard Industrial Classification of All Economic Activities (ISIC) Rev 3, published by the United Nations.

Education. Our education variable distinguishes four groups of workers: elementary, basic, medium, and high educated (skilled). In the Spanish Labour Force Survey I exploit the variable (estud) which indicates the highest qualification held by the interviewee. Both educational and vocational qualification levels are available in the list provided to respondents. The usual ISCED division into low, medium and high is then adopted, where low is equivalent to ISCED 0-2 (i.e., primary and lower secondary education), medium is given by ISCED 3-4 (i.e., upper secondary and post-secondary non- tertiary education) and high is ISCED 5-7 (i.e., tertiary education). The derived categorical variable for education takes value of 1 for low educated, 2 for medium and 3 for high.

Computer use. We create a variable that capture computer use. In the EWCS we use the question: "Does your main job involve ... working with computer, laptops, etc?" The variable ranges from 1 "all of the time" to 7 "never" ("almost all of the time", "around 3/4 of the time", "around 1/2 of the time", "around 1/4 of the time", and "almost never" correspond to middle answers).

Appendix F: First stage

(Chapter 5)

In order to calculate the first stage, the following equation model is used:

$$\mathrm{RSH}_{pt-1} = \alpha_t + \beta_1 \mathrm{RSH}^*_p + \gamma_c + \delta_t + \epsilon_{pct} \tag{7.1}$$

The results of the first stage are displayed in Table F1.

Table F1: First stage regression: regional industrial variation in 1997

	Dependent variable RSH_{pt-1}
	1994—2008
RSH^*_p	16.944*
	(9.690)
F-K test	6.990

Notes: The model includes an intercept, region dummies, and a time period dummy. Standard errors clustered at the province level are showed in parentheses. Observations are weighted by the initial share of national population. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA(1977, 1994, 2000, 2008) and O*Net.

Appendix G: Task items between O*Net and EWCS

(Chapter 5)

Table G1: Task items between O*Net and EWCS

Skill sub-type	O*Net	EWCS
Abstract tasks	1) GED match	1) Learning new things
	2) Administration and management	2) Solving unforeseen problems
Routine tasks	1) Finger dexterity	1) Physical stenght
	2)Customer and personal services	2) Repetitive hand or finger movements
		3) Painful positions at work
Manual tasks	1)Harm-hand steadiness	Does your main job involve:
	2) Manual dexterity	a) dealing with people
		b) repetitive tasks
		c) dealing with customers

Notes: Items selected in O*Net, EWCS, and PIAAC.
Sources: O*Net, EWCS, and PIAAC.

Appendix H: First stage

(Chapter 6)

In order to calculate the first stage, the following equation model is used:

$$(share_{short-migrant})_{rt} = \alpha_r + \beta_t + \gamma(share_{long-migrant})_{rt} + \epsilon_{rt} \tag{7.2}$$

Table H1 displays the results of the first stage using O*net (column 1), EWCS (column 2), and PIAAC (column 3).

Table H1: First stage regression: long-term migrants

	Dependent variable Short-term migrant share		
	O*Net	EWCS	PIAAC
	(1)	(2)	(3)
Long-term migrant share	0.172***	0.172***	0.150***
	(0.020)	(0.020)	(0.757)
F-K test	28.919	31.161	41.504

Notes: Standard errors robust to serial correlation and hetereskedasticity are reported in parentheses. Significance levels ***p<0.01; **p<0.05; *p<0.10.
Sources: Author's analysis from the EPA (1977, 1994, 2000, 2008), O*Net, EWCS, and PIAAC.

Appendix I: Task items among O*Net, EWCS, and PIAAC

(Chapter 6)

Table I1: Task items among O*Net, EWCS, and PIAAC

Skill sub-type	O*Net	EWCS	PIAAC
Dexterity	1) Finger dexterity 2) Arm-hand steadiness steadiness 3) Manual dexterity 4) Wrist-finger speed	1) Repetitive hand or arm movements	1) Skill use work - How often - Using hands or fingers
Coordination	1) Multi-limb coordination 2) Gross body coordination	1) Tiring or painful positions	
Strength	1) Static strength 2) Dynamic strength	1) Carrying or moving heavy loads	1) How often - Working physically for long period?
Oral	1) Oral comprehension 2) Oral expression	1) Dealing directly with people who are not employees at your workplace	1) How often does/did job usually involve making speeches or presentations in front of five people or more?
Written	1) Written comprehension 2) Written expression	1) Using internet/ email for professional purposes	1) How often does/did job usually involve selling a product or a service?

Notes: Items selected in O*Net, EWCS, and PIAAC.
Sources: O*Net, EWCS, and PIAAC.