Department of Political Sciences

PhD in Political Studies

Curriculum Government and Institutions

Doctoral Dissertation in Labour Economics

THE ROUTINIZATION HYPOTHESIS AND ITS EMPIRICAL APPLICATIONS

Supervisor | **Candidate**

Prof. Paolo Naticchioni | **Valerio Intraligi**

Rome

AY 2016/2017

To my old friend Simone Passa.

"Econometrics may be defined as the quantitative analysis of actual economic phenomena based on the concurrent development of theory and observation, related by appropriate methods of inference"

Samuelson et al. (1954)

PREFACE

This doctoral dissertation is submitted for the degree of Research Doctor in Political Sciences at the University of Rome Three. The research described therein was conducted under the supervision of Prof. Paolo Naticchioni in the Department of Political Sciences, University of Rome Three, from October 2014 to October 2017.

This work is to the best of my knowledge original, except where acknowledgements and references are made to previous work. Neither this, nor any substantially similar dissertation has been or is being submitted for any other degree, diploma or any other qualification at any other University.

The contents of this dissertation are exclusively attributable to the candidate, though part of this work (in particular, chapter I and III) is the result of a wider project conducted jointly by the candidate and Prof. Paolo Naticchioni.

Part of this research has been presented in the following publications:

- Valerio Intraligi and Paolo Naticchioni, "Progresso Tecnologico e Mercato del Lavoro: Una Survey." In: Magazzino, C. and Romagnoli G.C., Legge di Stabilità 2015 e Politica Economica Europea, Franco Angeli, Milano, 2015.

Part of this research has been presented in following conferences:

- ZEW/IAB Workshop on Spatial Dimensions of the Labour Market, March 30 2017, Mannheim, Germany.

- AIEL XXXII National Conference of Labour Economics, September 14 2017, Rende, Cosenza, Italy.

Table of Contents

Table of Figures

Chapter I

Chapter II

Chapter III

List of Tables

Chapter II

Chapter III

Acronyms and Abbreviations

2SLS – 2 Stages Least Squares

AIEL – Associazione Italiana Economisti del Lavoro (Italian Association of Labour Economics)

ANBERD – Analytical Business Enterprise Research and Development

BIBB - Bundesinstitut für Berufsbildung (Federal Institute for Vocational Education and Training)

CIS – Community Innovation Survey

CZ – Commuting Zone

ECHP - European Community Household Panel

EPSC - European Political Strategy Centre

ETC – Embodied Technological Change

EU-LFS - European Union Labour Force Survey

EU-SILC - European Union Statistics on Income and Living Conditions

GDP – Gross Domestic Product

GLS – Generalized Least Squares

GMM - Generalized Method of Moments

IAB - Institut für Arbeitsmarkt und Berufsforschung (Institute for Employment Research)

ICT – Information and Communications Technology

IFO - Leibniz Institute for Economic Research

ISCO – International Standard Classification of Occupations

JRC – Joint Research Centre

LLM – Local Labor Market

LSDVC – Least Squares Dummy Variable Corrected

MIT – Massachusetts Institute of Technology

NACE - Nomenclature Statistique des Activités Économiques dans La Communauté Européenne (Statistical Classification of Economic Activities in the European Community)

NRC – Non-Routine Cognitive

NRM – Non-Routine Manual

NUTS - Nomenclature des Unités Territoriales Statistiques (Classification of Territorial Units for Statistics)

OECD - Organization for Economic Cooperation and Development

O*NET – Occupational Information Network

OLS – Ordinary Least Squares

R&D – Research and Development

RC – Routine-Cognitive

RM – Routine-Manual

RRTC – Routine-Replacing Technical Change

SBTC – Skill-Biased Technical Change

SID – Sectoral Innovation Database

SOC – Standard Occupational Classification

STAN – Structural Analysis Database

WIOD - World Input-Output Database

ZEW - Zentrum für Europäische Wirtschaftsforschung (Centre for European Economic Research)

Abstract

This doctoral dissertation investigates the routinization hypothesis and its empirical applications. The topic is addressed by means of three different chapters, each of which focuses on different aspects of the subject matter. In the first chapter, I review the most important findings of the recent research activity on the relationship between technological progress and the labor market – to a large extent represented by the literature on the routinization hypothesis. By means of this survey, I show that albeit technical progress is rather unlikely to be detrimental for overall employment growth, the labor demand for different occupational tasks substantially changes as a consequence of technology - which is the main empirical evidence recovered by the literature on the routinization hypothesis. In the second chapter, I map U.S. occupational data into European employment data to assess the effects of exposure to automation on the decline of routine occupations in Europe. I document that, similarly to what found for the United States, higher regional specialization in routine employment is associated to more pronounced employment polarization patterns. Moreover, I find that the effect of exposure to routinization is predominantly associated to within-industry contractions in routine employment. In the third and last chapter, finally, I use German administrative data to assess whether urban agglomeration processes may account for a larger contraction in routine employment in cities. By taking into account the effects of automation and by addressing endogeneity concerns related to measures of employment density, I show that the effect of agglomeration on the contraction of routine tasks is stable, sizeable and highly significant.

Acknowledgements

I would like to express my gratitude to the University of Rome Three, the Professors and the PhD colleagues I met during my PhD course as well as to the administrative personnel of the Department of Political Sciences. Very special thanks go to my Supervisor Prof. Paolo Naticchioni. He indulged my passion and curiosity for the empirical research in labor economics, did care about my academic and professional education, helped me in properly addressing my research questions with his priceless comments and suggestions and was always available with his friendly support during the three years of my PhD course. Another special acknowledgement goes to the coordinator of the Curriculum Government and Institutions of the PhD in Political Studies Prof. Gian Cesare Romagnoli. I thank Prof. Romagnoli not only because he always provided me with important suggestions and crucial academic support, but also because - by supervising my Master's Degree dissertation before I enrolled in the PhD school - he drove me for the first time in the complex and interesting world of economic analysis. Without his former supervision, I would have never undertaken my research activity in empirical economics. I also want also to express my deepest gratitude to the Coordinator of the PhD in Political Studies Prof. Leopoldo Nuti, who made his best to avail my research activity in Rome as well as among the different international institutions I visited during the last three years.

Among the scholars I met abroad, a very important acknowledgment goes to Prof. Matias Cortes. His friendly availability as a Supervisor during my visiting period at the University of Manchester gave me the opportunity to enhance my research skills by benefitting of the wide supply of Master's Degree courses in Economics and Econometrics, in which Prof. Cortes held several lectures. Moreover, Prof. Cortes not only provided me with very useful comments and suggestions about the objectives of my researches, but also introduced me to important scholars in the field - such as Prof. Anna Salomons, who I also thank a lot for useful comments and advices about my research during my visit in Manchester.

A very special acknowledgement goes also to Prof. Wolfgang Dauth and Prof. Uwe Blien, who I had the pleasure to meet during my visiting period at the Institute for Employment research (IAB) in Nuremberg. Their friendly support at the IAB Regional Labor Markets Department, far away to be limited to data access and/or administrative issues, has been crucial for the realization of my PhD dissertation. Without their fundamental observations and advices, the quality of my research activity at the IAB would have definitely not been the same.

I also want to thank Prof. Marco Vivarelli as well as all the other scholars and researchers I had the pleasure to interact with in conferences, summer/winter schools and advanced courses I attended during my PhD course.

Last, but not least, I thanks a lot all my relative and friends, who loved me and supported me during this important experience. Among these, I particularly thank my father Augusto and my sister Eleonora, to who I dedicate this doctoral dissertation.

Introduction

This doctoral dissertation focuses on the “routine-replacing technical change” (RRTC) theory and on the related empirical research activity, that is, a relatively recent and fast-growing strand of the empirical literature in labor economics (see Autor et al. 2003, and Acemoglu and Autor, 2011). In a nutshell, the core idea behind the “routinization hypothesis” is that investments in computer technologies complement high-skilled workers (specialized in non-routine cognitive tasks), substitute for medium-skilled workers (specialized in routine tasks) and have an ambiguous effect towards low-skilled workers (specialized in non-routine manual tasks). According to this literature, such a mechanism may account for the lower wage growth in the middle of the wage distribution observed in the last decades in the U.S. (wage polarization) and for the relative contraction of employment in medium-skilled occupations observed both in the U.S. and Europe (employment polarization). By allowing for a better understanding of the consequences of technological progress for recent changes in labor-market dynamics, the evidences provided by the RRTC literature are indeed encouraging a growing research community to contribute to this strand. Moreover, it is worth noting that the most recent technological achievements, together with recent economic trends, are drawing the attention of scholars of different backgrounds - and more in general of the public opinion - to the topics that this literature addresses.

My dissertation contributes to the RRTC literature in several aspects. In particular, I focus on the routinization hypothesis by means of three separate papers that - in this dissertation – take the form of three different chapters. In chapter 1, I summarize the main findings of the research activity on the effects of technological change on the labor market. In particular, I introduce the reader to the most salient aspects of the present debate, by paying attention not only to the recent empirical findings in the field of labor economics, but also to a number of contributions from scholars and observers of different backgrounds. Moreover, in this chapter the routinization hypothesis is presented within the broader context of the empirical literature on the effects of technology, with particular reference to the impact on employment levels, the wage distribution and the occupational composition of employment. For these reasons, chapter 1 provides a useful starting point for those readers that are not familiar with the subject of this thesis, both for what concerns the RRTC framework and the empirical issues that I address in the remainder of my dissertation.

Moving to chapter 2, I provide novel evidence on the employment-composition effects of exposure to automation in Europe. In particular, I make use of U.S. data on occupational tasks from the Occupational Information Network (O*NET) to identify, in European data from the European Labor Force Survey (EU-LFS), those occupations that are supposed to be the most exposed to the substitution effect of technology (in the following, *routine occupations*). I use this information in order to calculate routine employment shares at the regional level for 23 European countries and - by comparing routine occupations trends with those of both low-skilled *service* jobs and managerial, professional and technical occupations - I show that the higher the degree of exposure to automation, the higher the extent of job-polarization among regions.

Moreover, I assess the relative importance of both the regional and the industrial dimensions of the decline in routine employment in Europe. In particular, I make use of a standard shift-share decomposition method, and decompose the total contraction of routine jobs in a within/between regions components. Further, I decompose each within region variation in a within/between industries components. By doing so, I show that the contraction of routine employment in Europe is entirely driven by the within-regions dimension - while around 40% of the within-regions dimension is driven by the between-industry dimension. Finally, I provide regression-based evidences on the within and between-industries impacts of exposure to automation on the decline of routine occupations. I do this by separately modelling the within and between-industry components as a function of the start of period routine employment share (Autor and Dorn, 2013). By using this approach, I show that - although the between-industry dimension accounts for an important part of the total decline of routine employment (as suggested by the shift share decomposition, and consistently with Goos et al., 2014) – the negative impact of exposure to automation is predominantly associated with the within-industries channel.

In chapter 3, I use German administrative data from the Institute for Employment research (IAB) to investigate for the first time the role of agglomeration forces in worsening the job polarization patterns documented by the RRTC literature. In order to measure the task-content of occupations, I use data from the German Qualification and Career Survey, jointly conducted by the Federal Institute for Vocational Education and Training (BIBB) and the IAB. By mapping this information into IAB administrative data, I document a strong negative monotonic relationship between employment density and changes in the employment shares of routine tasks in West Germany. By exploiting the longitudinal dimension of IAB data, I also provide interesting descriptive evidences on the possible channels that may account for this trend. Among these, I show that routine workers are more likely leave denser places relative to non-routine workers, whereas routine workers employed in large agglomerations are more likely to switch to non-routine occupations. I also find that higher contents of routine-manual tasks in cities significantly predict a higher probability to join unemployment. Finally, I try to disentangle the effect of exposure to automation from the effect of agglomeration on the contraction of routine tasks. More specifically, I try to assess whether a higher contraction of routine-tasks in denser places may be attributable to reasons that are directly related to urban agglomeration processes rather than to technological change. The intuition behind my research question relies on the idea that the interaction between congestion costs and task-biased asymmetries in agglomeration economies may increase the opportunity cost of using routine tasks in cities relatively to other tasks. In order to provide evidences that are consistent with the existence of such a mechanism, I adopt a two-fold empirical strategy. On the one hand, I adopt Autor and Dorn's (2013) empirical framework, which I use with the aim to take into account the effects of RRTC. On the other hand, I address the endogeneity of employment density with an instrumental variable strategy that relies on deep lags of population density (see Ciccone and Hall, 1998, Combes et al., 2008, Combes et al., 2010, Mion and Naticchioni, 2009). The evidences I provide by using this empirical framework indicate that - conditional on exposure to automation - the impact of agglomeration on the contraction of routine tasks is sizeable, significant and robust to different specifications - with particular reference to the use of different spatial unit of analysis and of alternative lags of population density as instrumental variable.

To recap, the remainder of the dissertation organized as follows: chapter I surveys the empirical literature on technological change and the labor market, whereas chapter II and III – each of which followed by a brief appendix – address the two empirical analyses, respectively.

Chapter I

Technological Change and the Labor Market: a Survey of the Empirical Literature

Abstract

The consequences of technological progress for the labor market have been a core topic in classical economics, and are now back as a particularly hot issue in nowadays' academic and public debate. While the literature in this field is large and heterogeneous, the trends detected by current empirical contributions are somehow uniform. This chapter summarizes the most recent empirical analyses on the relationship between technological change and the labor market. In particular, it focuses on the impact of technology on: a) employment levels, b) the evolution of the wage distribution, c) the occupational composition of employment. Employment levels result more likely to increase by means of compensation mechanisms, whereas the effect of technology on the wage distribution mainly depends on complementarity and substitution effects related to workers' skills and occupational tasks. Similarly, the literature shows that technological change has a polarizing effect on the occupational composition of employment - as technology substitutes for those occupations that are intensive in routine-tasks and that are typically located in the middle of the skill distribution.

1. Introduction

The implications of technological progress for the labor market represent an important subject matter of the empirical research in labor economics since the mid-nineties - i.e. about a decade later the advent of Information and Communications Technologies (ICTs) in production and the economy. However, in recent years the topic has turned into a particularly hot one. This is because, on the one hand, the rate of technological progress is perceived as faster than in the past - as suggested by the decline in digital technologies production costs and the consequent spread of the so called *digital economy*. On the other hand, persistent income inequalities patterns have worsened, especially after the advent of the Great Recession of 2008/2009. For these reasons, the topic aroused the interest of a growing audience of scholars and observers and encouraged the dissemination – besides academic research - of several popular and journalistic contributions. Just to give an example, in October 2014 the British newspaper *The Economist* dedicated a special report to what it defines - with the typical sensationalism of the popular press - "the modern digital revolution [...] that is disrupting and dividing the world of work on a scale not seen for more than a century ".[1]

This survey outlines a broad picture of the most recent economic research activity on technology and the labor market, without nonetheless neglecting worthy-of-mention contributions from scholars and thinkers of different backgrounds. In doing so - of course - it is maintained the rigor necessary to

[1] "The Third Great Wave", The Economist (special report), October 4-10, 2014.

guarantee to the reader an adequate comprehension of the achievements of the research in labor economics, with particular reference to the main theoretical assumptions, the methodology used and the empirical results obtained.

The remainder of this chapter is organized as follows. Section 2 briefly considers some future economic perspectives related to the evolution of computer technologies, while the following sections outline the main results of the academic research along three different dimensions. In particular, Section 3 focuses on the impact of technological progress on the employment levels, whereas Section 4 deals with the impact of technological progress on the evolution of the wage distribution. Section 5 addresses the impact of technological progress on the occupational composition of employment. Section 6 briefly reports some policy considerations, whereas section 7 summarizes and concludes the chapter.

2. ICT and the Economy: long-term trends and perspectives

The wide dissemination of computer technology - sustained by an impressive acceleration in technological progress – is raising numerous questions among economists, questions to which labor-market research is trying to provide adequate answers. Besides the analysis of recent dynamics, an interesting aspect of nowadays' debate concerns the long-term contribution of ICTs to the economy and, in particular, the future economic perspectives opened up by the so-called "digital revolution". Among others, this issue has been recently addressed by MIT scholars Erik Brynjolfsson and Andy McAfee (2011, 2014), who sought to identify the most salient trends as well as the main economic implications of the rapid technological progress. The main idea behind their contributions is that the recent acceleration in technological change is the result of an irreversible exponential growth process. For this reason, these authors argue that technology will soon lead to radical changes for the economy and the labor markets - as the most recent automotive and robotics achievements seem to confirm.[2] Such exponential growth rate would depend - in turn - on the intrinsic nature of digital technologies, as described by the so-called "Moore law". In 1965, Intel's co-founder Gordon Moore noted that - production costs constant - the number of transistors per integrated circuit was doubling about every year (Moore, 1965). As Brynjolfsson and McAfee (2011) point out, evidences suggests that indeed, for the same production costs, the performances of goods and services produced by the ICT sector doubles constantly - though on average they do so about every eighteen months. To give an insight about

[2] A significant example of this acceleration is the advent of self-driving cars, an innovation that only a decade ago seemed far away from the reach of technology. As Brynjolfsson and McAfee (2014) point out, during a competition of the Department of Defence held in 2005 several companies in the U.S. high-tech sector failed to take their self-driving vehicles more than a handful of miles into the desert. Nonetheless, after only six years, the giant digital firm Google announced the creation of the "Google-car" - which can autonomously drive itself on urban routes. A further interesting example is provided by the advent of simultaneous language translation systems, a fast-developing technology that in the long-run could lead to a reduction in the demand for human translators. As for robotics, of particular interest are the progresses made by the Honda ASIMO project - whereas in the field of artificial intelligence it is worth to mention the IBM "Watson" machine, which will find application also for healthcare consulting purposes (see Kelly and Hamm, 2013).

the economic consequences of exponential growth processes, these authors use a popular Chinese legend on the origins of chess. According to the story, the inventor was able to be rewarded by the emperor with a quantity of rice such that - starting from a single grain to be placed on the first piece of the chessboard - would have been doubled piece by piece up to the last one. This operation sums up to a total of 2^{63} grains of rice, a number which is close to nine billions of billions. According to some versions of the legend, when the second half of the chessboard was passed (threshold beyond which constant doubling began to affect whole rice cultivations) the emperor was forced to order the killing of the chess inventor. Brynjolfsson and McAfee (2011) use this popular legend to advance an insightful metaphor: by applying Moore's law from the late sixties (i.e. when the first microprocessors appeared), the threshold between the first and second half of the "chessboard of computers" would have been passed at the outset of the XXI century. Beyond the picturesque juxtaposition offered by these authors, it does not seem unreasonable to argue that - given the scope of technology today –a faster pace of technological progress may lead to substantial changes in terms of evolution of the production processes and labor market dynamics. Of course, estimating the impact of new technologies on the future of labor is - at least - a pretentious research aim. Nonetheless, the topic became so popular that some scholars rise to the challenge. This is the case of Oxford's researchers Frey and Osborne (2013), who - by means of a Gaussian-process classifier - estimate that over the coming two decades 47% of U.S. occupational categories risk to disappear because of computerization.[3]

[3] On the theoretical and empirical drawbacks of this research approach see Arntz et al.

Another crucial aspect of the long-term contribution of ICTs to the economy concerns the relationship between computers and labor productivity. It is well known that, during the early diffusion of ICTs, Nobel-Prize Robert Solow noted that the era of computers could be seen "anywhere except in productivity statistics" (Solow, 1987). This popular quote - passed on to history as the "Solow paradox" - gave rise to a long debate on the real contribution of ICTs to productivity which, to some extent, goes on to the present day.

On the one hand, among economists there is a wide consensus about the positive link between computer technologies and the productivity boom registered in the mid-nineties in the U.S. - i.e. when the country recovered from the long-lasting period of productivity stagnation started in 1973. With reference to this point, it is worth to mention the role of organizational innovations. In order to explain the time-gap between the early appearance of computers and the actual spread of their productivity effects, Brinjolfsson and McAfee (2014) compare the introduction of ICTs to the advent of electricity in the late XIX century. Indeed, before the necessary organizational adjustments electricity did not – by itself - contribute to productivity growth of U.S. farming sector. More specifically, at an early stage a single electric generator was replacing the old steam engine that was mechanically connected to the farming machines - whereas only decades later the machines were equipped with their own electric engine. This innovation enabled them to operate at larger distances from the central

---

(2016). For an authoritative contribution on the long-term perspectives of workplace automation, see Autor (2015).

engine and, in turn, significantly increased productivity. Similarly, ICTs would have needed time to trigger a significant impact on the production structure and foster productivity - being their potential related to the diffusion of best practices and organizational adjustments in production.

On the other hand, economists do not completely agree on the role of ICT for future productivity gains. According Jeorgenson et al. (2007), the role of ICT has been indeed crucial in accelerating U.S. productivity growth since the mid-nineties and - despite some slowdown in the years before the Great Recession - there is no basis to predict that this trend is set to low. Fernald (2014), in contrast, finds that the slowdown in U.S. productivity growth on the eve of the crisis - far to be attributable to financial reasons related to the housing bubble - mainly affected ICT-intensive sectors. Fernald (2014) argues that the boom of the nineties is more likely to have been a short-term phenomenon, and concludes that for the near future U.S. productivity growth is more likely to get back to a stagnant path rather than joining again an increasing trend.

Besides different perspectives on the contribution of ICTs for future productivity trends, the empirical evidence on current dynamics appears rather uniform - as the majority of studies find evidences of higher productivity gains in those sectors that invest more in innovation. In particular, the empirical literature surveyed by Cardona et al. (2013) shows that the positive impact of ICTs generally increases over time. Further, on aggregate the effect results larger in the United States than among European countries, though for what concerns firm-level evidences they are rather converging. Indicatively, most of these papers draw the attention on the crucial role of complementary investments (skilled-labor, organizational innovations, etc.), consistently with the idea that - without the necessary adjustments in production - the simple adoption of ICTs cannot trigger virtuous productivity-growth mechanisms. This seems particularly true with reference to investments in the so-called intangible assets (business models, organization of the production processes, adoption best practices related to ICT, etc.) – i.e. assets that are often difficult to quantify in economic terms.

Problems of economic measurement related to new technologies represent indeed another important issue. A particularly interesting example of such measurement drawbacks deals with the boom in the consumption of digital-goods.[4] On the one hand, the growing consumption of these goods (information, multi-media contents, tele-communications, social networks and related goods) is often associated to very large utility gains for consumers – generally difficult to quantify. On the other hand, these goods are often characterized by non-rivalry in consumption and by zero (or close to zero) marginal (re)production costs (Rifkin, 2014). This is particularly true in the case of the so-called user-generated contents – usually produced without remuneration and supplied for free on the internet. Good examples of these are the huge mass of audiovisuals uploaded and consumed daily on YouTube, the information available on Wikipedia, hotels and restaurants reviews generated and consulted by users on websites and smartphone apps. Important increases in consumers' utility also stem from the wide expansion

[4] "Digital goods" are all those goods and services convertible in a stream of bits (see Brinjolfsson and McAfee, 2014).

of free-telecommunications, as in the case of "Skype" and "What's app" - just to make two particularly well-known examples. Because of the negligibility of production costs and prices, the utility gains generated by the expansion of these markets are plausibly underestimated by traditional economic indicators such as the gross domestic product. Further, in the majority of cases these goods almost totally substituted non-digital traditional versions of the same goods - particularly in the industries of press, music and audiovisuals. Over the last years, production in these industries significantly lost shares of GDP, even though the consumption of the same products in digital format is dramatically increasing. Remarkably, production processes in these sectors were traditionally more labor-intensive, whereas the production (and reproduction) of nowadays digital goods involves relatively unimportant amounts of labor.

In sum, recent developments suggest that on the coming decades technological progress will force policy makers to deal with changes of structural nature. In this scenario, it will be crucial to understand not only to which extent technical progress may improve the economic perspectives, but also how and for which socioeconomic groups it may result in a well-being loss. Besides public policies, these outcomes will also depend on the adequateness of the economic research and on a proper understanding of the relationship between technology, the economy and the labor market.

3. Technology and employment: compensation vs. substitution

"….the opinion, entertained by the labouring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy"

(Ricardo, 1951, vol 1, p. 392; third edition, 1821)

"… We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment. This means unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour"

(Keynes, 1963, pp. 358-373; 1930)

"… the role of humans as the most important factor of production is bound to diminish—in the same way that the role of horses in agricultural production was first diminished and then eliminated by the introduction of tractors"

(Leontief, 1983)

The fear of a negative impact of technical progress on employment is an evergreen in economics and - as the opening quotes illustrate - concerned great economists across relatively different times. However, since the outset of the industrial era, productivity increases attributable to technological progress have been accompanied by a sustained growth of employment levels. For this reason, the fear of technological unemployment is often indicated with the title of "luddite fallacy".[5] Nonetheless, recent developments in computer technology as well as recent macroeconomic trends (in particular, the jobless nature of the recovery from the crisis in a number of countries) are encouraging these concerns to reemerge in the present economic debate. From a theoretical point of view, the topic is addressed substantially in the same way it was addressed by classical economists: today, just like in the past, concerns about technological unemployment are based on the hypothesis of a prevalence of the substitution effect. Similarly, the mechanisms supposed to counterbalance the substitution effect (a combination of theoretical postulates that Karl Marx called “the compensation theory”) where put forward for the first time during the first half of the XIX century (see Vivarelli, 2014).

In nowadays’ debate, the hypothesis of a prevalence of the substitution effect relies on the idea that the labor-saving bias of computer technology is stronger than in the case of past innovations (e.g. electricity), so that in the long-run technical progress might bring to mass technological unemployment. This idea became quite popular in the mid-nineties after the publication of Jeremy Rifkin's popular book (Rifkin, 1995) and found a first authoritative critic about a decade later with Levy and Murnane’s essay

[5] It is said that Ned Ludd was the charismatic leader of the Luddite movement, a group of British workers that during the first industrial revolution reacted to the fear of technological unemployment by destroying the first mechanic looms prototypes purchased by textile companies (see Hobsbawm, 1968).

(Levy and Murnane, 2004). The two authors point out that, though computer technology is particularly suitable in substituting for workers engaged in tasks that are based on fixed and explicit rules (i.e. strict automation), it has nonetheless important limits in substituting for those tasks that require complex cognitive processes or social interactions (i.e. artificial intelligence). In other words, technical progress would be detrimental only to a specific set of occupational groups (i.e. the so called "routine" jobs), and this scenario weakens the hypothesis of a long-run prevalence of the substitution effect. Nevertheless, as far as digital technologies are developing capabilities that seem to go far beyond mere automation (see footnote 1), in the present day this critique is somehow losing its edge.

In contrast, the "compensation theory" has its roots in those market mechanisms that may neutralize or even reverse the substitution effect of computer technology. The main channels through which the compensation effect should arise are basically three: a) decrease in prices, b) increase in incomes c) product innovation.[6] The first two cases differ from the latter inasmuch they stem from process innovation - i.e. when new technologies are adopted in order to reduce the cost of labor rather than to introduce new products.

The compensation via decrease in prices crucially relies on the hypothesis of perfect competition. In this case, the decline in production costs should be

[6] Channels that in the present debate are no longer considered are the compensation via new machines (if machines where produced by using more labor than that they may substitute, they would be no longer profitable to produce) and - because of the depressive effect on the aggregate demand - the compensation via decrease in wages (see Vivarelli, 2014).

reflected, indeed, in decreasing output prices. Higher product demand will, in turn, increase output and labor demand. Of course, the magnitude of the compensation effect will be proportional to the price elasticity of demand. In presence of inelastic product demand, the compensation effect is supposed to arise from the (indirect) positive income effect on consumers. This may result in higher demand for other products and, in turn, increase production and employment in other sectors of the economy. On the contrary, the compensation via (direct) increase in incomes holds especially under the hypothesis of non-competitive markets. In this case, the decline in production costs would generate extra profits and - depending on firms' propensity to invest and on workers' bargaining power – result in increasing investments, dividends or wages. The main difference with the compensation via decrease in prices is that, in this case, the increasing demand would stem from economic agents involved in the production process rather than from consumers.[7] However, it is worth noting that the compensation mechanisms described above are subject to two main critics. First, full compensation would take place only if the increase in demand is large enough to counterbalance the initial contraction in aggregate demand - i.e. the demand reduction associated to workers previously displaced by technology. Second, Keynesian-type effective demand constraints (such as employers' pessimistic expectations) may indefinitely delay the surge of compensation mechanisms

[7] Note that compensation via increase in investments is wakened if the new investments are capital-intensive, whereas the increase in dividends is more likely to raise incomes among agents with lower marginal propensity to consumption. Furthermore, has to be taken into account that - in the present institutional context - the compensation via increase in wages is less likely to take place.

- scenario in which the continuous path of technological progress may result in employment losses of structural nature (see Vivarelli, 2014).

In the case of product innovation, the labor-friendly effect of technology should stem from the demand for innovative products, which is assumed to be higher than the demand for older products (or older versions of the same products). This is a rather straightforward effect, since the creation of new markets is, indeed, plausibly more likely to increase employment. However, has to be bear in mind that nowadays' digital products – as pointed out in the previous section – are often characterized by a large substitution effect towards more mature products, whereas computer capital and digital goods production processes are less labor-intensive than those associated to past innovations.

For what concerns the empirical evidence, recent works on the impact of technological progress on employment levels are not very abundant - especially if compared with the large production of papers focused on the effects of technology on the wage and/or the occupational distribution. Among these works, industry-level and firm-level analyses are predominant, whereas - case by case - technological progress is approximated with different variables, ranging from investments in innovative capital to R&D investments.[8] Further, not all studies distinguish process innovation from product innovation, and when the distinction is adopted, it is not always done according to the same criteria. However - since the purpose of this

[8] Note that R&D expenditure is mainly associated with product innovation, whereas expenditure in innovative capital is predominantly associated with process innovation.

survey is to shed some light on the predominance of the mechanisms identified by the economic theory - the results obtained by this literature may be considered sufficiently converging in order to highlight some stylized facts. After reviewing some of the most recent studies, I report the main conclusions at the end of the section (for a survey of previous studies, see Sabadash, 2013, and Vivarelli, 2014).

For the U.S. case, an interesting paper is Coad and Rao (2011) - which uses hi-tech industries firm-level data over the period 1963-2002. In particular, the authors proxy for technological progress with the share of R&D expenditure on the volume of sales, whereas also considering the number of registered patents. By using conventional regression methods, this analysis provides evidences of a positive impact of technology on the employment levels of firms in these branches of production.

As for the European case, Harrison et al. (2014) use firm-level data from the European Community Innovation Survey (CIS). This study focus on the period 1998-2000 by considering data from France, Germany, Spain and Great Britain. In addition to employment levels and sales, the CIS contains information on the adoption of technological innovations that distinguish between product innovation and process innovation. By addressing the endogeneity of the main explanatory variables with an instrumental variable strategy, Harrison et al. (2014) recover evidences of a labor-friendly effect of process innovation. More specifically, whereas productivity gains result to always destroy jobs (i.e. either or not conditional on technology) over the period observed the increasing product demand considerably offset the negative impact of technology on employment. This set of evidences is fully consistent with the compensation theory. As for product innovation, the effect estimated is unambiguously positive. In this case, job creation results more pronounced in the manufacturing sector. Moreover, the contraction of employment attributable to business-stealing effects towards non-innovative firms corresponds to about one third of the net creation of jobs attributable to innovative firms.

By expanding the time-span, Bogliacino and Pianta (2010) match data from the Sectoral Innovation Database (SID) of the University of Urbino with information from the KLEMS and the OECD STAN databases. They analyze industry-level employment trends over the period 1994-2004 among eight European countries. In particular, these authors take into account the impact of technology on employment growth in terms of both technological-competitiveness (by using information on products turnover) and cost-competitiveness (by using the industry-level share of firms aiming to reduce labor costs). By means of a generalized least square regression method (GLS), Bogliacino and Pianta (2010) recover evidences of a positive effect of technology on employment growth when innovations are oriented towards the production of new goods (higher product turnover), and find evidences of a negative impact for what concerns the innovation of the production processes (share of firms aiming to reduce labor costs).

Bogliacino et al. (2012) use instead JRC-IPTS data from the European Commission on 677 European firms over the period 1990-2008, and proxy for technological progress with information on R&D expenditure (mostly associated with product innovation). By means of Least Square Dummy Variable Corrected estimations (LSDVC), these authors find a positive and significant effect (though small in magnitude) of R&D investments on employment growth, particularly in the case of the service sector and in hi-tech manufacturing. In the case of the traditional manufacturing sector, conversely, no significant evidence is recovered. Bogliacino and Vivarelli (2012) address the same issue by using industry-level data (OECD STAN and ANBERD) for 15 European countries over the period 1996-2005. With GMM-SYS panel estimations, this analysis recovers evidences of a positive impact of R&D expenditure on employment growth - confirming previous empirical findings on the topic. Further, Piva and Vivarelli (2017) make use of the same data sources to focus on 11 European countries over the period 1998-2011. They find that the labor-friendly impact of R&D expenditure is entirely due to medium and high-tech sectors, with no effect in low-tech industries.

Using CIS data for the biennium 2002-2004, Evangelista and Vezzani (2010) - although focusing on the effects of innovation on firms' output rather than employment - have the merit of taking into account, besides technological innovations, the role of organizational innovations. By grouping firms into four broad categories (product innovators, process innovators, organizational innovators and complex innovators - the latter being a combination of the former three categories), these authors find that complex innovation (mainly adopted among larger enterprises) is the most effective in terms of output increase, especially in the manufacturing sector. Though the employment effects of innovation are not directly took into account, and though the sample used is not fully representative of the universe of enterprises, these results obtained are consistent with the presence of compensation mechanisms related to technology.

For the German case, Lachenmaier and Rottman (2011) adopt a GMM-SYS estimation approach in a dynamic panel setting by using firm-level data from the IFO Innovation Survey for the period 1982-2002. Somehow, the evidences recovered make this paper an outlier of the literature, since the labor-friendly impact of process innovation results to be larger than that estimated for product innovation. Further, the overall positive effect of innovation is robust to different specifications.

Turning to Spain, Ciriaci et al. (2016) use CIS data on more than 3000 firms over the period 2002-2009. By using a semi-parametric quantile regression approach, they find that innovation fosters employment growth especially in small, younger firms. They also show that, among those firms that contributed more to job creation, innovative firms were able to sustain more employment growth relative to non-innovative firms. Using firm-level data from the Survey on Business Strategies (*Encuesta Sobre Estrategias Empresariales*, ESEE) for the period 2002-2013, Pellegrino et al. (2017) focus on the effect of R&D expenditure (product innovation) and on the effect of investments in innovative machineries and equipment (the so called "embodied technical change" – ETC - mostly associated to process innovation). By means of GMM-SYS panel estimations, they recover no labor friendly impact of innovation - neither in the case of R&D expenditure nor in the case of ETC. Nevertheless, they find that the positive effect of R&D is highly significant among high-tech firms, whereas ETC shows its labor-saving effects when excluding small and medium enterprises from the sample.

As for the Italian case, Hall et al. (2008) use Microcredit-Capitalia firm-level data relative to the period 1995-2003. In the case of process innovation, this study recovers weak and insignificant evidences of a substitution effect. Further, these authors argue that the slowdown in productivity growth observable after the 2000's may be related to a certain difficulty of Italian firms in the benefitting from innovation, though the overall trend results to be mostly driven by non-innovative firms. As for product innovation, evidences indicate an important labor-friendly impact, equal to a half of the overall job-creation during the period observed.

To sum up, the most recent empirical literature lacks of cross-country aggregate data analyses, which would be helpful to assess the impact of technology on aggregate employment.[9] Nevertheless, the available evidences - though somehow fragmented – present some degree of uniformity. Indeed, in the case of product innovation, all researches find evidences of a positive effect of technology on employment. For what concerns process innovation,

[9] Among the most recent empirical contributions, Feldmann (2013) is the only paper to use country-level aggregate data in this literature, detecting a medium-term negative effect of innovation on aggregate employment. For what concerns regional-level evidences, it is worth to mention the analysis of Acemoglu and Restrepo (2017). These authors consider the effects of industrial robots on U.S. local labor markets, providing evidences of a negative impact of exposure to robots on local employment levels and wages. Another interesting analysis making use of a regional approach is Blien and Ludewig (2017). By using German data, they show that the higher the price elasticity of industries in a given region, the higher the labour-friendly effect of technological progress.

on the contrary, evidences are more ambiguous - when not conflicting. Case-by-case, when estimates are significant, they range from positive to negative. In sum, the available empirical evidences do not seem to support the hypothesis of a prevalence of the substitution effect.

4. Technology and wages: from the skilled-biased technical change framework to the "routinization" hypothesis

This section surveys the most recent empirical findings on the relationship between technical progress and the wage distribution. This wide strand of the literature originates in the U.S. during the early nineties, with the aim to explain the increasing wage inequality observed in the country since the previous decade. Important contributions in this field (Katz and Murphy, 1992, Murphy et al., 1998, Card and Lemieux, 1998, Acemoglu, 2002) provide several evidences in favor of the well-known skill-biased technical change (SBTC) theory. Briefly, the SBTC hypothesis is based on the idea that computer capital mostly benefits the productivity of high-skilled workers, usually identified with higher educational attainment levels. According to the SBTC theory, therefore, investments in ICT capital increase the wage of high-skilled workers relative to the wage of low-skilled workers. Evidences provided by this literature point out that this mechanism may have significantly contributed to the increasing wage inequality in the U.S.[10]

[10] More specifically, the SBTC hypothesis accounts for the fact that- from the late seventies to the early nineties - wage inequality in the U.S increased despite a large increase in high-

However, during the nineties the pattern followed by the evolution of the wage structure in the U.S. experienced a substantial change. Relative wages at the bottom-end of the skill distribution ceased to decrease (or even started to increase), whilst continuing to drop around the center. In order to explain this phenomenon - usually indicated as "wage polarization" - the seminal paper of Autor et al. (2003) extended the SBTC framework - followed by several other important theoretical and empirical contributions (for instance, Autor et al., 2006, Autor et al. 2008, Autor and Acemoglu, 2011, Autor and Dorn, 2009, Autor and Dorn, 2013). This new literature builds on the idea that - rather than skills or educational attainment levels - complementarity and substitution effects of technology depend on the type of tasks that workers perform at their workplace. Crucially, the substitution effect of technology is supposed to affect occupational tasks that are typically located in middle of the skill distribution. More specifically, the classification of tasks accounts for two main dimensions: a) manual and cognitive, b) routine and non-routine. In these models, routine tasks can be carried out both by workers and machines (in the most extreme case it is assumed that the two inputs are perfect substitutes), whereas non-routine tasks can be supplied only by the labor force. In particular, the bottom-end of the wage distribution is supposed to predominantly match occupations that are intensive in non-routine manual tasks, whereas the top-end is mainly associated to non-routine cognitive tasks. As technological progress reduces the cost of

skilled employment. According to the SBTC theory, indeed, during the eighties - because of the complementarity between ICT capital and workers' skills - the relative demand for high-skilled labor increased more than the relative supply, generating wage inequality.

technology over time, it is assumed that firms will increase the use of machines to perform an increasing number of routine tasks. Because of this process, routine workers may experience decreasing wages - and may choose to allocate to the production of non-routine manual tasks. Moreover, due to the use of a Cobb-Douglas neoclassical production function, these models assume that the increase of routine tasks is complementary with the other two types of tasks in the economy - with a relative increase in their productivity. As the cost of computer capital declines, the model predicts: a) an increase in the wages of non-routine cognitive workers (because of the complementarity with routine tasks); b) a decrease in the wages routine workers; c) an ambiguous impact on the wages of non-routine manual workers. This ambiguity is essentially due to two opposing effects. On the one hand, there is a positive effect on the productivity of low-skilled workers because of the increase in routine tasks. On the other hand, there is an increase in the labor supply towards non-routine manual tasks - since displaced routine workers may prefer to allocate to occupations specialized in these tasks. Whenever the increase in the labor supply exceeds the positive effect on productivity, low-skilled workers will experience decreasing wages. In the opposite case, the model generates wage polarization.

This more nuanced theoretical framework, also indicated as *routine-biased* or - more recently - *routine-replacing* technical change (RRTC), better explains recent wage dynamics in the United States. In particular, during the eighties the labor supply effect towards non-routine manual tasks would have prevailed, depressing low-skilled workers' wages and resulting in a skill-biased trend (i.e. a monotonous growth of wages along the skill distribution). During the nineties, conversely, the productivity effect caused by the increase in the production of (cheaper) routine tasks is supposed to have more than counterbalanced the increasing labor supply for non-routine manual tasks, with a positive effect on the wages of low-skilled workers that resulted in the polarization of the wage structure (see Figure 1).

Besides the already mentioned papers, several studies empirically apply this framework to U.S. data. Among others, an important contribution is Firpo et al. (2011). This analysis shows that indeed - from the eighties to the first decade of the new century - the U.S. experienced a wage polarization process. In particular, the remuneration of low-skilled workers rose sharply, whereas the relative wages of medium-skilled employment (i.e. routine workers) contracted over time. More specifically, the wage polarization pattern is accounted for the fact that wages increased more at the bottom than the in the middle of the skill distribution. According to Firpo et al. (2011), two main forces have contributed to the polarization of wages in the United States. On the one hand, the pattern is the result of technical progress - as predicted by the RRTC framework. On the other hand, changes in U.S. labor market institutions concurred to increase overall polarization, since the decline of union power would have mostly affected workers located around the middle of the wage distribution.

Figure 1. *Wage polarization in the United States.*

Source : Acemoglu and Autor (2011).

Cortes (2016) considers instead routine workers' occupational mobility. By making use of longitudinal data from the Panel Study of Income Dynamics for the United States (PSID), Cortes (2016) recovers strong evidences of selection on ability. More specifically, routine workers with higher skill levels are more likely to move towards non-routine cognitive tasks, whereas routine workers with lower skill levels tend to allocate to occupations that are intensive in non-routine manual tasks. Interestingly, Cortes (2016) estimates occupation wage premiums controlling for the self-selection of workers into occupations based on unobserved ability, and shows that in the long-run routine workers switching to non-routine jobs experience faster wage growth relative to those who stay in routine jobs.

As for European countries, empirical evidences of wage polarization are somehow more limited. The most significant contribution is perhaps Dustmann et al. (2009), which analyze the case of Germany. This paper highlights a polarizing dynamic of labor income in the country that can be accounted for technological dynamics, also task-biased. Centeno and Novo (2009) observe a similar dynamic in Portuguese data. For the United Kingdom, Machin (2011) describes a growing inequality pattern and - for some periods but not in recent years - a dynamic of wage polarization. However, for a number of European countries there are no evidences of a wage-polarization process. Charnoz et al. (2011) analyze the French case and, though documenting that in recent decades there was a decrease in wage inequality (partly attributable to a decrease in returns to education), find no evidences of wage polarization. For the Spanish case, similarly, Izquierdo and Lacuesta (2006) document a reduction in wage inequality attributable to decreasing returns to education. Evidences are analogous also for the Italian case. Naticchioni et al. (2008) document stable trends in labor market inequalities, whereas Naticchioni and Ricci (2009) recover evidences of a decrease in wage inequality in the private sector and an increase in the public sector. According to Naticchioni et al. (2010), also for the Italian case decreasing returns to education may account for these trends. It is interesting to note that in three major European countries such as France, Italy and Spain, the empirical evidence shows a reduction in wage inequality and a decline in the skill premium. In other words, in these countries studying in the eighties and in the nineties was relatively more rewarding than studying in recent years, and the evolution of the wage structure is difficult to explain with skill-biased technical change arguments.

The empirical contributions mentioned so far separately analyze single national cases. Aiming at extending the analysis at a broader level, Naticchioni et al. (2014) looks at European countries as a whole. By using both industry-level and individual data, this paper not only documents recent changes in the distribution of wages at the European level, but also estimates the effect of technical progress on the evolution of the wage structure. For what concerns industry-level evidences (EU-KLEMS and WIOD for the period 1995-2007), results indicate that the distribution of wages in Europe is not evolving by following a polarization process. Overall, the remunerations of low, medium and high-educated workers are growing at the same rate, whereas the relative distance between the wages of high-skilled and medium-skilled workers - as well as the distance between medium and low-skilled ones – result to be rather stable. For what concerns the impact of technology on the remunerations of these three educational groups, this study use changes in ICT capital over industry value added as a proxy of technology. Regression-based evidences indicate the following relationships:

- a positive effect on the wage bill of high-skilled workers, confirming the greater complementarity of these workers with technology;

- a negative impact on the wage bill of medium-skilled workers, consistently with the idea that this category is more exposed to the substitution effect of technology;

- a non-insignificant impact on the wage bill of low-skilled workers.

However, by breaking down the impact on the total wage bill in an hours worked component and a wage component, Naticchioni et al. (2014) show that the polarizing impact of technology is accounted only for changes in the amount of hours worked. This outcome suggests that technological change in Europe may have a substantially different impact from that observed in the United States: in Europe ICTs seem to have an impact only on the composition of employment, whereas in the U.S. the effect of technology - besides relative quantities – also affects wages.

For what concerns the analysis of individual data, Naticchioni et al. (2014) match data from ECHP and EU-SILC data for the period 1996-2007 with occupational measures of task intensity (i.e. abstract, routine and manual), and use them in order to take into account the role of technology on the wage distribution. By means of a counterfactual distributional analysis, the authors show that the impact of these occupational measures on the wage distribution is indeed a polarizing one, though rather mild. More specifically, a higher intensity in non-routine manual tasks (as in the case of the so called “service jobs” - i.e. occupations specialized in the provision of low-skilled in-person services to households and businesses) predicts increase in the wages at the bottom end of the distribution. For what concerns the top end of the wage distribution, higher intensity in non-routine cognitive (or abstract) tasks predicts increasing wages - whereas higher routine-task intensity predicts a reduction of wages around the center, consistently with the predictions of the RRTC framework.

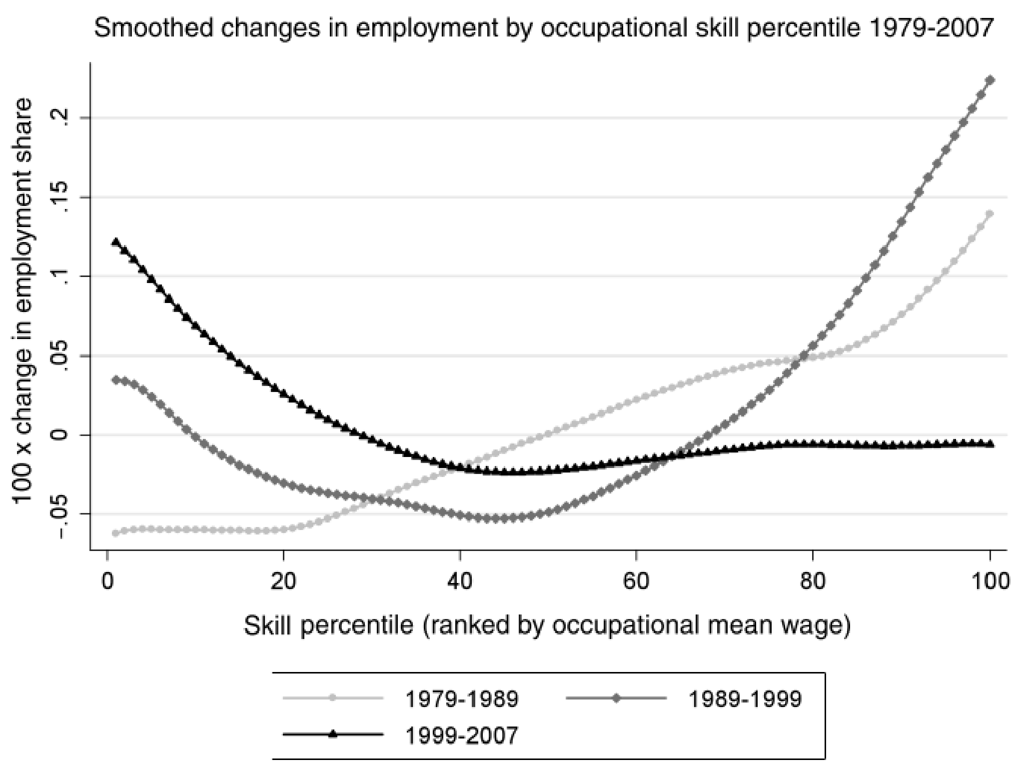
5. Technology and jobs: Routine-replacing technical change and job polarization

If the evidences on the consequences of technological progress for the wage distribution are somehow heterogeneous, those concerning changes occurred in the occupational composition of employment are comparatively more converging. Indeed, the literature seems to have achieved a certain consensus on the topic, reinforced by the substantial convergence observed in the employment patterns of U.S. and Europe. In particular, the empirical findings surveyed in this section represent the other side of the coin of the wage polarization phenomenon addressed in the previous section – since a wide number of papers in this literature adopt the RRTC framework to focus on the variations in the relative quantity of different jobs demanded by the economy.

As illustrated, the RRTC theory builds on the idea that computer technologies substitutes for workers engaged in routine tasks and complements for those specialized in non-routine tasks. Accordingly, employment is expected to increase less among routine jobs and to increase more among non-routine jobs. As far as routine jobs are mostly associated to medium-skilled employment, this phenomenon is supposed to trigger employment polarization. Note that the complementarity with technology is well established in the case of high-skilled workers (mostly employed in managerial, professional and technical occupations – i.e. specialized in non-routine cognitive tasks), but is less obvious in the case of low-skilled workers, mostly associated to service occupations. Nonetheless, these workers are not supposed to be subject to the substitution effect of technology, since they mostly supply non-routine manual tasks. Common examples of service occupations are personal care and personal service workers, protective service workers, cleaners and helpers, etc. – i.e. low-skilled jobs that involve complex interactions that are not easy to codify in a pre-fixed system of explicit instructions. According to the literature, indeed, «a task is *routine* if it can be accomplished by machines following explicit programmed rules» (Autor et al., 2003) or – in other words - routine-tasks are «tasks which are sufficiently well understood that can be fully specified as a series of instructions to be executed by a machine» (Acemoglu and Autor, 2011). Typical examples of medium-skilled jobs that are intensive in routine tasks are craft and production occupations (in particular, stationary plant machine operators and assemblers and precision handicraft occupations), usually identified as occupations intensive in routine-manual tasks, and clerical and administrative support occupations (office clerks, cashiers and tellers, bookkeepers, retail sales occupations, etc.) - i.e. jobs predominantly associated to routine-cognitive tasks.

For the U.S., the RRTC framework has proved to be particularly consistent with recent patterns followed by employment growth for different skill levels. Indeed, as shown in Figure 2, during the eighties employment growth mainly increased among high-skilled occupations – consistently with the skill-biased technical change explanation. From the nineties onward, however, this positive trend at the top end suffered a substantial slowdown - accompanied, on the one hand, by a contraction in the employment shares of medium-skilled occupations and, on the other hand, an expansion in the shares low-skilled ones.

Figure 2. *Job polarization in the United States.*

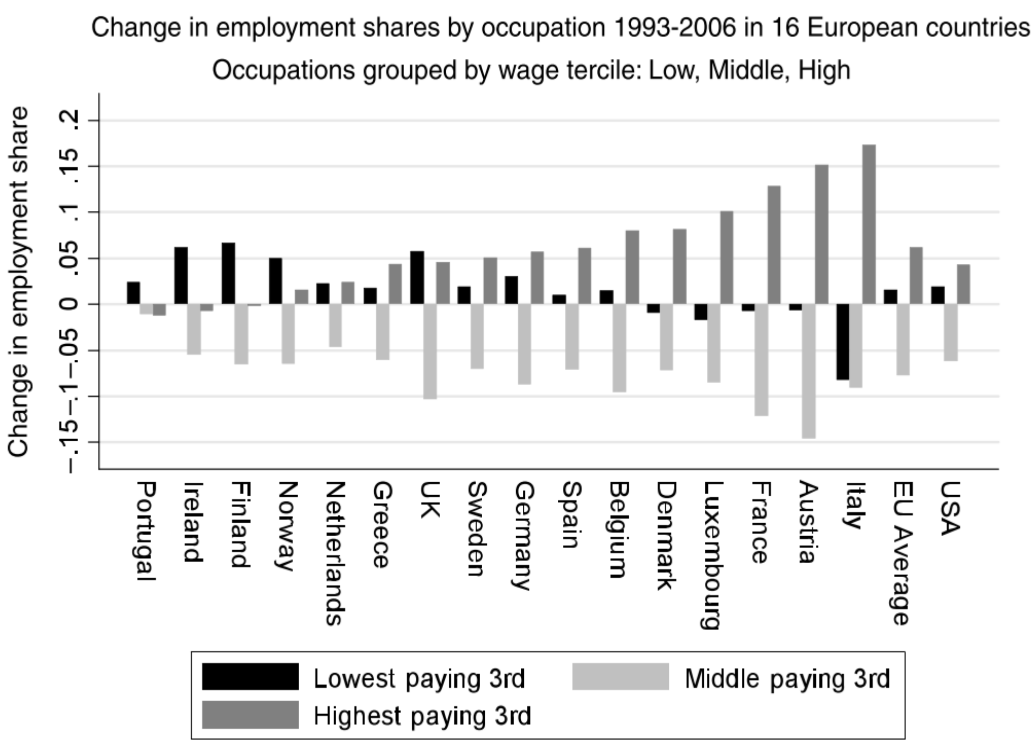


Source : Acemoglu and Autor (2011).

Autor and Dorn (2013) document that in the US the employment share of low-skilled workers in service occupations has grown by 50 percent between 1980 and 2005 - an increase that accounts for a significant part of the observed employment polarization. Moreover, in comparison to alternative explanations (such as changes in demographic trends and structural change patterns - with particular reference to the decline of the manufacturing sector and the growing import competition from emerging economies) the RRTC theory generally results to better account for job polarization. Aiming at disentangling the role of technology from that of international trade, Autor et al. (2015) provide valuable empirical evidence on this topic. By using regional information form U.S. census data, this paper estimate the impact of exposure to automation and that of exposure to imports from China on Unites States' local labor markets dynamics. The main results provided by Autor et al. (2015) reveal a substantial difference in the effect of these two forces. Further, this study also show that - conditional on the type of industry, occupation, education, age and gender - heterogeneities in these effects are at work. In particular, if regional exposure to China-imports negatively affects employment across all occupational groups (particularly in the manufacturing sector, with possible negative spillovers towards other industries), results point out that exposure to automation only triggers changes in the occupational composition. Consistently with the theory, indeed, both in the manufacturing and in the broad service sector technology predicts a contraction in routine employment which is entirely offset by the expansion of non-routine manual and non-routine cognitive occupations. According to Autor et al. (2015) evidences, a partial exception to this is represented by female workers, who after displacement result more likely to join unemployment rather than allocate to non-routine jobs.

As mentioned above, also in European countries employment trends are consistent with a process of employment polarization. Figure 3 plots changes in the employment shares of low, medium and high wage occupations for 16 European countries.

Figure 3. *Job polarization in Europe.*



Source : Acemoglu and Autor (2011) with data on European employment from Goos et al. (2009).

As Figure 3 shows, between 1993 and 2006 medium-wage occupations lost employment shares in all 16 countries, particularly in Austria, France, United Kingdom and Belgium. With reference to the growth of low-paid employment, conversely, employment shares have increased in the majority of cases. These evidences seem to suggest that employment polarization is the rule rather than the exception in Europe, whereas - as Figure 3 shows - the European (unweighted) average gets very close to the figure of the United States. Despite this similarity, the empirical literature on job polarization in European countries is relatively more limited.

As for single countries, evidences on job polarization and the role of technology are available for the United Kingdom and West Germany. For the West German case, Spitz-Oener (2006) not only documents a job polarization pattern consistent with the RRTC theory, but also provides interesting within-occupation evidences on the topic. More specifically, this study makes use of BIBB/IAB survey data in order to observe the within-occupation evolution of tasks over-time. Tasks are classified in the following groups: i) non-routine analytical, ii) non-routine interactive, iii) routine-cognitive, iv) routine-manual, v) non-routine manual. According to Spitz-Oener (2006), increasing computerization at the workplace is related to a higher contraction in routine tasks and a higher expansion in non-routine ones (in particular, analytical and interactive) even within occupation-education groups and occupation-age groups. Evidences of job polarization in West Germany are provided also by Dustmann et al. (2009). Similarly to Spitz-Oener (2006), this study measures occupational tasks by using

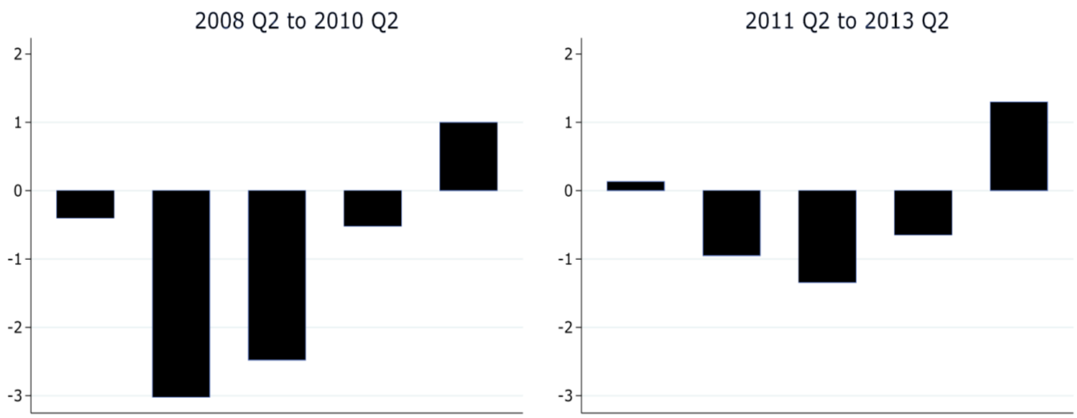
BIBB/IAB survey data. This paper clearly shows that also in Germany occupations around the middle of the skill distribution, relatively to those at the bottom end, have suffered higher employment shares losses. Indicatively, the descriptive evidence shows that major losses occurred in correspondence of those occupations for which routine-tasks are more important, whereas this trend results more pronounced during the nineties. However, Dustmann et al. (2009) also point out that increasing low-skilled employment shares in the nineties may be related to the annexation of the eastern part of the country - triggering inflows of unskilled labor force towards the west.

For the United Kingdom, Goss and Manning (2007) analyze wage and employment data over the period 1975-1999 and provide evidences of a job polarization process. By making use of U.S. occupational tasks measures, these authors compare different alternative explanations and conclude that the RRTC hypothesis is more likely to account for job polarization in this country.

By following the same line of research, Goos et al. (2009) analyze European data (EU-LFS) for 16 countries over the period 1993-2006. This study shows a pervasive pattern of employment polarization in Europe. Evidences indicate that, on average, medium paid occupations employment shares decreased by 8 p.p. - offset by an increase in high and low-wage occupations of 6 and 2 p.p., respectively (see Figure 3). The authors test different hypotheses on the determinants of job polarization (in particular, wage inequality, education and offshoring) by means of standard regression methods: results are clearly in favor of the RRTC explanation. By expanding the time-span to year 2010, Goos et al. (2014) show that the between-industry dimension of job-polarization in Europe accounts for an important part of overall job-polarization. The authors develop a theoretical framework which takes into account industry costs and prices in order to model the within and between-industry dimension of job-polarization as a function of RRTC and offshoring. Applying this framework to the data, they show that the RRTC explanations better accounts for polarization. Further, the predictions of their model fit pretty well the actual changes in the employment shares of different occupations, both for the within and the between-industries dimensions.

With reference to changes in the employment structure in Europe during the years of the economic crisis, to the best of my knowledge, no academic paper is yet available. Nevertheless, a recent report of the European Jobs Monitor (Eurofound, 2014) provides some interesting descriptive evidences on the topic. This section concludes by illustrating the main trends identified by the report. According to the report, between the second quarter of 2008 and the second quarter of 2010 the 28 European Union countries lost 5 million jobs, plus almost one million during the sovereign crisis debt between 2010 and 2011. The report documents a further decline in employment between the second quarter of 2011 and the second quarter of 2013, which affected another 1.3 million jobs. As Figure 4 clearly illustrates, such contraction mainly affected workers located towards the center of the job-wage distribution (in this case divided into quintiles).

Figure 4. *Percentage change in employment by job-wage quintile in the EU 27 (2008-2010, 2011-2013).*



Note: Croatia has been omitted for reasons of comparability. Source: Eurofound (2014).

In particular, between the second quarter of 2008 and the second quarter of 2010 employment in the bottom quintile suffered a relative contraction that is far less pronounced than that observable in the second and the third quintile. This trend is also observable between the second quarter of 2011 and the second quarter of 2013 – when employment in the bottom quintile slightly increases. According to the report, the polarization pattern observable in employment growth is mostly attributable to the sharp fall in the construction and the manufacturing sectors – i.e. industries that, on the one hand, are relative more intensive in medium-paid employment and that, on the other hand, have been strongly affected by the negative impact of the economic crisis. In contrast, the report shows that - between the second quarter of 2011 and the second quarter of 2013 - employment growth in both the top and the bottom quintile has been mostly driven by the service sector (Eurofound, 2014).

In sum, according to the descriptive evidences provided by Eurofund (2014), employment losses in Europe during the years of the economic recession have been somehow concentrated around the middling quintiles of the job-wage distribution, both before and after the spread of the European sovereign debt crisis. Overall, this suggests that technological and structural change dynamics at the base of job polarization may have been reinforced by the advent of the economic crisis.

6. Policy considerations

The empirical literature briefly surveyed in this survey indicates that the spread of digital technologies is leaving behind winners and losers in the labor market. On the one hand, the beneficiaries are mainly associated with high-skilled workers employed in high-paid occupations. On the other hand, medium-skilled workers employed in medium-paid occupations – often associated to routine tasks - results to be the most affected category. Indeed, compared to low-skilled workers, these workers result more likely to face income reductions and periods of unemployment as a consequence of technical progress. In case of technological displacement, these individuals - usually identified with prime-age workers endowed with somehow outdated skills - will have to allocate on a labor market where demand is predominantly moving towards higher skill levels.

Though the social-cohesion issues related to these trends are starting to draw the attention of the European policy-maker (EPSC, 2016), so far no specific policy on the topic has been implemented. The following lines will consider some possible policies that, in the coming years, might be included in the policy agenda.

With reference to labor market active policies, it is interesting to note that, in general, training and re-training policy frameworks are mainly oriented towards an audience of low-skilled individuals. This raises the issue of evaluating a new design for training policies. In particular, it may be necessary to also target medium-skilled individuals previously employed in routine-intensive occupations – who may find more difficult to reallocate in the labor market because of technological progress. However, extending the targeted population may not be an optimal choice. In fact, as observed by Mosso and Heckman (2014), corrective-type interventions in an advanced stage of workers' career seem to have little effect, whilst more significant results can be achieved in the long term by means of policies oriented to the early stages of education (in particular the primary education, by adopting a perspective that emphasizes the development of multiple skills and abilities).[11] According to these evidences, it would be - in principle - more efficient to limit training policies to younger individuals (i.e. at an early

[11] It may be argued that primary education systems are traditionally focused on the formation of the public servant or, in other words, disproportionally focused on the development of literacy and numeracy skills. Primary education programs may be reformulated in order to increase the complementarity between workers and machines, for instance, by emphasizing the role of information and data management skills rather than mere memorization skills.

stage of their careers, or before they enter the labor market), and reduce the welfare losses of workers negatively affected by technological progress by means of income-support measures.[12]

More in general, it would be appropriate to rethink labor-market policies in order to increase the degree of complementarity between workers and new technologies. Further, it would be interesting to better characterize the consequences of technological progress by taking into account the role of different institutional contexts. In particular, additional evidences would be necessary in order to assess whether different national labor market institutions play a role in mitigating or intensifying the consequences of technological progress in terms of employment and income dynamics.

7. Conclusions

The empirical evidence surveyed in this chapter suggests that technological progress, in recent years, has been not detrimental for overall employment growth. According to the literature, indeed, market-based compensation mechanisms seem to prevail on the substitution effect associated to labor-saving technologies. Nonetheless, the literature also points out that the increasing adoption of computer technologies triggered important shifts in the labor demand, and that these changes are crucially related to the type of

[12] There are also positions at odds from that of James Heckman. Indeed, it may be argued that the participation in the labor market cannot be evaluated only with reference to efficiency dynamics, since other important aspects (such as feeling part of a community through labor-market participation) should be taken into account to preserve social-cohesion.

tasks that workers perform. Accordingly, there is considerable heterogeneity in the effects of technical progress, differences that the literature identifies by classifying workers according to their level of educational attainment, average earnings, type of occupation and measures of task intensity. On the one hand, the adoption of computer capital tends to boost the demand for high-educated and high-income workers, mostly employed in managerial, professional and technical occupations. This is because these jobs are predominantly specialized in the provision of non-routine cognitive tasks, and these tasks are more complementary with technology. On the other hand, computer capital generates a relative contraction in the demand for routine-tasks – i.e. tasks that technology tends to substitute. Differently from the previous case, these tasks are mostly provided by medium-educated/medium-wage workers - mainly employed in craft and production occupations (routine manual tasks) or in clerical and administrative support occupations (routine-cognitive tasks). According to the literature, labor demand shifts induced by technology over the last decades are at the base of the main changes occurred in the labor markets of the United States and of some European country – namely - wage polarization and employment polarization.

Since the issues addressed in this literature are not yet fully-entered in the policy agenda, it may be necessary to increasingly raise the awareness on the topic among public institutions, even more so if the observed trends - alongside the rapid evolution of digital technologies - will intensify in the years to come.

References

Acemoglu, D. (2002) "Technical Change, Inequality, and the Labor Market", Journal of Economic Literature, 40, 7-72.

Acemoglu, D. and Autor, D. (2011) "Skill, Tasks and Technologies: Implications for Employment and Earnings", Hanbook of Labor Economics, vol. 4B (1043-1171).

Acemoglu, D. and Restrepo, P. (2017) "Robots and Jobs: evidences from U.S. labor markets", NBER Working Paper No. 23285.

Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris.

Autor, D. (2015) "Why Are There Still So Many Jobs? The History and Future of Workplace Automation", Journal of Economic Perspectives, 29(3), 3-30.

Autor, D. and Dorn, D. (2013) "The Growth of Low Skill Service Jobs and the Polarization of U.S. Labor Market", The American Economic Review, 103(5), 1553-1597.

Autor, D. and Dorn, D. (2009) "This job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure." The American Economic Rewiev, 99(2), 45-51.

Autor, D., Dorn, D., Hanson, G. (2015) "Untangling Trade and Technology: Evidence from Local Labor Markets*", Economic Journal*, 125(584), 621-646.

Autor, D., Katz, L., Kearney, M. (2006) "The Polarization of U.S. Labor Market", The American Economic Review, 96(2), 184-194.

Autor, D., Katz, L., Kearney, M. (2008) "Trends in U.S. Wage Inequality: Revising the Revisionists", Review of Economics and Statistics, 90(2), 300-323.

Autor, D., Levy, F., Murnane, R. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration", The Quarterly Journal of Economics, 118(4), 1279-1333.

Blien, U. and Ludewig, O. (2017) "Technological Progress and (Un)employment Development", IZA Discussion Paper Series 10472.

Bogliacino, F. and Pianta, M. (2010) "Innovation and Employment: A Reinvestigation Using Revised Pavitt Classes", Research Policy, 39(6), 799-809.

Bogliacino, F., Piva, M., Vivarelli, M. (2012) "R&D and Employment: An Application of LSDVC Estimator using European Micro-Data", Economic Letters, 116(1), 56-59.

Bogliacino, F. and Vivarelli, M. (2012) "The Job Creation Effect of R&D Expenditures", Australian Economic Papers, 51(2), 96-113.

Brynjolfsson, E. and McAfee, A. (2011) Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy. Digital Frontier Press.

Brynjolfsson, E. and McAfee, A. (2014) The Second Machine Age: Work, Progress and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Co. Press.

Card, D. and Lemieux, T. (2001) "Can Falling Supply Explain the Rising Return to College for Younger Men?", The Quarterly Journal of Economics, 116(2), 705–46.

Cardona, M., Kretschmer, T., Strobel, T. (2013) "ICT and Productivity: Conclusions from the Empirical Literature", Information Economics and Policy, 25(3), 109-125.

Ciriaci, D., Moncada-釘aternò-Castello, P., Voigt P. (2016) "Innovation and job creation: A sustainable relation?" Eurasian Business Review, 6, 189-213.

Centeno, M. and Novo, A. (2009) "When Supply Meets Demand: Wage Inequality in Portugal", IZA Working Papers, 4592.

Charnoz, P., Coudin, E., Gaini, M. (2011), "Wage Inequalities in France 1976-2004: A Quantile Regression Analysis", INSEE Working Paper, 6.

Coad, A. and Rao, R. (2011) "The firm-level Employment Effects of Innovations in High-Tech US Manifacturing Industries", Journal of Evolutionary Economics, Vol.21 (255-283).

Cortes, M. (2016) "Where Have the Middle-Wage Workers Gone? A Study of Polarization using Panel Data", Journal of Labor Economics, 34(1), p.t.1, 63-105.

Dustmann, C., Ludsteck, J., Schönberg, U. (2009) "Revisiting the German Wage Structure", The Quarterly Journal of Economics, 124(2), 843-881.

Evangelista, R. and Vezzani, A. (2010) "The Economic Impact of Technological and Organizational Innovations. A firm-level Analisys", Research Policy, 39(10), 1253-1263.

EPSC (2016) "The Future of Work. Skills and Resilience for a World of Change", Issue 13.

Eurofound (2014) Drivers of Recent Job Polarization and Upgrading in Europe. European Jobs Monitor 2014, Publications Office of the European Union, Luxemburg.

Feldmann,, H. (2013) "Technological unemployment in industrial countries", Journal of Evolutionary Economics, 23, 1099-1126.

Fernald, J. G. (2014) "Productivity and Potential Output Before, During and After the Great Recession", NBER Working Paper No 20248.

Firpo, S., Fortin, N., Lemieux, T. (2011), «Occupational Tasks and Changes in the Wage Structure», IZA Discussion Paper, 5542.

Frey, C.B. and Osborne, M.A. (2013) "The future of employment: how susceptible are jobs to computerisation?", Oxford University Working Paper, September 17, Oxford.

Goos, M. and Manning, A. (2007) "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", The Review of Economics and Statistics, 89, February, 118-133.

Goos, M., Manning, A., Salomons, A. (2009) “Job Polarization in Europe”, The American Economic Review: Papers & Proceedings 2009, 99(2), 58-63.

Goos M., Manning, A., Salomons, A. (2014) “Explaining Job Polarization: Routine Biased Technological Change and Offshoring”, The American Economic Review, 104(8), 2509-2526.

Hall, B., Lotti, F., Mairesse, J. (2008) “Employment, Innovation and Productivity: Evidence from Italian Microdata”, Industrial and Corporate Change, 17(4), 813-839.

Harrison, R., Jaumandreu, J., Mairesse, J. (2014) “Does Innovation Stimulate Employment? A firm-level Analisys Using Comparable Micro-data from Four European Countries”, International Journal of Industrial Organization, 35, 29-43.

Heckman, J. J. and Mosso, S. (2014) “The Economics of Human Development and Social Mobility”, Annual Review of Economics, Annual Reviews, 6(1), 689-733.

Hobsbawm, E. J. (1968) Industry and Empire: An Economic History of Britain since 1750. Penguin Books, Harmondsworth Middlesex.

Jeorgenson, D., Ho, M., Stiroh, K. (2007) “A Retrospective Look at the U.S. Productivity Growth Resurgence”, The Journal of Economic Perspectives, 22(1), 3-24.

Izquierdo M., Lacuesta A. (2006) “Wage Inequality in Spain: Recent Developments”, Banco de Espana Working Paper, 615.

Katz, L. and Murphy, K. (1992) “Changes in Relative Wages, 1963-87: Supply and Demand Factors”, The Quarterly Journal of Economics, 107, 35-78.

Kelly, J. and Hamm, S. (2013) Smart Machines: IBM's Watson and the Era of Cognitive Computing, Columbia University Press, New York.

Keynes, J. M. (1963) Essays in Persuasion. New York: W. W. Norton & Co.

Lachenmaier, S. and Rottmann, H. (2011) “Effects of Innovation on Employment: A Dynamic Panel Analisys”, International Journal of Industrial Organization, 29(2), 210-220.

Leontief, W. (1983) National Perspective: The Definition of Problems and Opportunities, in: National Academy of Engineering Symposium, The Long-Term Impact of Techonology on Employment and Unemployment, National Academy Press, Washington D.C.

Levy, F. and Murnane, R.J. (2004) The New Division of Labor: How Computers are Creating the Next Job Market. Princeton University Press.

Machin, S. (2011) “Changes in UK Wage Inequality Over the Last Forty Years”, in: Gregg P., Wadsworth J. (eds.), The Labour Market in Winter – The State of Working Britain. Oxford University Press.

Moore, G. (1965) "Cramming More Components onto Integrated Circuits", Electronics Magazine, 38(8), 114-117.

Murphy, K., Riddell, W., Romer, P. (1998) “Wages, Skills and Technology in the United States and Canada”, in: General Purpose Technologies. E. Helpman, MIT Press.

Naticchioni, P., Ragusa, P., Massari, R. (2014) “Unconditional and Conditional Wage Polarization in Europe”, IZA Discussion Paper Series 8465.

Naticchioni, P. and Ricci, A. (2009) “Decreasing Wage Inequality in Italy: The Role of Supply and Demand for Education”, DSE-ISFOL Working Paper, No 9.

Naticchioni, P., Ricci A., Rustichelli E. (2008) “Wage Inequality, Employment Structure and Skill-Biased Change in Italy”, Labour, 22(1), 27-51.

Naticchioni, P., Ricci, A., Rustichelli, E. (2010) “Far Away From a Skill-Biased change: Falling Educational Wage Premia in Italy”, Applied Economics, 42(26), 3383–3400.

Pellegrino, G., Piva, M., Vivarelli, M. (2017) “Are Robots Stealing our Jobs?”, IZA Discussion Paper Series 10540.

Piva, M. and Vivarelli, M. (2017) “Technological Change and Employment: Were Ricardo and Marx Right ?”, IZA Discussion Paper Series 10471.

Ricardo, D. (1951) Principles of Political Economy. In P. Sraffa (ed), The Works and Correspondence of David Ricardo. Cambridge: Cambridge University Press, vol. 1, third edn 1821.

Rifkin, J. (2014) The Zero Marginal Cost Society: The Internet of Things, the Collaborative Commons, and the Eclipse of Capitalism. St. Martin Griffin, New York.

Rifkin, J. (1995) The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era. Putnam Publishing Group, New York.

Sabadash, A. (2013) “ICT-induced Technological Progress and Employment: A Happy Marriage or a Dangerous Liason? A Literature Review”, JRC-IPTS Working Papers, JRC76143, Institute for Prospective and Technological Studies, Joint Research Centre.

Solow, R. (1987) “We'd better watch out”, The New York Times Book Review, July 12.

Spitz-Oener, A. (2006) “Technical Change, Job Tasks and Rising Educational Demand: Looking Outside the Wage Structure”, Journal of Labor Ecoonomics, 24(2), 235-270.

Vivarelli, M. (2014) “Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature”, Journal of Economic Issues, 48(1), 123-154.

Chapter II

Exposure to Automation and the Decline of Routine Employment across European Regions

Abstract

The literature shows that job polarization in Europe is mainly driven by routine-replacing technical change (RRTC), since the contraction of medium paid employment mainly involves occupational groups highly related to routine-tasks. However, no paper makes use of European data to qualify in major detail routine occupations, whereas less is known about the regional-level effects of RRTC in the old continent. By using EU-LFS and O*NET data, this chapter analyzes routine employment trends among 23 European countries by paying particular attention to the regional dimension. By comparing routine occupations trends with those of both low-skilled service jobs and managerial, professional and technical occupations, I show that the higher the degree of exposure to automation, the higher the extent of job-polarization among regions. Moreover, I find that the decline of routine employment in Europe is exclusively driven by within-regions contractions. By means of OLS and 2SLS regressions, I also show that - though around 40% of the drop in routine labor can be attributed to between-industries variations - routine-replacing technical change is predominantly a within-industries phenomenon.

1. Introduction

Since the early 90's, the composition of European employment is following a job-polarization pattern - i.e. medium-paid occupations are losing employment shares in favor of low-paid and high-paid occupations. The empirical literature suggests that - similarly to the U.S - the main driver of this phenomenon is *routine-replacing technical change* (RRTC) (Goos et al. 2009, 2014). That is, technological change substitutes for routine task - which are mainly performed by workers employed in occupations predominantly located in the middle of the skill distribution (Autor et al. 2003). By using European data, Goos et al. (2009. 2014) consider alternative explanations (SBTC, offshoring) and show that the routine-tasks content of occupations is the strongest predictor for negative employment growth. However, no analysis has so far qualified in major detail routine employment in Europe, whereas no evidences about the regional dimension of RRTC in the old continent are available. Moreover, though national-level evidences confirm that routine-intensive occupations are indeed declining in most advanced European economies (Goos and Manning, 2007, Spitz-Oener, 2006, Dustmann et al., 2009) an overall picture summarizing the geographic distribution of the routinization phenomenon between Western and Eastern European countries is still missing in the literature. Using survey microdata from the European Labor Forces Survey (EU-LFS) and occupation information provided by the Occupational Information Network (O*NET), this study analyzes the decline of routine employment in 23 European countries by paying specific attention to the regional dimension. In particular, I analyze routine employment shares variations over the 2000's in 174 NUTS regions, while adopting a task-based perspective of job-polarization instead of a wage-based one. More specifically, whereas Goos et al. (2009, 2014) rank occupations according to their average wage, I gather occupations in broad tasks clusters, and rank them according to their educational-attainment composition. This approach enables me to provide interesting empirical evidences on the decline of routine employment and RRTC in Europe, and at the same time it allows comparing European findings with United States' ones (Autor and Dorn, 2013, Autor et al., 2015).

First, this study documents that also in Europe – similarly to the U.S. - it is possible to detect a strong relationship between exposure to automation, the decline of routine employment and the broader job-polarization phenomenon (Autor and Dorn, 2013). Over the period under analysis, however, such relationship seems predominantly biased towards the right tail of the skill distribution. That is, whereas employment growth in non-routine hi-skilled occupations has been higher in regions more exposed to automation, employment growth in low-skilled service occupations has been roughly the same among regions with different degrees of exposure.[1]

For what concerns the decline of routine employment, I document that over the last decade routine occupations employment shares decreased at a steady pace from about 30 to roughly 25 per cent. In order to assess whether

[1] In this literature, "service occupations" indicates a group of low-skilled/low-wage occupations specialized in the provision of personal services. Therefore, it has not to be confused with employment in the service sector, i.e. the broad industrial category canonically distinguished from the farming and the manufacturing sector (Autor and Dorn, 2013).

differences in regional employment growth may account for this trend, I use a standard shift-share decomposition method to divide the total routine employment contraction in a between-regions and a within-regions components. Interestingly, I find that the total reduction is entirely accounted for the within-regions dimension. Moreover, I show that the intensity of the within-regions component varies considerably across regions. In general, routine employment dropped relatively more among regions in France, Belgium and Italy, whereas regions in northern and mittel-European countries (as well as several regions in other southern-European countries) experienced comparatively less pronounced losses - or even increases in routine employment shares. In order to assess the role of regional-level industry composition shifts, I further separate each within-regions variation in a within-industries and a between-industries component. I find that about 40 per cent the reduction is accounted for the between-industries dimension. Finally, I try to quantify the relative importance of the within and between-industries channels of RRTC. In particular, I make use of the empirical framework proposed by Autor and Dorn (2013), and model both components as a function of exposure to automation. By adopting this strategy, I find that the within-industries component accounts almost entirely for the reduction of routine employment explained by RRTC.

The remainder of the chapter is organized as follows: section 2 reviews the most important findings of the RRTC literature for Europe and the U.S., whereas section 3 describes the data and the methodology adopted to identify routine occupations. Further, section 3 provides descriptive evidences on job polarization in Europe from a task-based perspective, and explores the relationship between exposure to automation, routinization and job polarization among European regions.[2] Section 4 reports and discusses the main results of the shift-share decomposition and describes the spatial distribution of the contraction of routine employment shares across regions. In section 5, the contraction of routine employment shares explained by exposure to automation is decomposed in a within and a between-industries components. Section 7 briefly concludes the chapter.

2. Local-level evidences of RRTC for U.S. and Europe

Since its recent formulation (Autor et al. 2003), the task-based framework has proved to be particularly fruitful in the study of the relationship between technological progress and recent labor markets dynamics, encouraging the faster growth of an important strand of the empirical literature. Among several other studies, see Goos and Manning (2007) for U.K., Spitz-Oener (2006) and Dustmann et al. (2009) for Germany, Goos et al. (2009, 2014) for Europe, Acemoglu and Autor (2011) for the U.S. and Europe, and Autor and Dorn (2013) for the U.S. Focusing on the phenomenon of employment polarization - i.e. a U-shaped pattern of employment growth along the skill distribution, reducing medium-skilled occupations employment shares relative to those of both high-skilled and

[2] In this paper I make use of the term "routinization" to indicate the automation of routine labor.

low-skilled occupations - and on the related *routine-replacing technical change* (RRTC) explanation[3], this literature provide clear evidences on the decline of routine employment across several developed economies.[4]

For the United States, well-known studies in which local-level employment shares variations have been used to provide evidences on the effects of RRTC are Autor and Dorn (2009, 2013), and Autor et al. (2015). In particular, Autor and Dorn (2013 - Autor and Dorn hereafter) represent the main point of reference, together with Goos et al. (2014), for the implementation of this study. Autor and Dorn develop a spatial equilibrium model where the falling price of automating routine tasks causes faster RRTC in regions more endowed with routine labor (i.e. more specialized in routine-intensive activities, hence more exposed to automation). As for changes in the composition of employment, the model predicts: 1) greater adoption of computer technology and consequent displacement of routine labor; 2) larger inflows of high-skilled workers - caused by the complementarity with

[3] According to the RRTC theory, the widespread decline in ICT and automation costs observed over the last decades - accompanied by a faster technological progress - may have led to a progressive displacement of that part of the labour forces previously employed in "routine-task intensive jobs" - often located in the middle of the skill/wage distribution. The underlying intuition is that "routine workers" mainly perform standardized tasks that, by following easy-to-codify explicit rules, are also easily executable by machines. On the other hand, as provided by the well-known *skill-biased technical change* framework, new technologies are more likely to complement high-skilled workers (mainly employed in non-routine-cognitive task intensive jobs). As for low-skilled workers (mostly associated with jobs intensive in non-routine manual tasks), the RRTC framework predicts an ambiguous effect of technology.

[4] It is important to clarify that, although RRTC implies a reduction of medium-skilled/routine employment shares, the contraction of routine occupations does not necessarily imply job-polarization. Assuming increasing hi-skilled employment, job-polarization crucially depends on the non-negative growth of low-skilled employment.

technology; 3); greater reallocation of low-skilled routine workers into service occupations (jobs that involve assisting or caring for others, thus are difficult to automate). The empirical framework developed by them confirms these predictions, providing important evidences on the relationship between automation and job and wage polarization in the U.S over the period 1980-2005.[5] For what concerns this analysis, I rely on the main assumption of Autor and Dorn's model, and assess to which extent European regions more exposed to automation experienced more pronounced job-polarization patterns.

Another important contribution for the U.S. is Lindley and Machin (2014). Rather than focus "directly" on RRTC, these authors consider the existence of agglomeration effects on job-polarization. By classifying U.S.' States accordingly to their degree of polarization, they show that within strongly polarized states there is a significant positive correlation between the spatial concentration of high-skilled workers, technology, and the demand for goods and services provided by low-skill occupations (see also Mazzolari and Ragusa, 2014).[6]

The literature on job-polarization in the old continent has not focused yet on the regional dimension of routinization, but has nonetheless provided very

---

[5] Wage polarization is the increase of wages at the end and at the top of the wage distribution observed in the U.S. over the last decades, strictly linked to the displacement of routine labor and the growth of low-wage occupations. Despite the existence of positive evidences of job-polarization in Europe, this phenomenon seems to be absent in the old continent (see Naticchioni et al., 2014).

[6] For an extensive review of the theoretical and empirical literature on agglomeration economies and their implications for labor market dynamics see Rosenthal and Strange (2004) and Puga (2010).

valuable evidences on the relationship between RRTC and job-polarization in Europe (Goos et al., 2009, 2014).[7] By using EU-LFS and O*NET data, Goos et al. (2009) analyze employment shares variations of 21 different ISCO-88 sub-major groups (i.e. 2-digits) in 16 western European countries over the period 1993-2010. In this study, occupations are sorted according to their (imputed) average wage, and classified as high-paid, medium-paid and low-paid occupations. Goos et al. (2009) show that job-polarization is pervasive in Europe, and find that measures of routine intensity better explain the contraction of medium-paid jobs and the increase of high and low-paid ones. Following a similar approach, Goos et al. (2014) decomposes occupation employment shares variations in a within and a between-industries component. They show that within-industries there is a significant relative demand shift away from both routine and offshorable jobs, finding that the much more important effect is towards routine-intensive occupations. Further, they develop a theoretical model in which both the within-industries and between-industries components are a result of RRTC. Bringing their model into the data, they show that both dimensions of RRTC are important in accounting for overall job-polarization in Europe.

This study contributes to the existing literature on job-polarization in Europe in three main aspects. First, it pays particular attention to the

[7] To the best of my knowledge, Gregory et al. (2016) is the only study to consider European regional data in this literature. However, these authors focus on the impact of automation on levels of employment, whereas my analysis focuses on the regional dimension of the decline of routine occupations. Local-level evidences of polarization and RRTC are available for Germany in particular (see Dauth, 2014, and Senftleben and Wielandt, 2013).

regional dimension, while also considering eastern European countries beside western ones. Second, by classifying occupation groups according to their task-domain, it analyzes job polarization from a task-based perspective. More precisely, by matching occupational O*NET data into EU-LFS data at the ISCO-88 3-digit occupation level, it qualifies for the first time routine occupations in Europe. On the one hand, this approach makes possible comparing routine employment trends with those of low-skilled service and high-skilled non-routine occupations. On the other hand, it allows measuring the degree of regional exposure to automation by relying on the main assumption of Autor and Dorn's spatial equilibrium model. Third, this study contributes to the literature not only by exploring the within and between-regions dimensions of the decline of routine occupations, but also by assessing for the first time the relative importance of the between-industries and within-industries channels of RRTC for the overall contraction of routine employment.

3. Data, measurements and descriptive evidences

In this section, I describe the data as well as the procedure I follow in order to define routine-intensive, non-routine cognitive and "service" occupations in the EU-LFS database. After summarizing the educational-attainment composition of these occupation groups, I also provide graphical evidences on job polarization at the European-level, and describe national differences among the 23 countries under analysis. Finally, I report broad descriptive evidences on the relationship between the degree of exposure to RRTC, the contraction of routine employment shares and the extent of job-polarization among European regions.

3.1. Data sources and measurements

As in Goos et al. (2009, 2014), the main data source for this analysis is the European Union Labor Forces Survey (EU-LFS), whereas a particular feature of this analysis is the use of the 3-digit level ISCO-88 occupational classification, ensuring a more precise mapping of U.S.' occupational tasks measures to European occupations. Crucially for my purposes, EU-LFS data also reports the spatial location of surveyed workers according to the 2-digit level European Nomenclature of Territorial Units for Statistics classification (NUTS 2). Conversely, workers' industry information is classified according to the 1-digit level European Statistical Classification of Economic Activities (NACE Rev. 1.1). I reduce the overall sample to individuals between age 15 and 64 and, because of data harmonization drawbacks, to countries reporting at the same time both ISCO-88 3-digit occupations and NUTS 2 regions (when not available, I use the broader NUTS 1 level and, where also this level is missing, I include only small countries as single regions). In this way, I end up with 174 European territorial units covering 23 countries over the period 2002-2010.[8] As in Goss et al. (2009, 2014), labor input is measured

[8] Although national level data - which I use for several descriptive statistics in this section - are available from 1999 for all countries, the starting period of the empirical analysis (i.e. 2002) is conditioned to the inclusion of Germany, for which regional information are not available up to 2001. Finland has been excluded because of a break in the NACE industry classification. In particular, the sample includes: Austria, Belgium, Switzerland, Cyprus,

as individual weekly hours worked times official EU-LFS weights. The analysis excludes the agriculture and fishing industries, the public sector and those workers employed in extra-territorial organizations and bodies.[9]

As for additional regional-level data, I rely on NUTS-level aggregated data available on the Eurostat web-site[10]. In particular, I pick two relevant proxies of the role of technology and the degree of technological innovation at the regional-level, respectively, the share of the R&D expenditure on the (regional) GDP and the number of registered patents per capita. Further, from this database I also take regional-level population density, which I use to explore the possible correlation between urban agglomeration and the decline of routine employment.

As mentioned above, this study relies on the 3-digit ISCO-88 occupational classification in order to assign U.S. occupations task-contents to European occupations. As in Goos et al. (2009), I rely on U.S. data of the Occupational Information Network (O*NET), which is the new version of the Dictionary of Occupation Titles (the DOT, used by Autor and Dorn and several other papers). In order to take advantage of more complete data without relying on

Czech Republic, Germany, Estonia, Spain, France, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxemburg, Latvia, Netherlands, Norway, Portugal, Sweden, Slovakia and United Kingdom.

[9] The analysis therefore considers the remaining 13 broad industry sectors of the NACE rev. 1.1 classification.

[10] Http://ec.europa.eu/eurostat/web/regions/data/database.

a different source, I use the last available update of the database used in their study.[11]

3.2. Measuring routine occupations employment shares and describing job polarization from a task-based perspective

In this subsection, I provide preliminary descriptive evidences of job polarization in Europe by adopting a task-based perspective rather than a wage-based one. In particular, I divide overall European employment into four broad occupational task-groups, and rank them accordingly to their educational-attainment composition. Indeed, as observed by Acemoglu and Autor (2011), the use of broad occupation groups can be particularly useful if they logically map into the main task-clusters identified in this literature. Following their observation that, broadly speaking, managerial, professional, and technical occupations are mostly specialized in abstract, non-routine cognitive tasks, whilst service occupations are mostly specialized in non-routine manual tasks, I define these two relevant categories by simply relying on ISCO-88 1-digit and 2-digit occupation groups. In particular, I define "non-routine cognitive occupations" ISCO-88 major groups 1 (legislators, senior officials and managers), 2 (professionals) and 3 (technicians and associate professionals), and define "service

[11] In particular, Goos et al. (2009) use O*NET-SOC 2006 version 11.0. Since O*NET data are subject to periodical updates with survey data, I prefer to use the newer O*NET-SOC 2006 version 13.0 (see the update summary available on the O*NET website). Indeed, O*NET releases between 1998 and 2003 were based on information provided, to some extent arbitrarily, by occupation analysts only. Since then, the database have been updated several times until the recent release of O*NET-SOC 2010 version 21.0 (August 2016).

occupations" ISCO-88 sub-major groups 51 (personal and protective services workers) and 91 (sales and services elementary occupations).

Since the definition of routine occupations is crucial for my analysis, I follow as close as possible the procedure proposed by Autor and Dorn, which compute the Routine Task Index (RTI) for each occupation and define as "routine" those occupations falling above the 66th percentile of this index. To map U.S. task data into the EU-LFS database, I pick the 16 O*NET indicators considered by Acemoglu and Autor (2011) and average them on ISCO-88 occupations.[12] Hence, I standardize raw indicators to have mean 0 and variance 1 by using EU-LFS employment shares in 2002 as weights, and aggregate them by occupation into three broad task-categories according to Acemoglu and Autor's (2011) classification.[13] The resulting three aggregated indexes are rescaled to positive values (adding one) to allow the log-transformation required by the RTI formula:

$$RTI_k = \ln\left(T^R_{k,o*net}\right) - \ln\left(T^C_{k,o*net}\right) - \ln\left(T^M_{k,o*net}\right), \tag{1}$$

where T^R_k, T^C_k and T^M_k are the aggregate indicators of the intensity in, respectively, the routine, non-routine cognitive and non-routine manual task

[12] The 16 O*NET indicators used in Acemoglu and Autor (2011, p. 1163) scores from 1 to 5 for each occupation. I map these indicators by averaging them from O*NET-SOC-00 to SOC-00 occupations and from SOC-00 to ISCO-88 occupations by means of official crosswalks (https://www.xwalkcenter.org). Since the mapping is done on ISCO-88 4-digits occupations, as a last step I collapse the indicators at the 3-digits level.

[13] In particular, Acemoglu and Autor (2011) assign O*NET task indicators to the following six task categories: 1) non-routine cognitive analytical, 2) non-routine cognitive interpersonal, 3) routine cognitive, 4) routine manual, 5) non-routine manual interpersonal, 6) non-routine manual physical. To obtain three aggregate indicators for each occupation, I collapse these six categories into three main ones.

content of occupation k. This measure is then standardized on ISCO-88 3-digit occupations to have mean 0 and standard deviation 1. Hence, according to Autor and Dorn, I compute routine occupations employment shares as:

$$RSH_t = \left(\sum_{k=1}^{K} L_{kt} \times 1[RTI_k > RTI^{66p}]\right) \times \left(\sum_{k=1}^{K} L_{kt}\right)^{-1}, \quad (2)$$

where L_{kt} is employment in occupation k at time t, and $1[\cdot]$ is an indicator function which takes the value of one if the occupation is intensive in routine tasks according to their definition.

Table 1 shows the nomenclature of those occupations defined as routine-intensive by following the outlined procedure and the corresponding RTI ranking[14], whereas Table 2 reports the educational-attainment composition of each of the three occupational task-groups defined in this section. Please note that in Table 2 I also report statistics for the residual group of occupations left outside these three clusters. Interestingly, such group is mainly composed by craft and production occupations that are not classifiable as "routine-tasks intensive" by following the approach described above.[15]

---

[14] Three of the 35 ISCO-88 3-digit occupations falling above the 66th percentile of RTI (312, 512 and 913) are excluded from the routine occupation definition inasmuch they are also contained in the 2-digit and 1-digit major groups I use to define service and non-routine cognitive occupations. The only exception to this is the category of administrative associate professionals (343), containing secretarial and bookkeeping workers – typical examples of routine-cognitive jobs in the literature. Although not overlapping with other categories, I arbitrarily exclude from routine occupations forestry and related workers (614), ending up with 31 occupations classified as routine-tasks intensive.

[15] In 1999, respectively 70 and 20 per cent of workers in the residual group was employed in occupations belonging to ISCO-88 major group 7 (craft and related trades workers) and 8 (plant and machine operators and assemblers).

Table 1. *Routine-tasks intensive occupations.*

ISCO-88 code	ISCO-88 nomenclature	*RTI*
731	Precision workers in metal and related materials	.382
822	Chemical-products machine operators	.419
414	Library, mail and related clerks	.433
733	Handicraft workers in wood, textile, leather	.456
833	Agricultural and other mobile plant operators	.488
829	Other machine operators and assemblers	.507
814	Wood-processing-and papermaking-plant operators	.553
825	Printing, binding and paper-products machine operators	.685
824	Wood-products machine operators	.704
828	Assemblers	.708
422	Client information clerks	.720
817	Automated-assembly-line and industrial-robot operators	.743
413	Material-recording and transport clerks	.754
821	Metal and mineral-products machine operators	.760
421	Cashiers, tellers and related clerks	.784
827	Food and related products machine operators	.793
522	Shop salespersons and demonstrators	.943
741	Food processing and related trades workers	.966
412	Numerical clerks	.976
812	Metal-processing-plant operators	1.021
932	Manufacturing laborers	1.073
823	Rubber and plastic-products machine operators	1.145
343	Administrative associate professionals	1.159
419	Other office clerks	1.170
734	Printing and related trades workers	1.189
732	Potters, glass-makers and related trades workers	1.223
813	Glass, ceramics and related plant-operators	1.272
826	Textile, fur and leather-products machine operators	1.373
411	Secretaries and keyboard-operating clerks	1.435
742	Wood treaters, cabinet-makers and related trades workers	1.514
744	Pelt, leather and shoemaking trades workers	4.041

Note: ISCO-88 3-digits occupations. The table reports code, nomenclature and RTI index of those occupations classified as routine-intensive.

Table 2. *Occupation groups educational-attainment composition (1999 and 2010).*

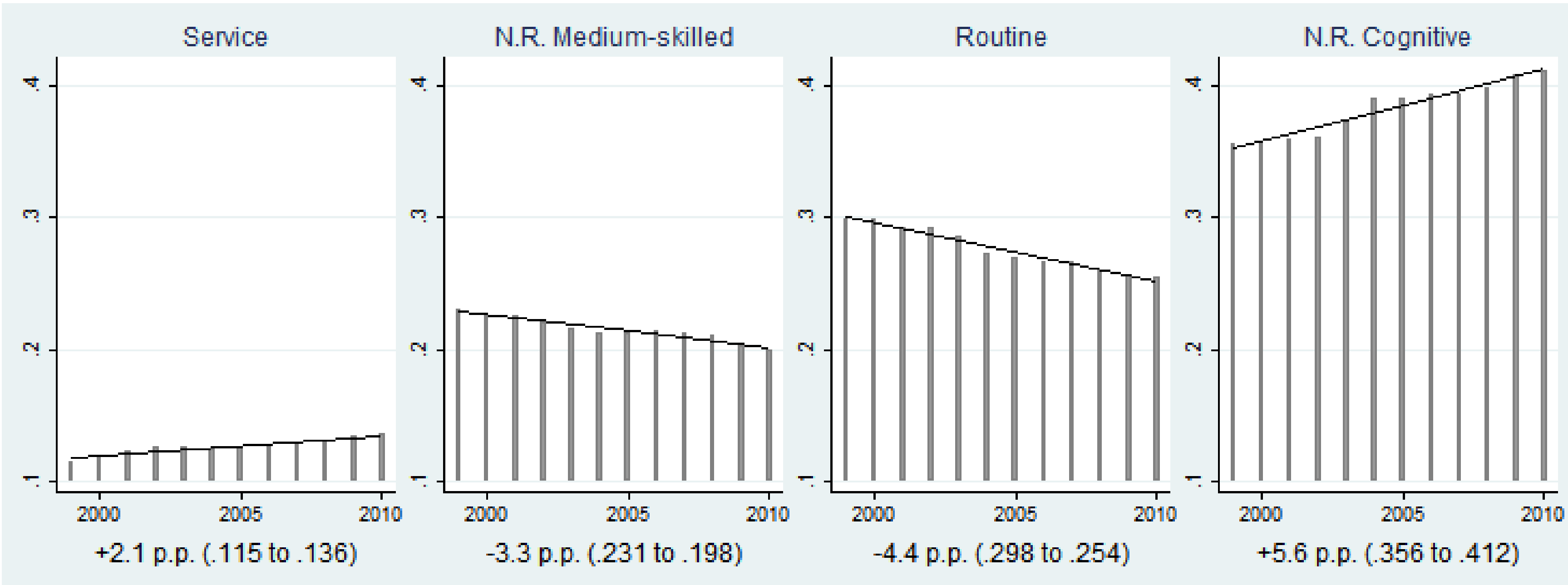
	Service			N.R. Craft & Pr.			Routine			N.R. Cognitive		
Education	**Low**	**Med**	**Hi**	**Low**	**Med**	**Hi**	**Low**	**Med**	**Hi**	**Low**	**Med**	**Hi**
Share in 1999	.50	.44	.06	.42	.52	.07	.34	.56	.10	.11	.37	.52
Share in 2010	.40	.52	.08	.37	.58	.05	.25	.62	.13	.08	.35	.57
100 × Change	-10	8	2	-5	6	-2	-9	6	3	-3	-2	5

Notes: EU-LFS data, ISCED classification. Low = lower-secondary, med = upper-secondary, high = tertiary.

As Table 2 shows, service occupations are relatively more abundant in low-educated workers, whereas - not surprisingly – the opposite applies in the case of non-routine cognitive occupations. Conversely, the routine group is the most abundant in workers with medium educational attainment, confirming the close association between routine occupations and medium-skilled employment. Further, Table 2 makes clear that the residual craft and production cluster is also intensive in medium-skilled workers, though to a less extent in comparison to the routine group, and with relatively higher shares of low-educated workers. For these reasons, in the following I rank this group above the service group and below the routine one (as done in Table 2) and refer to it as the "non-routine medium-skilled group".

By pooling the overall sample at the European level, Figure 1 plots the annual employment shares of the four groups over the period 1999-2010 among the 23 countries considered. The job polarization pattern showed by Figure 1 is rather clear: low-skilled service and hi-skilled non-routine cognitive occupations increases their employment shares over time at the expenses of both medium-skilled routine and non-routine occupations, with routine occupations suffering the greater losses. More precisely, the considerable increase of non-routine cognitive occupations (5.6 p.p.) has been accompanied by a sharp reduction of routine-intensive jobs (-4.4 p.p.) and by an important but less pronounced increase of service occupations (2.1 p.p.). The picture also points out that - though this composition change took place in a general context of decreasing low and medium-skilled craft and production occupations (-3.3 p.p.) - the magnitude of the decline of routine employment results far from negligible. Indeed, if at the beginning of the 2000's 30% of the labor force was employed in routine-intensive occupations, at the end of the decade this figure drops to about one worker out of four. In sum, Figure 1 clearly shows that it is possible to observe a job-polarization pattern of the employment structure in Europe also when clustering occupations in broad tasks/skills aggregates. It is also interesting to note that service employment shares are extremely close to those observable in the States: according to Autor and Dorn, they amounted to 12.9 per cent of U.S. non-farm employment in 2005, whilst in the same year in Europe this figure is of 12.6 per cent.

Figure 1. *Occupation-groups employment shares in Europe (1999-2010).*

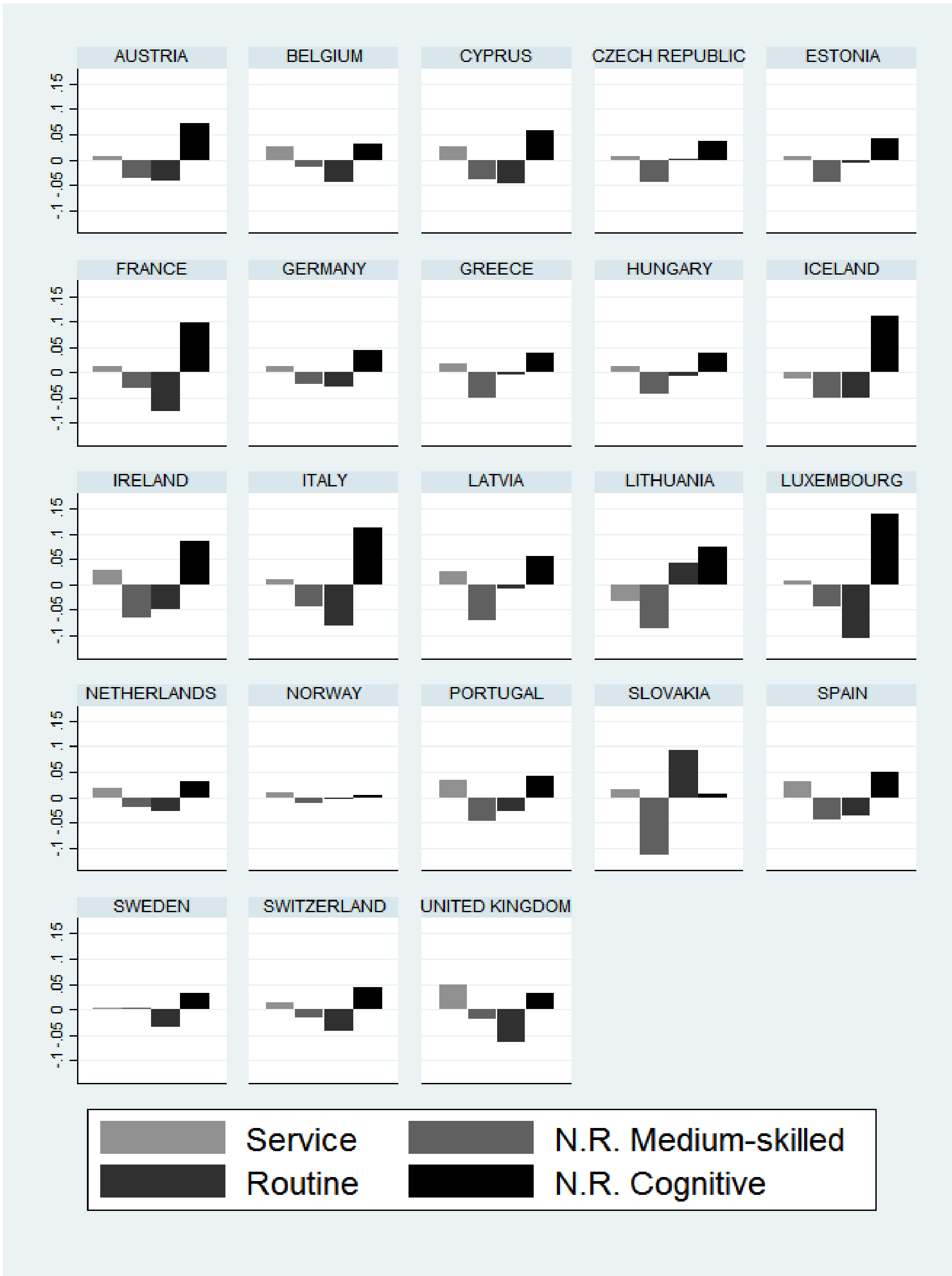


Notes: EU-LFS data, 23 European countries

To provide country-level evidences and explore the existence of national heterogeneities, Figure 2 plots occupation groups employment shares variations over 1999-2010 by country.[16] Though national trends are somehow heterogeneous, in almost all cases variations at the country level have the same sign of that observable for all Europe. In contrast with the general trend is, in particular, the increase of routine occupations shares in Czech Republic (+0.2 p.p.), Lithuania (4.3) and Slovakia (9.4), whereas service occupations shares decrease in Lithuania (-3.2 p.p.) and Iceland (-1.2). Interestingly, Figure 2 clearly shows that – with the exception of Greece and Norway - routine occupations shares decrease especially among western European countries, with contractions between -2.8 and -10 p.p.

[16] Figure 1 in the appendix repeats the same exercise for the period 1999-2007, showing that very similar trends emerge also when excluding the years of the Great Recession.

Figure 2. *100 x Occupation-groups employment shares changes by country (1999-2010).*



Notes: EU-LFS data, 23 European countries.

Moreover, changes in occupation-groups employment shares show different intensities. For instance, they are more pronounced in the case of France, Luxembourg and Italy, whereas they are rather mild in The Netherlands and Germany. Also, it can be easily observed that in some cases the "shape" of the job-polarization pattern differs sensibly from the European level one. For instance, in the United Kingdom service occupations increase more than non-routine cognitive occupations (respectively 5 p.p. vs 3.3 p.p.), whereas in Austria, France, Italy, Luxembourg, the increase of service occupations is quiet negligible if compared to the expansion of non-routine cognitive ones. Finally, we can see that in peripheral countries such as Ireland, Greece, Spain, Portugal, the contraction of routine employment is less pronounced than the contraction of the non-routine medium skilled group. Nonetheless, from Figure 2 we can see that, even if the job-polarization pattern detected in Figure 1 arises from heterogeneous national trends, country-level evidences are consistent with a process of job polarization in almost all cases.

3.2.1. Assessing the relationship between exposure to automation, routinization and job polarization in Europe

In what follows, I make use of the broad task-based classification proposed in this section in order explore whether Autor and Dorn's model predictions also apply to Europe. According to the model, regions more endowed with routine employment experience relatively higher contraction of routine labor, larger inflows of high skilled employment and greater reallocation of routine workers into low-skilled service occupations.[17] To provide evidences on these relationships, I first divide the distribution of the 174 regional units under analysis on population-weighted terciles of the regional routine employment share in 2002, and then I compute the regional-level (population-weighted) average growth over 2002-2010 of each of the four occupation groups defined in the previous sub-section. Figure 3 provides a graphical summary of this simple exercise. It comes out that exposure to automation has a strong *negative* monotonic relationship with the growth of routine employment shares, but a strong *positive* one with the growth of non-routine cognitive employment. This is consistent with the idea that technology substitutes for medium-skilled routine labor but, at the same time, is complementary with high-skilled/non-routine cognitive occupations. On the contrary, exposure to automation appears to be rather unrelated with the growth of the other groups. In the case of service occupations, this is somehow in contrast with the evidences provided by Autor and Dorn for the U.S.[18][19]

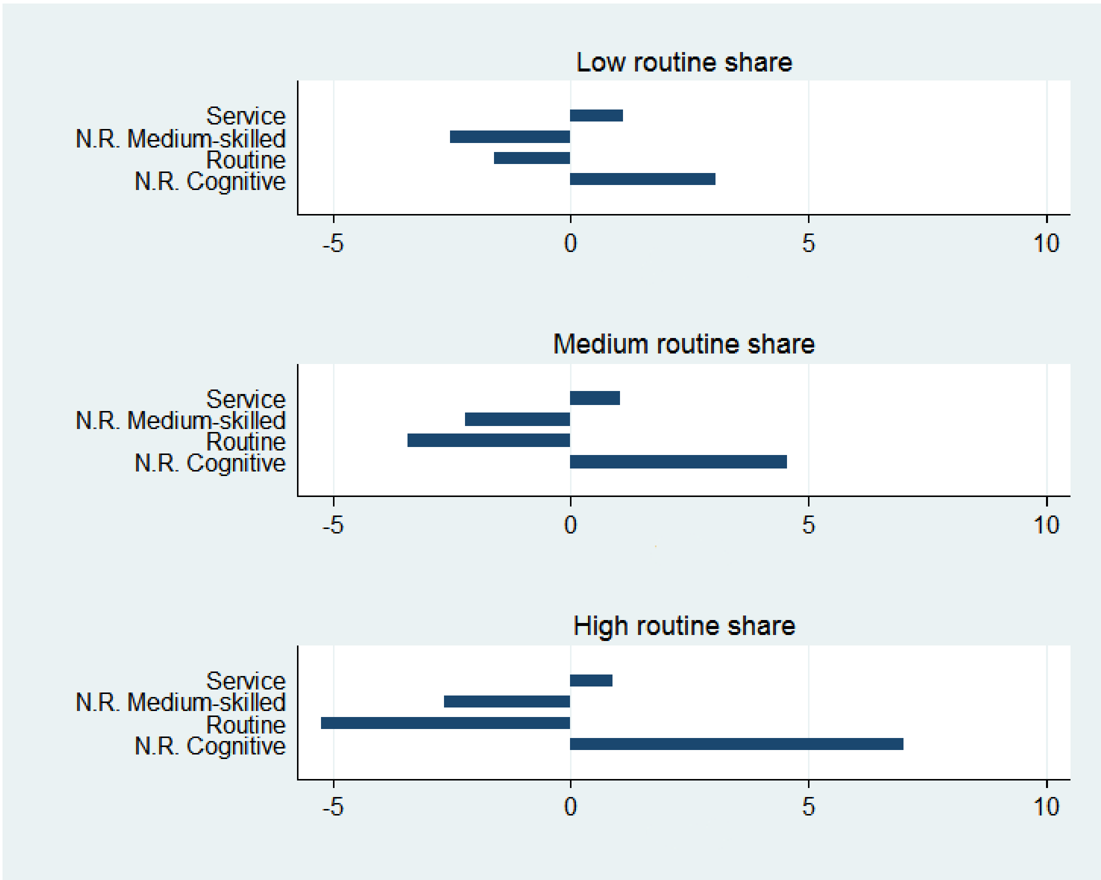
---

[17] In their analysis Autor and Dorn graphically show that, in that part of the U.S comprising those commuting zones (CZs) with a routine employment share above the grand mean in 1980, employment polarization results sensibly more pronounced than in the rest of the country.

[18] This outcome may be also related to the shorter time span observed in my analysis. Further, the fast increase of service employment observed in the U.S. over 1980-2005 may have, reasonably, already took place in the Europe of the 2000's – as also suggested by the very similar share of service occupations in U.S. and Europe in year 2005.

[19] In Figure 2 in the appendix I repeat the same exercise of Figure 3 by splitting regions on terciles of the non-routine medium-skilled group. No clear pattern emerges in this case. Further, the appendix reports the same graph for the period 2002-2007 (Figure 3), showing no substantial deviations from the trend detected here.

Figure 3. *Occupation groups population-weighted average 100 × change in employment shares (2002-2010), regions split on population-weighted terciles of routine occupations employment shares in 2002.*



Notes: EU-LFS data, 174 regions. Average changes weighted for regions population share of total population in 2002.

To sum up, from the task-based perspective proposed in this study it comes out that regions more exposed to automation have suffered more severe routine employment contractions and, consequently, a more pronounced job-polarization pattern - though mostly biased towards the right tail of the skill distribution. That is, whereas the growth of low-skilled service employment seems to be roughly the same along the routine share distribution, the positive relationship between the growth of high-skilled/non-routine cognitive employment and the start of period routine share results particularly strong.

4. The contraction of routine employment in Europe: shift-share decomposition

The aim of this section is to assess how much of the total decline of routine employment is attributable, to the one hand, to employment growth differentials between regions and, on the other hand, to industry-composition shifts within-regions. As for job polarization, the between-industry dimension has been already considered by the literature. According to Goos et al. (2014), industries more affected by RRTC will use less employment for a given level of output and, in turn, decreasing overall employment shares.[20] Further, they show that the between-industry component accounts for an important part of job polarization in Europe. According to these evidences, we might expect a non-negligible component of the decline of routine employment within-regions to be driven by the

[20] In particular, Goos et al. (2014) model the between-industries component of job polarization as the result of two counteracting channels of RRTC. First, a substitution effect reducing overall employment shares of those industries more endowed with routine labor - hence more affected by RRTC. Second, a compensation effect (i.e. lower industry costs and prices stemming from RRTC lead, in presence of elastic product demand, to higher output and higher labor demand) which, as their data show, mitigates but is not sufficient to overturn the former effect.

between-industries dimension.[21] On the contrary, it is not clear if regions (rather than industries) more exposed to RRTC may consequently experience employment shares contraction and, in particular, if this channel is important in accounting for the decline of routine employment shares in Europe. Indeed, if workers' spatial mobility is at work, RRTC may not affect regional-level employment growth in the same way it is expected to do at the industry level.

To assess the relative importance of these different dimensions, I decompose routine occupations employment shares variations over the period 2002-2010 (period for which I have complete regional information) into four distinct components. More specifically, I first divide the overall routine contraction in a within and a between-regions components, whereas I further divide each regional-level variation in a within and a between-industries components. To better understand the decomposition, please consider, together with equation (2), the regional-level routine employment share, similarly defined as:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \times 1[RTI_k > RTI^{66p}]\right) \times \left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \qquad (3)$$

[21] Note that the between-industry component computed in this section cannot be attributed to technology. More generally, it is assumed to be driven by regions' patterns of structural change - i.e. the contraction of sectors traditionally more endowed with routine labor (e.g. manufacturing) and the expansion of sectors relatively less routine-intensive (e.g. financial services). Nevertheless, in section 5 I assess how much of the impact of exposure to automation is related to the between-industry dimension.

where RSH_{jt} is the routine employment share in regional unit j at time t. Now, let ESH_j equal region j's employment share on total European employment. The total variation of routine employment can be expressed as:

$$\Delta RSH = \overbrace{\textstyle\sum_j \Delta RSH_j \times ESH_{j,t_0}}^{Within-Regions} + \overbrace{\textstyle\sum_j \Delta ESH_j \times RSH_{j,t_0}}^{Between-Regions} + \overbrace{\textstyle\sum_j \Delta ESH_j \times \Delta RSH_j}^{Interaction} \quad (4)$$

where the operator Δ indicates the variation between t_0 and t_1. Now, let $RSH_{j,i}$ equal the routine employment share in industry i within regional unit j, and let $ESH_{j,i}$ equal the regional-level industry i employment share. Hence, regional-level routine share variations (i.e. each element of the vector represented by the first term of the within-regions component) can be furtherly decomposed as:

$$\overbrace{\textstyle\sum_j \left(\overbrace{\textstyle\sum_{j,i} \Delta RSH_{j,i} \times ESH_{j,i\,t_0}}^{Within-Industries} + \overbrace{\textstyle\sum_{j,i} \Delta ESH_{j,i} \times RSH_{j,i\,t_0}}^{Between-Industries} + \overbrace{\textstyle\sum_{j,i} \Delta ESH_{j,i} \times \Delta RSH_{j,i}}^{Interaction} \right) \times ESH_{j,t_0}}^{Within-Regions} \quad (5)$$

In words, equation (4) splits the European-level routine employment share reduction into three components, each resulting from the scalar product of two vectors. These are, respectively: i) the reduction attributable to the contraction of routine employment shares within regional units (by keeping constant regional employment shares of total European employment); ii) the reduction attributable to changes in regions' employment shares of total employment (by keeping regions' routine shares constant); iii) the variation resulting from the interaction between these two forces. In expression (5), each element of the first vector of the within-regions component (i.e. each regional-level routine share variation, ΔRSH_j) is decomposed into three additional components (again, resulting from the scalar product of two vectors). These are, respectively: i) the reduction accounted for the contraction of routine employment shares within industries within regions (by holding industries employment shares of regional employment constant); ii) the reduction accounted for changes in industries employment shares of regional employment (by keeping industries routine shares constant); iii) the variation resulting from the regional-level interaction between both forces.

Panel A of Table 3 reports annual routine occupations employment shares and variations, whilst Panel B summarizes the main results of this simple counterfactual exercise. Further, Table 4 summarizes the (unweighted) regional-level routine employment shares and variations as well as the within and between-industries components obtained from the shift-share decomposition. Finally, Figures 4 to 7 display the geographic distribution of these variables.

Table 3. *100 × routine occupations employment shares changes: shift-share decomposition.*

Panel A	Actual routine occupations employment shares and variations								
Year	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Share	29.3	28.6	27.3	27	26.6	26.6	26	25.6	25.5
Variation	.	-0.7	-1.3	-0.3	-0.4	0	-0.6	-0.4	-0.1

Panel B	**Shift-share decomposition**						
		European level variations			**Within-regions variations (population-weighted average values)**		
	Total variation	**Within regions**	**Between regions**	**Interaction term**	**Within industries**	**Between industries**	**Interaction term**
Total 2002-2010	-3.83	-3.78	0.03	-0.08	-2.03	-1.32	0.00
Pre-crisis 2002-2007	-2.69	-2.68	0.02	-0.04	-1.57	-0.88	0.00
Post-crisis 2007-2010	-1.14	-1.1	-0.02	-0.02	-0.42	-0.44	-0.02

Notes: 23 European countries, 174 regions. Panel A reports total routine occupations employment shares and variations over 2002-2010. Panel B reports the main results of the shift-share decomposition.

As shown in Table 3, over the period 2002-2010 the overall routine employment reduction amounts to almost 90 per cent of that occurred over 1999-2010 (see Figure 1), hence, it can be considered as highly representative of the decline occurred in Europe over the whole decade. Moreover, more than 2/3 of this reduction took place in the period prior the Great Recession, although I am not able to observe the entire time span of the (long-lasting) economic crisis in Europe.[22]

Table 4. *100 × regional-level routine occupations employment shares and variations.*

Variable	Min.	Max.	Mean	Median	Std.
Routine share 2002	19.49	44.42	29.33	29.58	4.66
Routine share 2010	11.27	37.1	25.8	25.78	4.18
2002-2010 variation	-12.42	5.59	-3.53	-3.21	3.3
Within–industries	-10.69	5.21	-2.07	-1.65	3.07
Between-industries	-7.48	1.68	-1.50	-1.38	1.30

Notes: unweighted statistics, 174 regions.

[22] This drawback is due to the break between the ISCO-88 and the ISCO-08 occupational classification in EU-LFS data.

Interestingly, the shift-share decomposition in Table 3 shows that the total reduction of routine employment shares in Europe is entirely accounted for within-regions contractions, both before and after the advent of the crisis. In other words, employment growth differentials between regions have no explanatory power. As pointed out above, workers' spatial mobility may explain this outcome. Indeed, the result is consistent with the predictions of Autor and Dorn's spatial equilibrium model - according to which regions more affected by RRTC experience larger inflows of high-skilled employment because of the complementarity with technology. Of course, the presence of this mechanism may neutralize (or even overturn) the total loss of employment caused by RRTC.[23] Conversely, it comes out that industry-composition shifts within-regions do have a very important role. In particular, the between-industries component captures - on average - about 40% of within-regions routine employment contractions. Moreover, in the years of the Great Recession this component increases in relative size, by explaining about a half of the contraction over the period 2007-2010. This is consistent not only with the fact that - as the literature already shown - the between-industries dimension accounts for an important part of job-polarization in Europe, but also with the idea that RRTC depresses medium-paid employment also through the between-industries channel (Goos et al., 2014).

---

[23] This interpretation is also supported by the descriptive evidence in Table 3, which shows that in those regions initially more endowed with routine labor (and subsequently more affected by routine employment contractions) non-routine cognitive employment shares increased visibly more. Besides spatial mobility, of course, this outcome may be also related to the existence of compensation mechanisms related to technology or - better said - interpreted as an indirect evidence of such mechanisms (see Chapter I).

As for the geographical distribution of the decline of routine employment in Europe, Figure 4 clearly shows that - at the outset of the century - routine occupations were relatively less abundant in northern countries, particularly in the United Kingdom and in the Netherlands – the latter considered as a single region. In these countries, routine shares were amounting, on average, to less than 24 percentage points, i.e. even below the European average at the *end* of the decade[24]. With reference to the U.K., this can appear consistent with the fact that job-polarization in this country, similarly to the U.S., is a phenomenon started between the 80's and the 90's (Goos and Manning, 2007). Nonetheless, we can see that although analogous evidences have been also founded for western Germany (Dustmann et al., 2009), the German average regional routine employment share in 2002 – even though below the European mean - is sensibly higher than in the U.K. (28.5 vs 23.9).

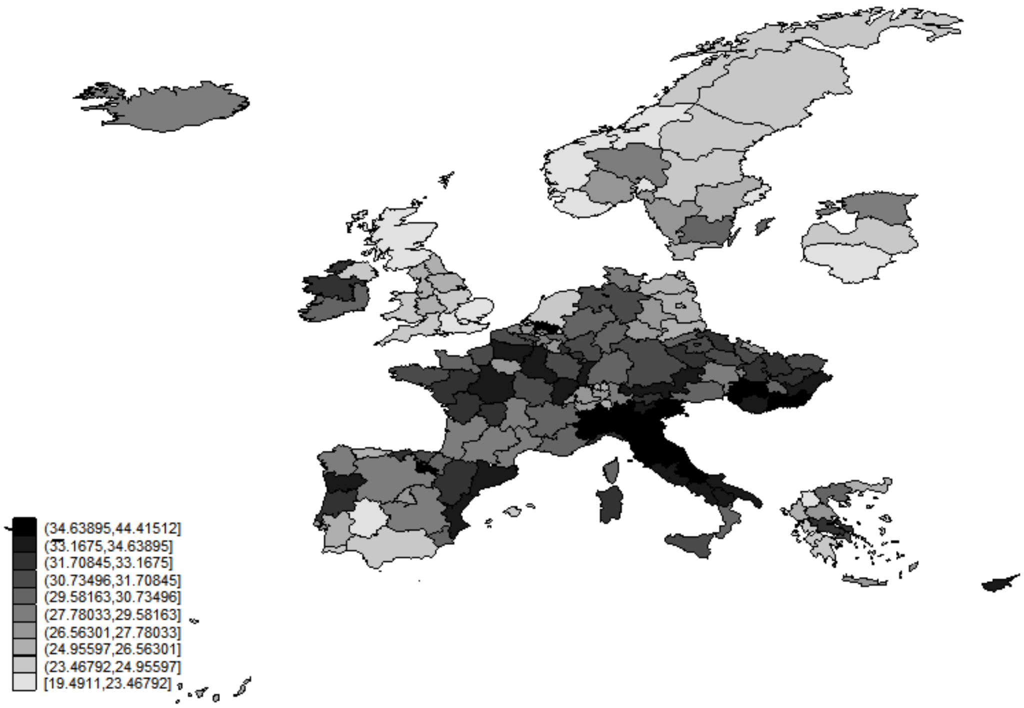
As for the rest of Europe, the spatial distribution is rather heterogeneous, but some regularity is easily detectable, above all, the fact that Italy appears to be highly routine-specialized (with an average routine share of 36 percentage points). Indeed, the top three regions of the distribution of $RSH_{j\,2002}$ are, in increasing order, Piedmont, Friuli-Venezia Giulia and Marche, where about 4 workers on 10 were employed in routine occupations in 2002. Figure 2 also shows that there are a number of other relatively routine-intensive regions - i.e. above one standard deviation of the

[24] As it can be seen, also in the case of Baltic countries - as well as some southern regions in Spain and Portugal – routine employment shares in 2002 were relatively less important.

distribution. Among these regions we can see, in particular, Central and Western Transdanubia (Hungary), the Provinces of Antwerp and Limburg (Belgium), La Rioja and Catalonia (Spain), the regions of Champagne-Ardenne and Centre (France) and Cyprus (considered as a single region) - regional units in which more than 1 worker on 3 was employed in a routine job.

Even if Figure 5 shows a rather complex picture, it clearly illustrates that the most severe reductions have mainly interested regions in Italy, France and Belgium. Moreover, although relatively scarce in 2002, routine occupations have presumably followed to decrease in the U.K., even more than in Germany. In the latter (apart from those small regional units as Bremen and Hamburg, in which routine shares decreased sensibly, and Saxony-Anhalt and Schleswig-Holstein, where on the contrary increased), the pattern is similar to that observable in Eastern countries - where regional routine shares contracted less than in western countries. Figure 5 also shows that in some regions routine occupations have increased their employment shares, as it can be seen in the case of Greece, Norway (although marginally), western Spain, and in Latvia and Lithuania (considered as single regions).

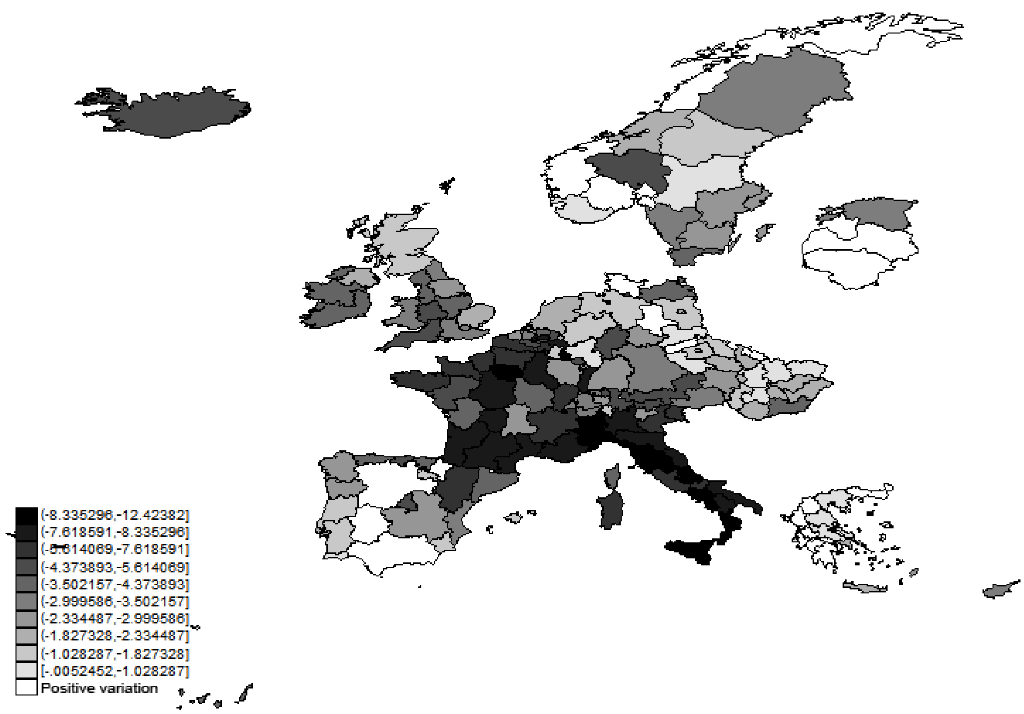
Figure 4. *100 × regional-level routine occupations employment shares (2002).*



Notes: 174 regions. Regions split on unweighted deciles of routine employment shares in 2002 (the higher the routine employment share, the darker the color of the region).

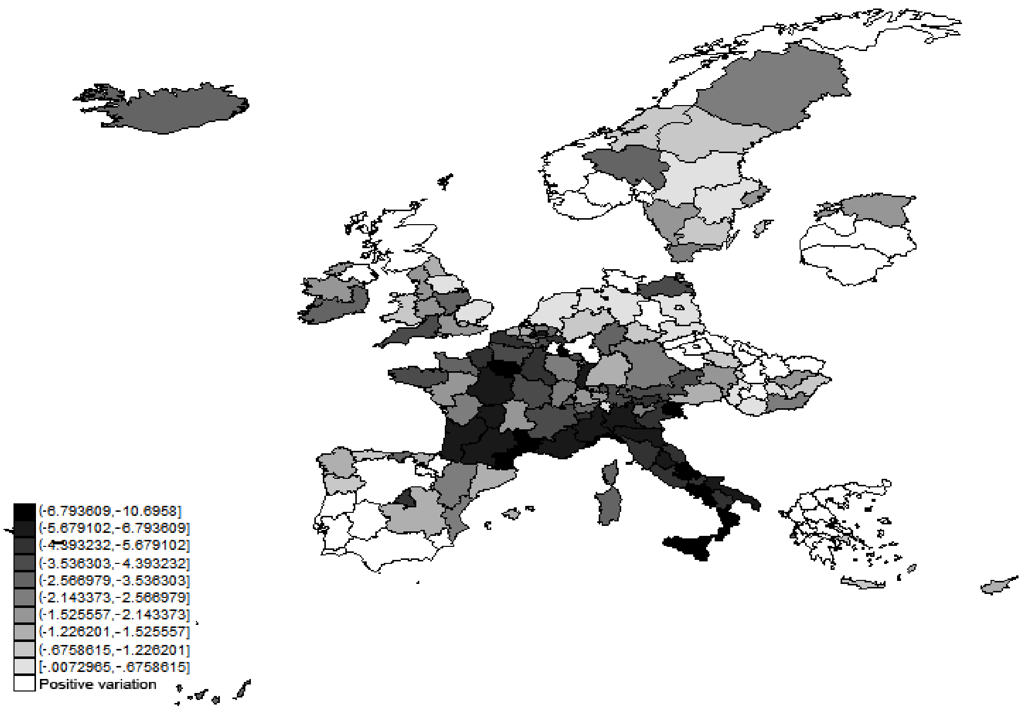
Figure 6 illustrates the within-industries variations. Although closely following the pattern in Figure 5, the picture seems to somehow amplify the concentration of higher contractions in Italy, France and Belgium (i.e. the within-component has been relatively more important in these three countries in comparison to others). Interestingly, in some regions (for instance in Scotland, Northern Ireland and regions across Eastern European countries) is possible to observe that routine occupations declined exclusively because of the contraction of regional employment shares of routine-intensive industries, even if routine occupations increased their shares *within*-industries. Finally, the intensity of the between-industry component plotted in Figure 7 appears to be rather scattered across the continent. Nonetheless, it is interesting to observe that this component is relatively more important in the U.K. (also in Wales, in the West-Midlands and in the North-West), and that Italy, France and Belgium are particularly affected by this channel too.

Figure 5. *100 × regional-level negative changes in routine occupations employment shares (2002-2010).*



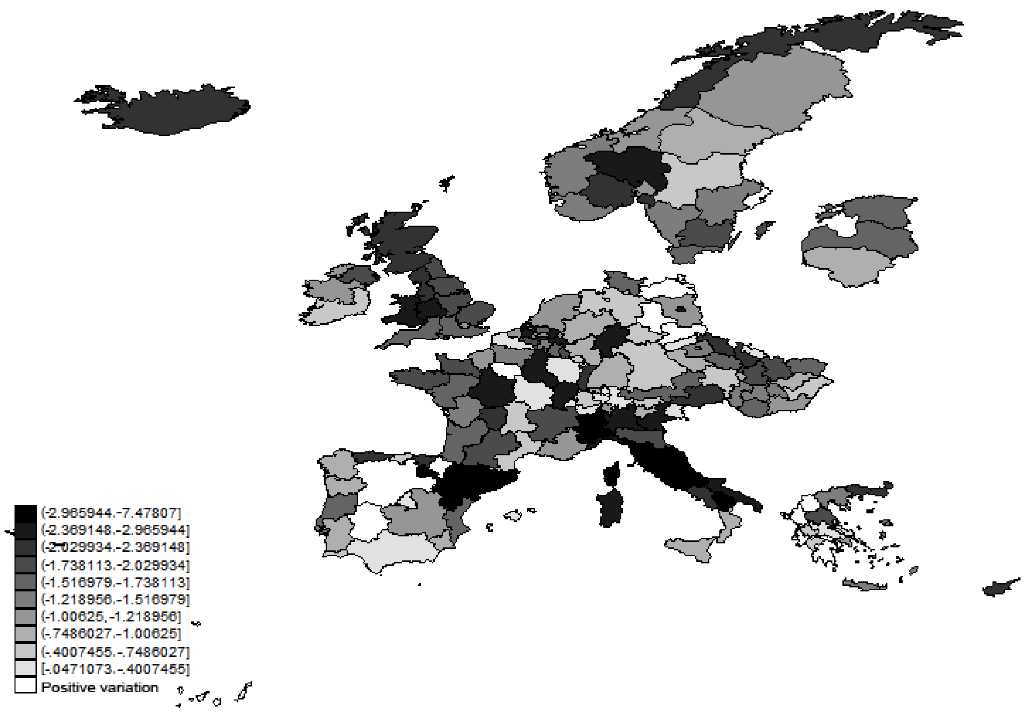
Notes: 174 regions. Regions split on unweighted deciles of negative variations in routine employment shares (the higher the routine employment share contraction, the darker the color of the region). Regions in white indicate a positive variation.

Figure 6. *100 × regional-level within-industries negative changes in routine occupations employment shares (2002-2010).*



Notes: 174 regions. Regions split on unweighted deciles of within-industries negative variations in routine employment shares (the higher the routine employment share contraction, the darker the color of the region). Regions in white indicate a positive variation.

Figure 7. *100 × regional-level between-industries negative changes in routine occupations employment shares (2002-2010).*



Notes: 174 regions. Regions split on unweighted deciles of between-industries negative variations in routine employment shares (the higher the routine employment share contraction, the darker the color of the region). Regions in white indicate a positive variation.

Further, the difference between the patterns of Figure 5 and 7 - compared with the similarity between Figure 5 and 6 - graphically suggests that the geographical distribution of the contraction of routine employment in Europe is mainly driven by the within-industry component.

5. Exposure to automation and contraction of routine employment: empirical evidences

In this section, I adopt Autor and Dorn's empirical framework in order to: 1) estimate the effect of exposure to automation on the contraction of routine employment shares in Europe, 2) assess the relative importance of the within and between-industry dimensions of this impact.[25] More specifically, I rely on the assumption that the cost of technology followed to decrease over the 2000's, and proxy for exposure automation (or exposure to RRTC) by using regions' start of period routine employment shares. As a first step, I provide descriptive evidences on the strength of this variable by comparing its explanatory power with that of other relevant (potentially endogenous) proxies of technological progress. In a second step, I estimate the relationship of interest by using a regression model that closely follows Autor and Dorn. To account for the endogeneity of the start of period routine share, I use an IV strategy that adapts their methodology to European regional data. Since within-regions routine employment shares contractions are composed by a within and between-industry component (see Section 4), in a last step I separately run different regressions with different response

[25] Autor and Dorn's units of analysis are consistently defined local labor markets – i.e. clusters of U.S. counties taking into account workers' commuting flows. Unfortunately, this information is not available in European data. Moreover, in their regressions Autor and Dorn pool data over three decadal-equivalent periods between 1980 and 2005, whereas in my analysis both variations and start of period conditions will be considered over the only decadal period available, that is, 2002-2010. Note also that Autor and Dorn mainly rely on the routine share variable in order to estimate the impact of automation on the growth of service employment. However - as also shown in Figure 3 - this relationship appears to be rather absent in last decade's Europe. Nevertheless, in Table 1 in the appendix I provide empirical evidences on the relationship between the routine share and the growth of the other occupation groups, showing that in all 3 cases there are no evidences of a significant impact.

variables (i.e. total, within and between-industry routine shares changes) and assess the contribution of both dimension to the total effect of exposure to automation in Europe.

To give an idea of the explanatory power of the start of period routine share, I consider two different proxies of technology: a) the start of period share of R&D expenditure on the regional GDP, b) the start of period per capita rate of patent registrations. These variables are rather straightforward indexes of, respectively, the importance of innovation in the economy and the propensity to innovate in a region. Since a negative correlation with agglomeration may apply (see Lindley and Machin, 2014), among these variables I also consider regions' start of period population density.[26] I provide preliminary descriptive evidences on the relative strength of these relationships in Figure 8, which summarizes the output of four simple unweighted univariate OLS models and displays the corresponding bivariate scatterplots. Each model estimates a simple equation of the form:

$$\Delta RSH_{j,2002-2010} = \alpha + \beta \mathrm{X}_{j,2002} + e_j, \tag{6}$$

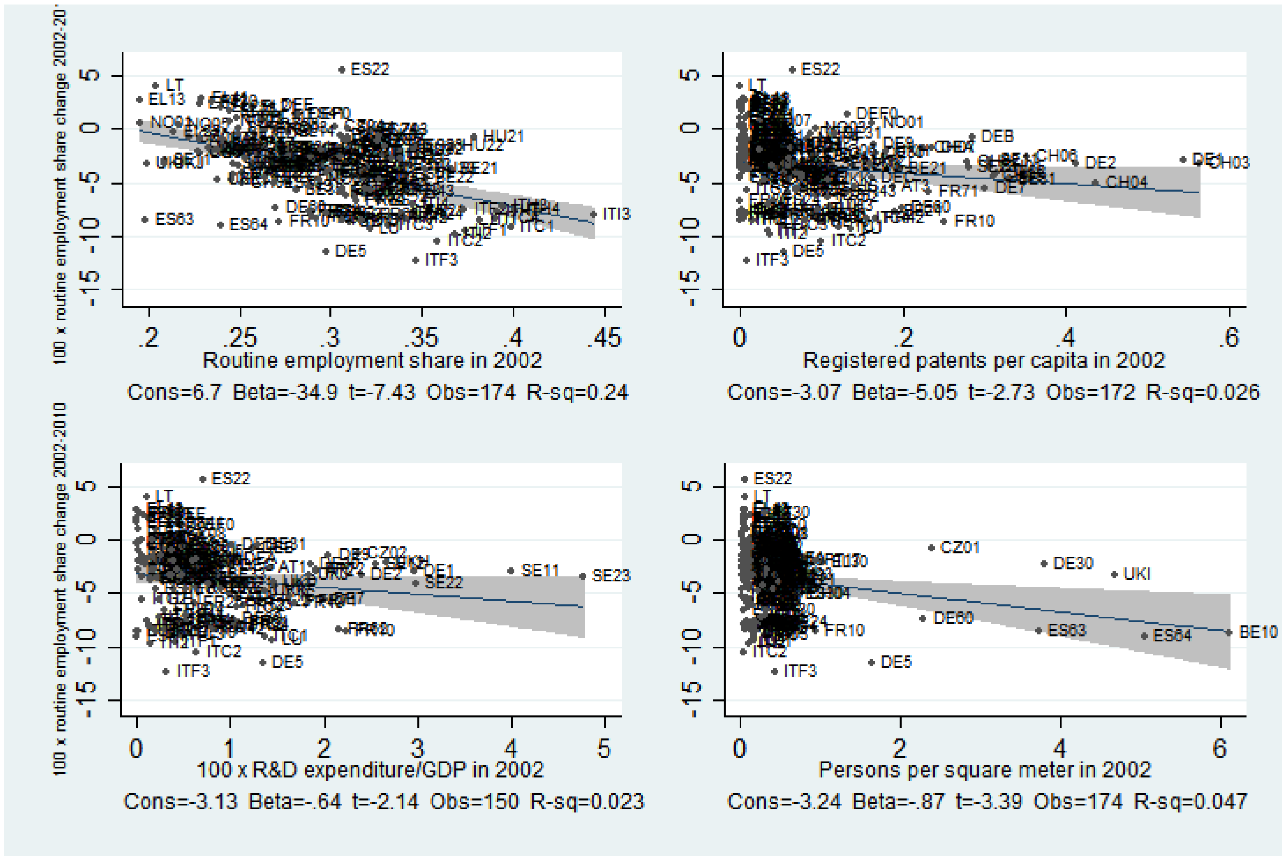
where $\mathrm{X}_{j,2002}$ represents, for each estimation, the start of period value of one of the four explanatory variables for region j. As shown by the t-statistics in Figure 8, each coefficient has the expected sign and results statistically not

[26] For a small fraction of regions, some of these aggregate variables are not available for year 2002. By mainly relying on years between 2000 and 2004 (and by giving priority to previous years), I use data from the closest year available to replace these missing values. Unfortunately, data on R&D expenditure are not available for Switzerland, Norway and Belgium (except for Brussels), whilst data on patents registrations are not available for the Spanish overseas territories of Ceuta and Melilla (ES63 and ES64).

different from zero. Interestingly, the routine share reveals to be the most predictive, i.e. five times more explicative - in terms of raw variations of ΔRSH_j - than population density, and even ten times more than the considered technological variables (R^2 are reported in Figure 8). Although data on local expenditure in R&D are available for a sub-sample of 150 regional units only, it worth noting that the fraction of variation explained by this variable is virtually the same of that explained by the number of registered patents per capita (2.3% vs. 2.6%)[27]. As for population density, results need to be interpreted with some caution, as the picture makes clear that the distribution of this variable is extremely right-skewed (mostly reflecting the uneven repartition of regions over space).

[27] Note that the correlation coefficient between the two variables, jointly covering 148 observations, amounts to 0.75

Figure 8. *100 × Routine occupations employment share change by regional units (2002-2010) vs. start of period: Routine occupations employment shares, Number of registered patents per capita, R&D expenditure/GDP ratio and Population density.*



Notes: unweighted OLS regressions with robust standard-errors. Lines represent the slope of OLS coefficients and the shaded areas the corresponding 95 per cent confidence interval.

As this preliminary descriptive evidence shows, the routine employment share captures a huge fraction of the variations in the response variable - i.e. around a quarter (the R^2 is of 24%). This indicates that the proxy of exposure to automation does indeed a good job in explaining the contraction of routine employment in Europe. To obtain a more possible adequate estimate of its impact, I follow as close as possible Autor and Dorn's empirical approach. More specifically, I estimate an augmented version of equation (6) by, on the one hand, weighting regressions for regions' population share on total population in 2002 and, on the other hand, by clustering standard errors by 35 NUTS1 or NUTS0 regions.

In order to address potential endogeneity drawbacks related to the routine share measure, Autor and Dorn rely on 1950 U.S. Census data in order to capture the "quasi-fixed component" of the local-level industrial structures that determines the routine share.[28] For the set of countries under analysis, unfortunately, the EU-LFS database reports complete regional data only from 1999 onward. Nonetheless, I claim it is still possible to induce an exogenous variation in $RSH_{j\,2002}$ by, on the one hand, relying on data from 1999 and, on the other hand, by exploiting the heterogeneity of European economic trends across broad economic geographical areas. In this manner, I do not claim I am able to recover the "quasi-fixed long-run component" of the local routine occupations employment shares (as Autor and Dorn do), but, less ambitiously, that I can at least get rid of the bias stemming from

[28] For instance, unobservable cyclical demand shocks towards routine-intensive industries at the start of period might lead to a biased estimate of the coefficient on the routine share. See Autor and Dorn for a detailed formalization of the endogeneity bias issue.

regional-level idiosyncratic shocks. More specifically, Autor and Dorn's instrumental variable consists in the interaction between the local industrial structure in 1950 of local unit j and the contemporary industry-level routine employment shares in all U.S. states *except* the state containing local-unit j. Following their approach, I compute my instrumental variable as follows:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1999} \times R_{i,-j,1999}, \qquad (7)$$

where $E_{i,j,1999}$ is the 1999 employment share of industry i in regional-unit j, and $R_{i,-j,1999}$ is the 1999 routine occupations employment share in industry i in all European countries *except* those belonging to the geographical area where regional unit j is located[29]. The augmented "horizontal" dimension of this IV aims to compensate the lack of "vertical" exogeneity that a longer time-span of European regional data, if available, would have provided in this framework. Being determined by the local industrial structure three years before the reference period and by the 1999 industry-level routine employment shares in those European countries in which cyclical-shocks are arguably uncorrelated with local-specific ones, I expect this instrument to be correlated with the structural component of routine employment shares across regions but uncorrelated with local-level idiosyncratic short-term conjunctures.[30] As Panel B column 1 of Table 5 shows, $\widetilde{RSH}_j$ is indeed highly

[29] For the repartition of Europe into broad geographical areas, I build four blocks: northern countries (U.K., Ireland, Sweden and Norway); eastern countries (Baltic Republics, Czech Republic, Slovakia and Hungary); southern countries (Portugal, Spain, Italy and Greece) and central countries (Austria, Germany, Switzerland, France and Benelux countries).

[30] Since regional data in 1999 are not available for Switzerland and Germany, for these countries I compute regional-level industries employment shares by using, for Switzerland,

predictive of the routine share in 2002: the Kleibergen-Paap rk Wald F-statistic amounts to 21.37, whereas the first-stage t-statistic on $\widetilde{RSH}_j$ (not reported for sake of space) scores to 4.58.

Formally, the regression model estimates the equation:

$$\Delta RSH_{jc,2002-2010} = \alpha + \beta RSH_{j,2002} + \mathbf{X}'_{j,2002} + \gamma_c + e_{jc}, \tag{8}$$

where $\Delta RSH_{jc,2002-2010}$ is the variation of routine occupations employment shares in regional unit j within NUTS0/NUTS1 region c, $RSH_{j,2002}$ is regions j's start of period routine share and $\mathbf{X}'_{jc,2002}$ is a vector of region j's start of period control variables. Since I include the set of 35 country/region dummies γ_c, β is identified by variations within NUTS0/NUTS1 regions.[31] Table 5 reports the benchmark specification (Column 1) and the results obtained by adding different regional characteristics as control variables (Columns 2 to 8). Further, the most complete models are separately run by using the within and between-industries components of routine employment shares variations as response variables (Columns 4, 5, 7 and 8).

For those regions at the 80th percentile of the start of period routine share relative to those at the 20th, the OLS coefficient in panel A Column1 of Table 5 (-2.807) predicts a 2.1 p.p. larger contraction of routine employment

2001 EU-LFS data and, for Germany, 1998 administrative aggregate data provided by the Institute for Employment Research (IAB).

[31] NUTS2 regions are clustered by NUTS1 regions, whereas NUTS1 regions are clustered by NUTS0 regions. In order to preserve observations, I cluster six countries (i.e. NUTS0) under two broader clusters: the first covering Estonia, Latvia and Lithuania, the second covering Belgium, Luxembourg and the Netherlands (the main results are not sensitive to this procedure). Because of the absence of within-cluster variation, Iceland and Cyprus - overseas NUTS0 regions – are dropped from the regressions.

shares. Interestingly, this figure is quiet close to the 1.8 p.p. recovered for the U.S. by Autor and Dorn.[32] Moreover, the corresponding 2SLS estimate in Panel B does not deviate much from the OLS one. Column 2 control for the (potentially endogenous) alternative explanatory variables considered above (note that, since the R&D variable is missing for a number of regions, regressions in Column 2 are run on only 146 observations). The three variables enter with the expected sign, though the patent per capita one results non-significant. As for the coefficient on the routine share, it slightly increases and remains highly significant.

Column 3 includes a set of four additional control variables to the model (note that, since the use of the R&D variable considerably restricts the sample, this and following specifications omit this covariate in order to maximize the number of observations). In order to take into account region's industrial structure and labor market conditions I consider, respectively, the broad manufacturing employment share and the share of employed on the working-age population. Moreover, I also control for two relevant regions' labor markets characteristics, by including the share of graduate workers on the labor force and the female participation rate. All of these variables results non-significant except the manufacturing share. The fact that the corresponding coefficient is positive indicates that those regions in which manufacturing employment was relatively more abundant in 2002 experienced, on average, a slower decline of routine employment (in other words, manufacturing-specialized regions result to be relatively more

[32] Note that the (population weighted) 80-20 percentile range of the routine share in 2002 is of 0.075.

resilient in terms of routine employment shares contractions). Coefficients on population-density and the number of registered patents per capita still show the expected sign, and result significant (though only at the 10% level in the case of population density). Overall, from Column 3 we can see that the estimate on the routine share considerably increases in magnitude when all controls are included. In particular, the OLS estimate in panel A (-5.738) indicates that regions at the 80th percentile of $RSH_{j,2002}$ have suffered a contraction of routine occupations employment shares 4.3 p.p. larger respect to those at the 20th, an effect considerably large in magnitude and significant at the 1 per cent level.

As a final step, Column 4 and 5 replicate the model in column 3 by splitting the dependent variable, respectively, in the within-industries and the between-industries components computed in section 4.[33] As clearly shown, the effect of automation is almost entirely related to within-industries routine employment contractions, and only to a minor extent to between-industries ones. More specifically, the coefficient on the routine share in Column 4 (within-industry component) captures about 90% of the overall effect observable in column 3, and is almost 5 times greater than the corresponding coefficient in Column 5 (between-industry component), both in OLS and 2SLS models. Further, the impact of the routine share on the

[33] Note that, in order to equal coefficients in Table 3, one should sum up coefficients in Columns 4 and 5 with the corresponding coefficients on the interaction term – not shown in Table 5 inasmuch they cannot be unambiguously interpreted. However, Table 3 clearly shows that the interaction term has almost no contribution to within-regions changes in routine employment shares.

between-industry component is less significant in the 2SLS estimate, where the confidence interval includes the zero (Column 5 Panel B).

Since the patents per capita as well as the population density variable may raise some endogeneity concern, columns 6 to 8 omit these controls from the full-fledged model.[34] Though 2SLS estimates increase in magnitude in comparison to OLS ones, the relative importance of the two components for the total effect is the same observable by comparing Column 3 with Column 4 and 5. Overall, this confirms that the depressing effect of exposure to automation on routine occupations employment shares is predominantly a within-industry effect.[35]

[34] In Table 2 in the appendix I repeat the same regressions of Table 5 for the period 2002-2007. Though OLS estimates on the routine share are very similar, 2SLS estimates in columns 1 to 5 result non-significant. Nevertheless, I recover substantially similar results when the set of potentially-endogenous variables are omitted from the specification (Columns 6 to 8).

[35] This may be due also to the fact that, as pointed out by Goos et al (2014), compensation effects associated to labour-saving technologies may mitigate the reduction of overall employment shares of those industries more affected by RRTC.

Table 5. *Routine shares and contraction of routine employment within-regions: within and between-industries evidences (dependent variable: 10 x routine occupations employment share change, 2002-2010).*

	(1) Overall	(2) Overall	(3) Overall	(4) Within	(5) Between	(6) Overall	(7) Within	(8) Between
Panel A: OLS								
Routine share-1	-2.807***	-3.454***	-5.738***	-5.209***	-1.103***	-5.723***	-5.213***	-1.068***
	(0.738)	(0.638)	(0.525)	(0.566)	(0.273)	(0.688)	(0.713)	(0.284)
R&D/GDP-1		-0.059**						
		(0.028)						
Patents per capita-1		-0.228	-0.604***	-0.560***	-0.028			
		(0.325)	(0.104)	(0.131)	(0.063)			
Population density-1		-0.093***	-0.057*	-0.025*	-0.021			
		(0.028)	(0.031)	(0.012)	(0.020)			
Manufacturing share-1			1.733***	1.954***	-0.054	1.623***	1.781***	-0.010
			(0.381)	(0.369)	(0.239)	(0.445)	(0.440)	(0.236)
Employed/Population-1			-0.424	-0.360	-0.035	-0.747**	-0.706*	0.009
			(0.284)	(0.368)	(0.151)	(0.337)	(0.411)	(0.137)
Female/Labor force-1			-0.090	0.305	-0.469	1.575*	1.625*	-0.181
			(1.118)	(1.242)	(0.541)	(0.793)	(0.872)	(0.598)
Tertiary education/Labor force-1			-0.080	-0.260	0.237	-1.035**	-0.949**	0.044
			(0.344)	(0.436)	(0.295)	(0.386)	(0.388)	(0.246)
Observations	172	146	170	170	170	172	172	172
R^2	0.720	0.787	0.815	0.799	0.614	0.784	0.776	0.576
Panel B: 2SLS								
Routine share-1	-2.884***	-3.344***	-5.387***	-4.594***	-1.037*	-9.216***	-7.753***	-1.721**
	(0.663)	(0.794)	(1.026)	(1.220)	(0.605)	(1.278)	(1.343)	(0.833)
Wald rk F statistic	21.37	68.60	20.43	20.43	20.43	12.69	12.69	12.69
R^2	0.724	0.732	0.761	0.798	0.614	0.768	0.755	0.565

Notes: all models include an intercept and 35 NUTS0/NUTS1 dummies (clustering Benelux and Baltic countries under two broader distinct dummies, respectively). Robust standard errors in parentheses are clustered by NUTS1/NUTS0 regions. All regressions are weighted by regions' start of period share of total population. ***p<0.01, **p<0.05, *p<0.1.

In sum, this set of evidences support the interpretation according to which technology substitutes for routine tasks by reshaping the composition of employment predominantly *within* economic-activity branches (see Autor et al., 2015). On the one hand, indeed, my results point out that the overall employment shares of those industries that are more endowed with routine labor (i.e. more exposed to automation) may actually decline as a consequence of RRTC - as already observed by Goos et al. (2014). On the other hand, however, the between-industry channel results to account for a rather marginal component of the overall impact of exposure to automation, suggesting that the effects of RRTC are predominantly associated to changes in the within-industry dimension.

6. Conclusions

In this chapter, I showed that the decline of routine employment in Europe in the past decade has been substantial, though relatively heterogeneous in geographical scope. I also documented that, among regions more endowed with routine labor, the occupational composition of employment experienced more pronounced polarization patterns. Finally, I showed that the impact of exposure to automation mostly depressed routine employment shares through the within-industries channel. Indeed, albeit the evidences point out that exposure to RRTC may negatively affect overall employment shares of routine-intensive industries, they also indicate that the role of this dimension is considerably less important.

References

Acemoglu, Daron, and David Autor. (2011). “Skills, Tasks and Technologies: Implications for Employment and Earnings.” *Handbook of Labor Economics*, Vol 4, part B, edited by Orley Ashenfelter and David Card, 1043–1171. Amsterdam: Elsevier.

Autor, David, and David Dorn. (2009). “This job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure.” *American Economic Rewiev*, 99 (2): 45-51.

Autor, David, and David Dorn . (2013). “The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market.” *American Economic Review*, 103 (5):1553–1597.

Autor, David, David Dorn and Gordon H. Hanson. (2015). “Untangling Trade and Technology: Evidence from Local Labor Markets*”, Economic Journal*, 125 (584): 621-646.

Autor, David, .H., Frank Levy and Richard J. Murnane. (2003). “The Skill Content of Recent Technological Change: An empirical exploration.*” Quarterly Journal of Economics*, 118 (4): 1279–1333.

Dauth, Wolfgang. (2014). “Job Polarization on Local Labor Markets.”, IAB Discussion Paper 18/2014.

Dustmann, Christian, Johanna Ludsteck and Uta Schoenberg. (2009). “Revisiting the German Wage Structure.*” Quarterly Journal of Economics*, 124 (4): 843–881.

Goos, Marteen, and Alan Manning (2007). “Lousy and Lovely Jobs: the Rising Polarization of Work in Britain.” *The rewiev of Economics and Statistics*, 89 (1): 118-133.

Goos, Marteen, Alan Manning and Anna Salomons. (2009). “Job Polarization in Europe.*” American Economic Review*, 99 (2): 58–63.

Goos, Marteen, Alan Manning and Anna Salomons. (2014). “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring.” *American Economic Review*, 104 (8): 2509–2526.

Gregory, Terry, Anna Salomons and Ulrich Zierahn (2016): "Racing With or Against the Machine? Evidence from Europe." ZEW Discussion Paper.

Lindley, Joanne, and Stephen Machin. (2014). “Spatial changes in labour market inequality.*” Journal of Urban Economics*, 79, 121-138.

Mazzolari, Francesca, and Giuseppe Ragusa. (2013). “Spillovers from High-skilled Consumption towards Low-skilled Labor Markets.” *The Rewiev of Economics and Statistics*, 95 (1): 74-86.

Naticchioni, Paolo, Giuseppe Ragusa and Riccardo Massari. (2014). “Unconditional and Conditional Wage Polarization in Europe.” IZA Discussion Paper 8465.

Puga, Diego. (2010). “The Magnitude and Causes of Agglomeration Economies.” *Journal of Regional Science*, 50 (1): 203-219.

Rosenthal, Stuart S., and William C. Strange. (2004). “Evidence on the Nature and Sources of Agglomeration Economies.” In: Henderson, V., Thisse, J.-F. (Eds.), *Handbook of Urban and Regional Economics*, Vol. 4, 2119-2171. North Holland.

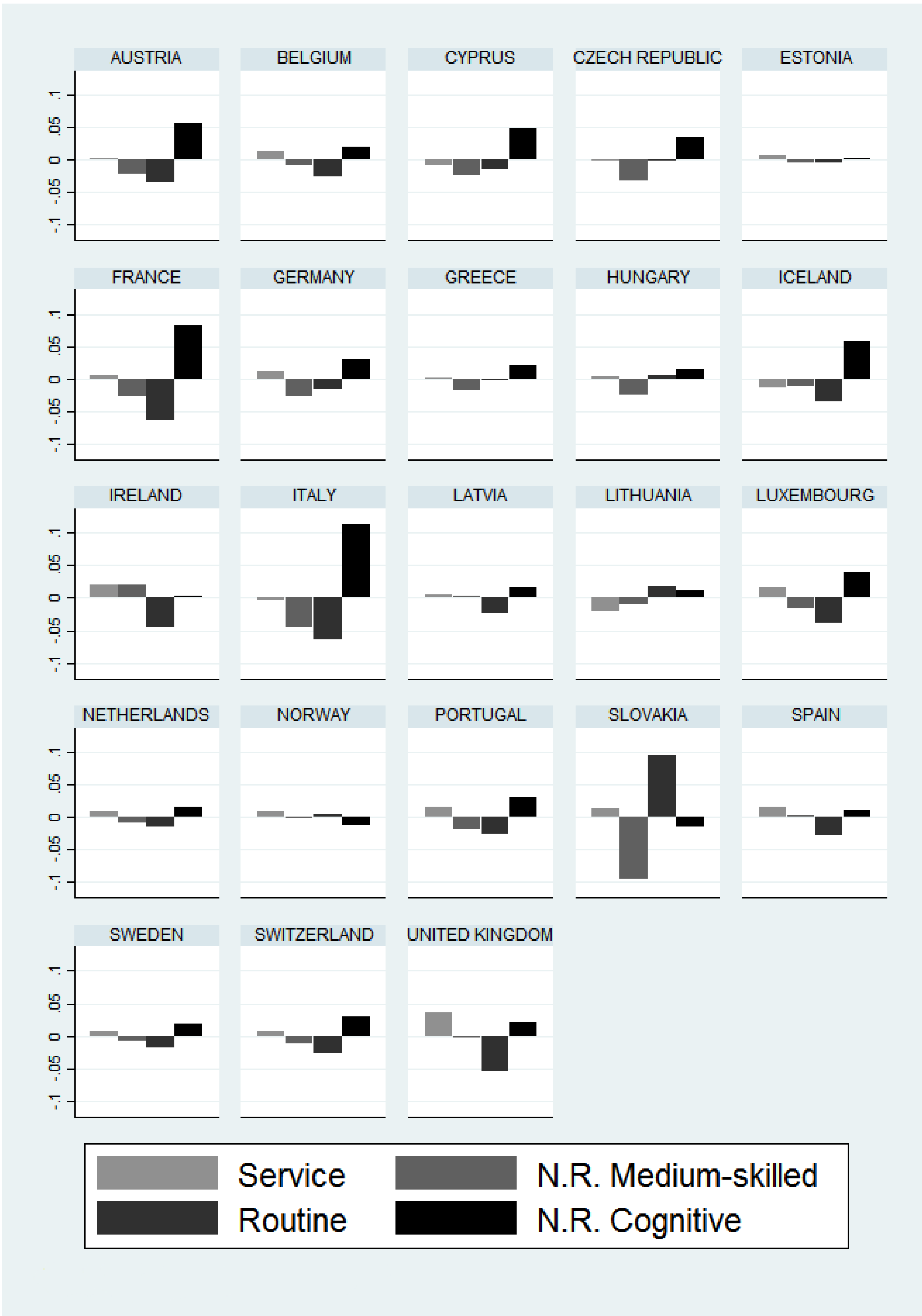
Senftleben, Charlotte, and Hanna Wielandt. (2013). “The Polarization of Employment in German Local Labor Markets”, SFB 649 Discussion Paper 2012-013.

Spitz-Oener, Alexandra. (2006). “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure.” *Journal of Labor Economics*, 24 (2): 235–270.

Exposure to Automation and the Decline of Routine Employment across European Regions

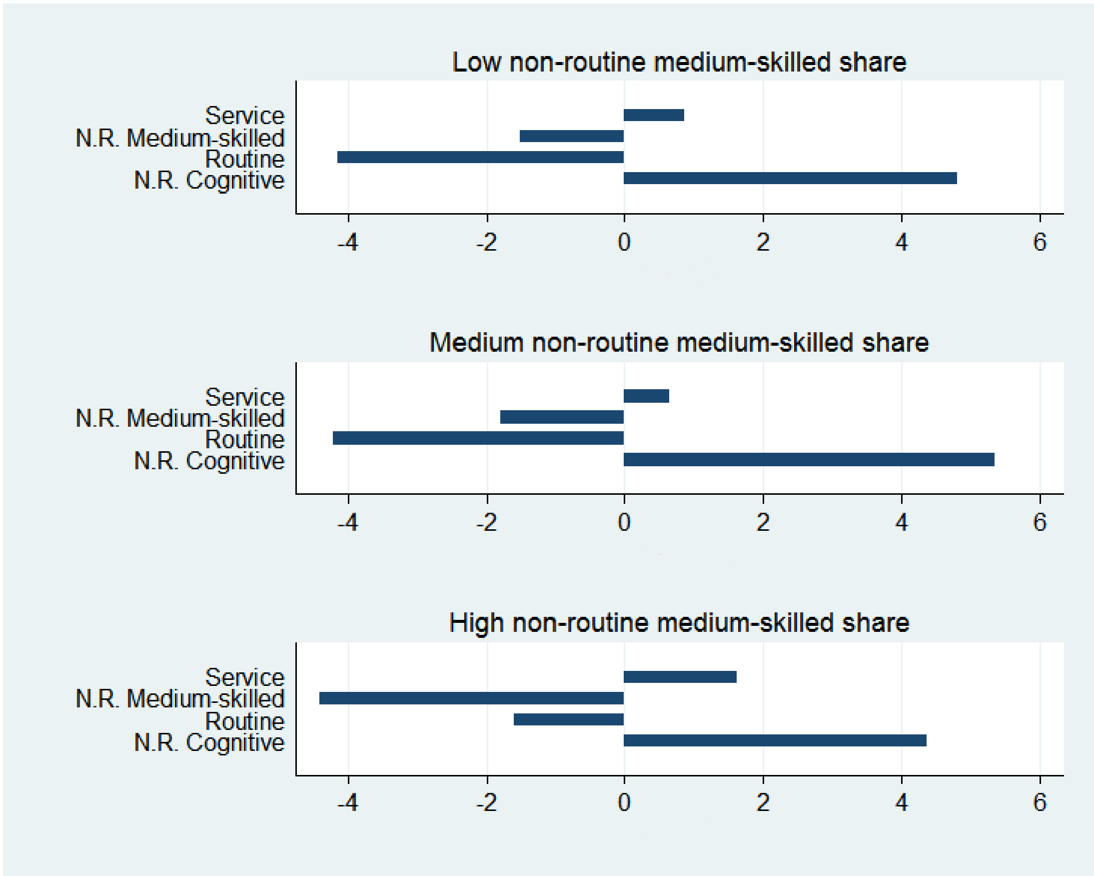
Appendix

Figure 1. *100 x Occupation-groups employment shares changes by country (1999-2007).*



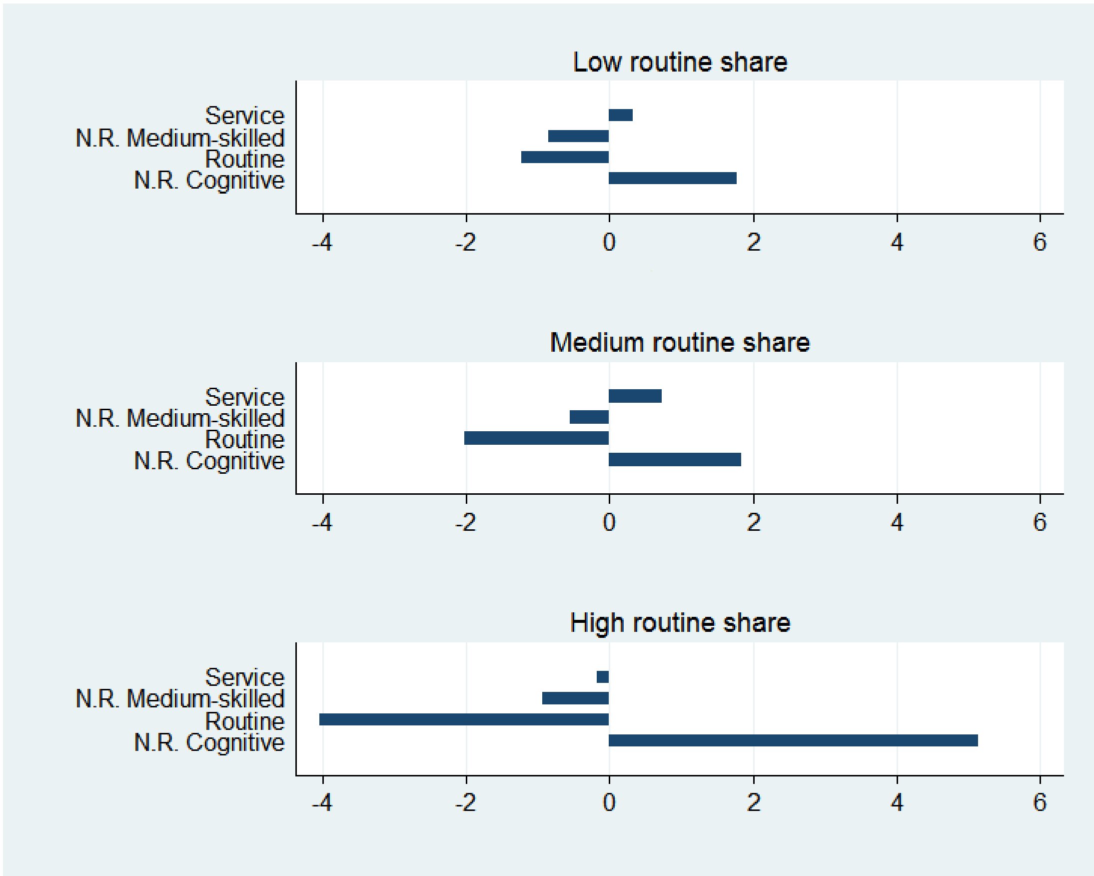
Notes: EU-LFS data, 23 European countries.

Figure 2. *Occupation groups population-weighted average 100 × change in employment shares (2002-2010), regions split on population-weighted terciles of non-routine medium-skilled occupations employment shares in 2002.*



Notes: EU-LFS data, 174 regions. Average changes weighted for regions population share of total population in 2002.

Figure 3. *Occupation groups population-weighted average 100 × change in employment shares (2002-2007), regions split on population-weighted terciles of routine occupations employment shares in 2002.*



Notes: EU-LFS data, 174 regions. Average changes weighted for regions population share of total population in 2002.

Table 1. *Routine share, technological proxies and non-routine occupation groups employment within regions. (Dependent variable: occupation group 10 x employment share change by regional units, 2002-2010).*

	(1)	(2)	(3)
	Service	N.R. Medium Skilled	N.R. Cognitive
OLS			
Routine share$_{-1}$	0.589	1.024	1.195
	(0.566)	(0.917)	(1.451)
Observations	172	172	172
R^2	0.484	0.566	0.604
2SLS			
Routine share$_{-1}$	0.427	1.459	0.998
	(0.742)	(0.931)	(1.004)
Wald rk F	21.37	21.37	21.37
R^2	0.483	0.604	0.565

Notes: OLS estimates. All models include an intercept and 35 NUTS1/NUTS0 dummies (clustering Benelux and Baltic countries under two broader different dummies). Robust standard errors in parentheses are clustered by NUTS1/NUTS0 regions. All models are weighted by regional-units start of period share on total population. ***p<0.01, **p<0.05, *p<0.1.

Table 2. *Exposure to automation and decline of routine employment: within-industries and between-industries evidences (dependent variable: 10 x routine occupations employment share change by regional units, 2002-2007).*

	(1) Overall	(2) Overall	(3) Overall	(4) Within	(5) Between	(6) Overall	(7) Within	(8) Between
Panel A: OLS								
Routine share-1	-2.016***	-1.903***	-3.944***	-3.214***	-0.960***	-4.015***	-3.285***	-0.941***
	(0.511)	(0.537)	(0.695)	(0.694)	(0.276)	(0.537)	(0.507)	(0.271)
R&D/GDP-1		-0.008						
		(0.028)						
Patents per capita-1		-0.277*	-0.457**	-0.503**	0.014			
		(0.156)	(0.170)	(0.201)	(0.066)			
Population density-1		-0.028	0.004	0.014	-0.013			
		(0.027)	(0.029)	(0.040)	(0.016)			
Manufacturing share-1			1.234***	1.273**	0.098	1.032**	1.025*	0.139
			(0.396)	(0.487)	(0.198)	(0.386)	(0.510)	(0.199)
Employed/Population-1			0.280	0.326	-0.074	-0.088	-0.089	-0.030
			(0.256)	(0.299)	(0.126)	(0.275)	(0.324)	(0.102)
Female/Labor force-1			-1.076	-0.680	-0.605	-0.295	0.116	-0.495
			(1.151)	(1.127)	(0.740)	(1.064)	(1.012)	(0.608)
Tertiary education/Labor force-1			-0.326	-0.294	0.047	-0.692*	-0.630	-0.045
			(0.500)	(0.579)	(0.310)	(0.396)	(0.485)	(0.257)
Observations	172	146	170	170	170	172	172	172
R^2	0.734	0.759	0.786	0.762	0.445	0.770	0.741	0.433
Panel B: 2SLS								
Routine share-1	-0.956	0.088	-1.400	-2.259*	0.934	-3.248***	-4.197***	0.682
	(0.716)	(0.783)	(1.308)	(1.207)	(0.692)	(1.161)	(1.341)	(0.848)
Wald rk F	21.37	68.60	20.43	20.43	20.43	12.69	12.69	12.69
R^2	0.724	0.732	0.761	0.758	0.318	0.768	0.738	0.340

Notes: all models include an intercept and 35 NUTS0/NUTS1 dummies (clustering Benelux and Baltic countries under two broader distinct dummies, respectively). Robust standard errors in parentheses are clustered by NUTS1/NUTS0 regions. All regressions are weighted by regions' start of period share of total population. ***p<0.01, **p<0.05, *p<0.1.

Chapter III

Agglomeration and the Decline of Routine Tasks

Abstract

In this chapter, I use IAB data on West Germany to address the role played by agglomeration economies in explaining the decline of routine tasks in cities. The main theoretical intuition is that agglomeration externalities asymmetrically benefit routine and non-routine tasks, and that congestion costs stemming from agglomeration relatively increase the opportunity-cost of using routine tasks in cities. I document a strong monotonic relationship between employment density and the contraction of routine tasks over the period 1991-2010. By exploiting the longitudinal dimension of IAB data, I find that workers employed in routine jobs are more likely to leave denser areas, whereas routine workers remaining in cities are more likely to switch to non-routine occupations. I also find that workers employed in routine-manual occupations have higher probability to join unemployment in cities. Finally, I show that even when accounting for the endogeneity of employment density and controlling for exposure to automation, the impact of agglomeration on the decline of routine tasks is stable, sizeable and highly significant.

1. Introduction

The empirical literature well establishes the existence of a positive link between urban agglomeration and workers' skills (Glaeser and Maré, 2000, Glaeser and Saiz, 2004, Glaeser and Resseger, 2010). Further, recent analyses suggest that agglomeration economies are mostly biased towards high-skilled occupations. Bacolod et al. (2009) show that productivity gains, as measured by the urban wage premium, mostly accrue among workers employed in occupations that require cognitive or interactive skills – whereas no evidences of such benefits can be found for occupations involving manual or physical-strength skills. Interestingly, occupational asymmetries in agglomeration benefits also emerge from task-based perspective – i.e. by distinguishing between routine tasks and non-routine tasks (see Autor et al., 2003). As pointed out by Andersson et al. (2014), indeed, agglomeration externalities mainly reward workers employed in non-routine jobs, whereas the urban wage premium is almost non-existent for workers employed in routine occupations. Besides the relevance of these findings from a micro-foundation point of view (see Rosenthal and Strange, 2004, Duranton and Puga, 2004, Puga, 2010), the labor demand implications of such asymmetries for what concerns the recent changes in the employment structure of cities have not been empirically addressed yet. Moreover, though descriptive evidences of a certain association between agglomeration and employment polarization are somehow available (Lindely and Machin, 2014, and Dauth, 2014), so far no study has analyzed changes in the task composition of employment in the space dimension, but only the correlation of job polarization with agglomeration.

By using survey-data from the German Qualification and Career Survey (BIBB/IAB) and a 30% random-sample of German administrative data from the Institute for Employment Research (IAB), this study investigates the role of agglomeration economies in explaining the contraction of routine tasks in large urban agglomerations. By adopting Autor et al. (2003) taxonomy of occupational tasks-contents, I describe changes in tasks employment shares among locations characterized by different levels of employment density.

I document a strong monotonic relationship between employment density and the contraction of routine tasks in West Germany over the period 1991-2010. I also show that this correlation stems from a faster contraction in routine-manual tasks, whereas a slight expansion characterizes routine-cognitive tasks. Further, I document that the contraction of routine tasks in denser places results more pronounced in the manufacturing sector, while the slower growth of routine-cognitive tasks in cities results entirely related to non-manufacturing activities. I therefore provide some possible explanations for the possible mechanisms that may account for these trends.

On the one hand, I provide descriptive evidences by mainly exploiting the longitudinal dimension of IAB data. In particular, I consider four different possible channels of the hollowing out of routine tasks in cities:

1) Routine workers' spatial mobility from high-density to low-density areas. To investigate on this channel, I make use of a spatial transition matrix, and show that routine workers are more likely to leave denser places relative to non-routine workers.

2) Higher routine workers' occupational mobility towards non-routine occupations in denser areas. To explore this possibility, I model the probability of routine workers to switch to non-routine jobs as a function of employment density, finding that the higher the level of agglomeration, the higher the probability of routine workers to move towards non-routine tasks.

3) Routine workers' probability to join unemployment in cities. I address this point by using an empirical approach similar to the one of point 2. My results suggest that this channel may apply for workers specialized in routine-manual tasks – whereas I find that the probability to join unemployment for workers in routine-cognitive jobs (which is negative unconditional on density) in cities decreases.

4) Higher contraction of routine tasks among younger workers in cities. To provide evidences on this channel, I analyze changes in the task composition of employment for different age groups, and find no differences in the relative changes of routine tasks between cities and non-cities among young and prime age workers.

Overall, it is interesting to stress that I find evidences that are consistent with a possible role played by these channels in three cases out of four.

On the other hand, I try to disentangle the role of technology from that of agglomeration with an identification strategy that builds on two pillars. The first pillar concerns the role of routine-replacing technical change (RRTC), which I account for by means of an empirical framework that uses routine employment shares to proxy for labor local labor markets (LLMs) exposure to automation (see Autor and Dorn, 2013). The second pillar concerns instead the endogeneity of employment density. I address this problem by following a long tradition in urban economics, which uses deep lags of population density as instrumental variable (on the identification of agglomeration economies, see Combes et al. 2011, Baum-Snow and Ferreira, 2015, Combes and Gobillon, 2015). My main theoretical intuition follows the idea that – for a given rate of routine-replacing technical change – agglomeration penalizes the use of routine tasks relatively to other tasks. My theoretical intuition relies on the idea that the opportunity-cost of using routine-tasks increases in large agglomerations. This happens, on the one hand, as a consequence of rising congestion costs (for instance, increasing rents and prices due to agglomeration) and, on the other hand, because of tasks-biased asymmetries in agglomeration economies (as in Bacolod et al., 2009, and Andersson et al., 2014). My results are consistent with the theoretical intuition - i.e. these mechanisms may indeed account, in a causal way, for a higher contraction of routine tasks in large agglomerations. In particular, I find that one standard deviation increase in employment density causally predicts approximately a 0.12 standard deviations contraction in routine-tasks employment shares. Moreover, I document that this effect is mainly driven by the routine-manual component, whereas the routine-cognitive component results to play a minor role.

I also show that the impact I identify is robust to different specifications, with particular reference to the use of alternative definitions of the spatial unit of analysis and of alternative lags of population density as instrumental variable.

The remainder of this chapter is organized as follows: Section 2 describes the data and the methodology used in order to measure the task content of occupations, whereas Section 3 describes changes in the task composition of employment in the space dimension. Section 4 provides descriptive evidences on the possible channels of the contraction of routine tasks in cities, while Section 5 outlines my main theoretical assumptions and discusses the results obtained with my empirical analysis. Section 6 concludes.

2. Data and measurements

2.1. Data overview

In my analysis, I use two West German data sources. The first is the German Qualification and Career Survey - conducted jointly by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment Research (IAB). This survey has the goal of tracking skill requirements by occupations. My second data source is a 30% random sample of compulsory social security notifications to the

Federal Employment Agency (BA), which is available to visiting researchers at the IAB.[1] I restrict my IAB sample to marketed economic sectors and focus on the period 1991-2010.[2] I consider 87 occupations, classified accordingly to the 2-digits German occupational classification (Kldb-88).[3] Since I do not have information about employees' hours worked, I measure employment as days worked and – as standard in employment analysis with IAB data – I compute full-time equivalents for part-time workers by weighting minor part-time with 16/39 and major part-time with 24/39 (see Dauth, 2014, Blien and Dauth, 2016).[4] The main spatial units of the analysis are 326 NUTS-3 districts – i.e. the most detailed territorial repartition available in the IAB dataset. Nonetheless, in my robustness checks I also consider a higher aggregation level composed by 108 commuting zones/local labor markets (see Kosfeld and Werner, 2012).

---

[1] Employment subject to social security in Germany excludes categories such as civil servants and the self-employed, and represents about 80 per cent of the German labor force (for more details about IAB data see Dustmann et al. 2009). I thank Uwe Blien and Wolfgang Dauth for office space and data access at the IAB.

[2] In particular, I exclude from my analysis the Agriculture and Fishing industries (NACE rev 1.1 A and B), the public sector (L, M and N) and Extraterritorial organizations and bodies (Q).I drop years after 2010 because of a break in the occupational classification.

[3] In both my datasets, occupation 78 (office clerks) and 76 (bank and insurance clerks) cover jointly a relatively large share of overall employment (17 per cent in 1991). To allow for a higher degree of variation for clerical and administrative support occupations (particularly relevant in the RRTC literature) I split these two occupational groups according to workers' educational attainment and consider the resulting groups as different occupations. In particular, I define "low-skilled" workers those without a vocational training degree, "medium-skilled" those with a vocational training degree, and "high-skilled" those with a degree from a University or a University of Applied Sciences.

[4] Employment is computed by excluding students in vocational training programs.

2.2. Measuring tasks across occupations

In order to analyze changes in the task composition of employment, I measure the task content of occupations by exploiting data from the Qualification and Career Survey. This is standard in the literature that applies the task approach to Germany (see, for instance, Spitz-Oener, 2006, Spitz-Oener and Black, 2009, Antonczyk et al., 2009, Dustmann et al., 2009). I then match this data with the administrative labor market data by occupation, i.e. both datasets follow the same occupation classification (see also Spitz-Oener and Black, 2009).

In my analysis, I do not allow for over-time variations in the task content of occupations. This is because I adopt the empirical framework proposed by Autor and Dorn (2013), which analyze changes in the occupational distribution of employment by holding tasks constant. To capture the task content of occupations at the start of period of my analysis, I use the 1991 wave of the Qualification and Career Survey. In this wave, respondents were asked to select from a list of 27 items "all tasks that belong to your job". As shown in Table 1, I pool these tasks into the four main categories defined by the RRTC literature: non-routine cognitive (in the following, NRC), routine-cognitive (RC), routine-manual (RM) and non-routine manual (NRM) (see Acemoglu and Autor, 2011). I do so according to the classification adopted by Spitz-Oener (2006) (see also Dustmann et al., 2009).

Table 1. *Assignment of activities to broad tasks categories*

Task category		Activities in the 1991 Qualification and Career Survey
NON-ROUTINE COGNITIVE		Interpreting laws
		Teaching
		Managing personnel
		Coordinating and organizing
		Designing
		Programming ICT
		Buying, selling, negotiating
		Analyzing, researching
		Entertaining, advertising
ROUTINE	COGNITIVE	Sorting, filing, archiving
		Typing, correcting texts and data
		Calculating, bookkeeping
	MANUAL	Setting up/ programming machines/ equipment
		Operating/controlling machines/ equipment
		Feeding/repairing machines/equipment
		Packing and shipping
NON-ROUTINE MANUAL		Controlling vehicles
		Cleaning
		Guarding, monitoring, watching
		Hosting, serving, accommodating
		Caring, hairdressing
		Cropping, raising cattle
		Repairing, restoring, renewing houses and buildings
		Expanding, installing, mounting buildings and infrastructures
		Cooking and food processing
		Disposing waste
		Extracting/processing raw materials

Notes: German Qualification and Career Survey activities, 1991.

Hence, I build my set of tasks-measures by computing, for each respondent, the share of tasks performed in a given category over *all* tasks performed. I do this by following Antonczyk et al. (2009) – which slightly modify the methodology proposed by Spitz-Oener (2006) - as follows:

$$T_{ij} = \frac{number\ of\ tasks\ in\ category\ j\ performed\ by\ i}{total\ number\ of\ tasks\ performed\ by\ i\ over\ all\ categories}, \quad (1)$$

where T_{ij} can be considered as a proxy of the time spent by respondent i in performing tasks belonging to category j.[5] To obtain occupational level measures, I simply collapse individual information by occupation. I describe the main characteristics of my measures in Table 2, which considers the first five occupations scoring at the top in each category. In particular, it is worth noting three main characteristics of these occupational tasks measures:

1) By construction, this set of task measures sum up to one for each occupation.

2) For each task category, these measures assign higher scores to occupations typically identified by the literature as "intensive" in the

[5] Both in Spitz-Oener (2006) and Spitz-Oener and Black (2009) the denominator in equation (1) only includes tasks belonging to category *j*. Therefore, the resulting task indexes cannot be considered as a proxy of the time spent by workers in performing a given set of tasks. This is the reason why I prefer to apply Antonczyk et al. (2009) methodology. However, the reader has to bear in mind that different tasks may have time-requirements that are very different in different sectors/occupations. Unfortunately, BIBB/IAB survey data do not provide information about the time spent by workers in each activity.

corresponding task category. For instance, routine-manual tasks are highly concentrated among craft and production occupations, whereas routine-cognitive tasks are relatively more concentrated among clerical and administrative support ones. Moreover, low-skilled jobs such as cleaning and construction workers score very high in non-routine manual tasks, whereas typically high-paid and knowledge-intensive jobs – such as teachers and judicial officers - exhibit very high shares of non-routine cognitive tasks.

3) This set of task measures makes possible to sum single task indicators along the routine/non-routine dimension in a meaningful way. For instance, for those workers that in 1991 were employed in Communication traffic occupations, routine tasks represented 73 per cent of total tasks performed (i.e. 38% routine-cognitive + 35% routine-manual), whilst the remaining 27 per cent of their time was allocated to non-routine tasks. This is an appealing property of these measures, since for each occupation it allows considering routine-tasks on aggregate or, alternatively, in their two different manual and cognitive dimensions. [6]

---

[6] BIBB/IAB data also report information about *how* workers generally perform activities. According to Becker and Muendler (2015), two variables in particular properly match the fundamental features of routine-tasks as described by the literature - i.e. "codifiability" and "routineness" of the tasks performed. These are variables are named, respectively, *Work procedures described in detail* and *Repeated work steps* - that survey respondents can report as more or less frequent on a scale 1 (never) to 5 (always). To assess to which extent my aggregate measure of routine-tasks is related to these variables, for each occupation I compute a single "routine requirement" indicator (I simply interact the two variables after collapsing them by occupation) and check its correlation with my aggregate measure of routine tasks (cognitive + manual). Interestingly, the correlation coefficient amounts to 63% (by construction, -63% for non-routine tasks).

Table 2. *Task measures of top-five occupations in each task category*

Task category	Top 5 Occupations	Task measures NRC	RC	RM	NRM
NON-ROUTINE COGNITIVE	Teachers	0.82	0.13	0.02	0.03
	Chemists, physicists, mathematicians	0.79	0.10	0.06	0.06
	Judicial officers	0.73	0.18	0.01	0.08
	Legislators and administration officials	0.73	0.24	0.01	0.02
	Skilled bank and insurance clerks	0.72	0.27	0.00	0.01
ROUTINE COGNITIVE	Unskilled office clerks	0.41	0.51	0.04	0.03
	Office clerks	0.42	0.51	0.04	0.03
	Unskilled bank and insurance clerks	0.53	0.40	0.04	0.03
	Bank and insurance clerks	0.58	0.39	0.02	0.02
	Communication traffic occupations	0.16	0.38	0.35	0.12
ROUTINE MANUAL	Textile refinement workers	0.04	0.14	0.82	0.00
	Metal machine-cutters	0.06	0.01	0.81	0.12
	Weavers and spinners	0.00	0.07	0.80	0.13
	Metal moulders	0.05	0.05	0.76	0.14
	Machine operators	0.06	0.03	0.73	0.19
NON-ROUTINE MANUAL	Cleaning and waste disposal workers	0.02	0.02	0.05	0.92
	Unskilled agricultural workers	0.07	0.07	0.08	0.79
	Unskilled construction workers	0.04	0.01	0.17	0.78
	Housekeeping occupations	0.15	0.06	0.02	0.77
	Building construction workers	0.09	0.03	0.11	0.77

Notes: my calculations on West German data from the BIBB/IAB Qualification and Career Survey (1991 wave).

I now explore to which degree my task measures capture different wage and skills groups into IAB data. I define as routine intensive those occupations for which more than 50% of tasks are routine tasks. For non-routine occupations (i.e. with 50% of tasks in the non-routine dimension), I further distinguish between non-routine manual and non-routine cognitive intensive occupations. I do this in the same way - i.e. by considering those jobs for which more than 50% of tasks are, respectively, non-routine manual and non-routine cognitive tasks. [7] In Table 3, I report the educational attainment composition and the average (imputed) gross daily wage of workers in each of these three occupation groups, both computed across the whole period under analysis (1991-2010).[8]

From the first column we can clearly see that, as expected, routine-intensive occupations are mostly related to medium-paid employment, though the distance from average earnings of non-routine manual intensive occupations is less pronounced than the distance from those of non-routine cognitive ones. Further, the remaining three columns show that, although medium-educated employment is dominant in all groups, it is relatively more concentrated among the routine-intensive group, whereas high-education and low-education employment tend to

[7] Note that, over the whole sample, 97 per cent of observations are captured by these occupation groups, for a total of 95 million observations. The remaining 3 per cent is composed by ten different occupations for which none of the three measures scores above 50 per cent.

[8] Since in IAB data part-time and female workers may be source of some drawbacks in the imputation of occupational daily wages, I compute average earnings by using full-time males only.

concentrate, respectively, among non-routine cognitive and non-routine manual intensive occupations.

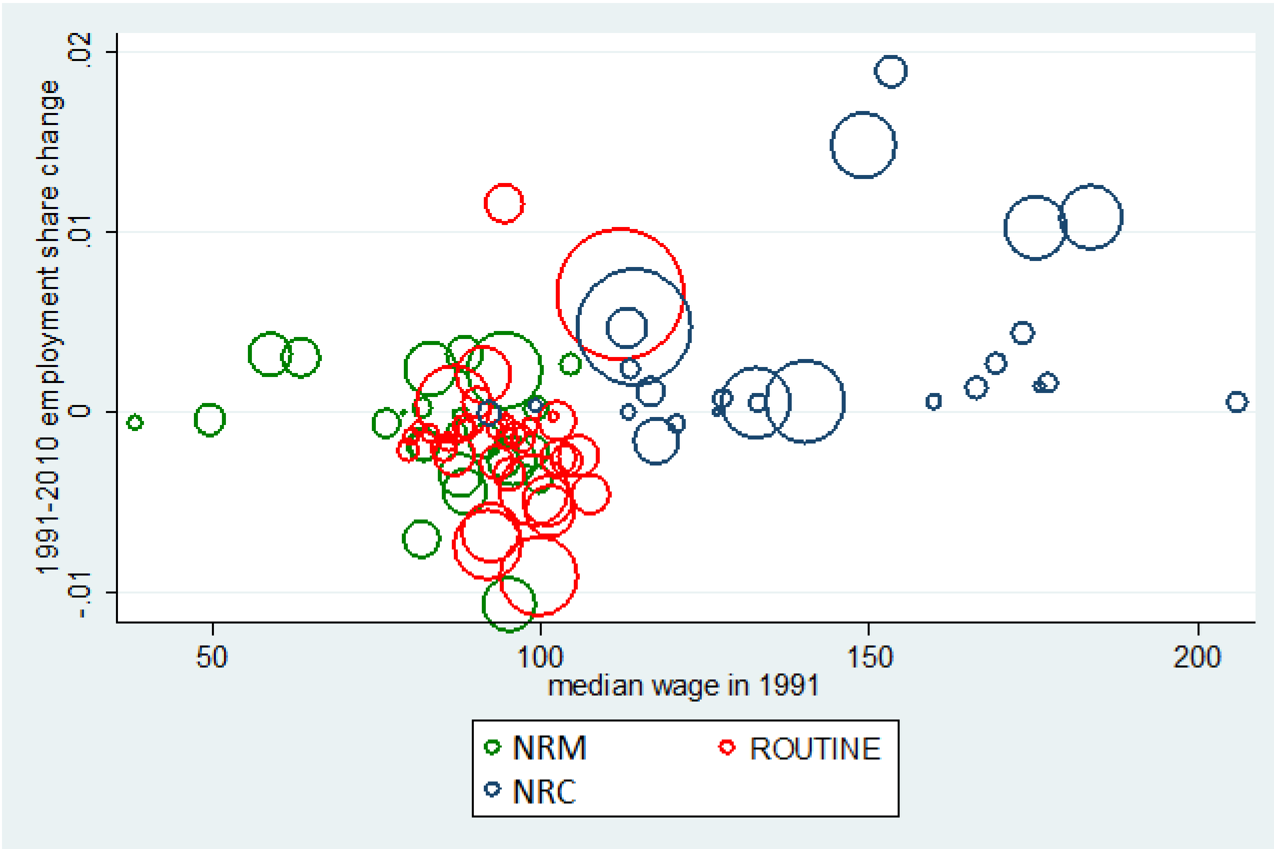
Table 3. *Occupation groups mean wage and educational attainment composition, 1991-2010.*

Occupation group	Mean gross daily wage	% low educ	% med educ	% graduates
NRC >.5	180€	5.30	66.47	28.23
ROUTINE >.5	103€	17.01	82.24	0.75
NRM >.5	88€	22.14	76.53	1.32

Notes: IAB administrative data, 95 million observations. Low-skilled: without a vocational training degree; medium-skilled: with a vocational training degree; high-skilled: with a degree from a University, or a University of Applied Sciences.

Turning to occupation-level evidences, I now check to which extent my measure of routine tasks is able to detect the decline of medium-wage jobs. In particular, in Figure 1 I rank occupations according to their 1991 median daily gross wage, and plot on the y-axis the corresponding (weighted) employment share change in over 1991-2010. As expected, routine-intensive occupations are mostly concentrated towards the middle of the wage distribution (red markers), whereas non-routine manual and non-routine cognitive intensive occupations tend to locate, respectively, towards the bottom and top ends (green and blue). Even if some the non-routine manual occupations that tend to locate around the center contract sharply, we can clearly see that most of the declining occupations are occupations for which more than 50% of tasks are indeed routine tasks.

Figure 1. *1991-2010 employment shares changes by occupation in Western Germany. Occupations ranked by median daily gross wage in 1991.*



Notes: IAB administrative data. Markers size reflects occupations employment shares in 1991. Those occupations for which no measure scores above 50% have been assigned to the task group in which they score higher.

In contrast with the general trend for routine occupations is the relative increase of (medium-educated) office clerks (the largest marker in Figure 1). However, from Table 2 we know that workers employed in this occupation - even if mainly performing routine-cognitive tasks - also perform an important share of non-routine cognitive tasks. Overall, the descriptive evidences I provide here show that my measure of routine tasks is indeed closely related to the so called "hollowing-out" of middle-class occupations, and the changes I detect in the occupational composition of employment are consistent with a process of employment polarization.

3. Spatial dimension of task composition of employment

In this section, I investigate the evolution of the task composition of employment in Western Germany over the period 1991-2010 and focus on its spatial distribution across different employment density quantiles. Note that in this exercise task employment shares are considered both in their four distinct components and in their manual/cognitive and routine/non-routine aggregations. As a first step, in Table 4 I report results for all West Germany considered, that is, unconditional on employment density. As we can see from Panel A, Western German employment experienced a large expansion of cognitive tasks at the expenses of manual task. Nevertheless, this strong upgrading trend along the manual/cognitive dimension is characterized, at the same time, by a sizeable contraction of routine tasks along the routine/non-routine dimension (Panel C). Indeed, from Panel B we can see that the positive shift towards cognitive tasks is mainly driven by the increase of *non-routine* cognitive tasks, which accounts for more than 2/3 of the overall change (4.48 of 6.59). This suggest that the demand for routine-cognitive tasks increased considerably less than the demand for non-routine cognitive ones. The opposite applies to the decline of manual tasks, for which 2/3 of the total contraction is attributed to the reduction of *routine*-manual tasks (4.43 of 6.59). This means, on the contrary, that the demand for routine manual tasks dropped considerably more than the demand for non-routine manual ones. According to these evidences, it would be not appropriate to describe the evolution of the task-composition of employment in West Germany as a simple upgrading process from manual to cognitive tasks. Indeed, the pattern I detect along the routine/non-routine dimension appears to be rather crucial in order to understand how the task-structure of employment has changed over the period under analysis.[9]

[9] According to the RRTC framework, non-routine manual tasks are expected to increase, or to decrease less, relative to routine tasks. However, the literature also point out that the increase in non-routine manual tasks typically stems from a higher demand of *service occupations* (for an extensive definition of service occupations, see Autor and Dorn, 2013). Although this analysis directly focuses on the broader category of non-routine manual tasks, in the appendix I also provide evidences on service occupations (for instance, housekeeping occupations, cooks, guard and watchmens, etc.). In my data, service occupations score very high in the non-routine manual measure - and exhibit at the same time the lowest earnings and the highest concentration of low-skilled workers. Consistently with the RRTC framework, I document that this occupational group does indeed moderately expand its employment shares over time. In the appendix, I also show that the results of my analysis do not change when considering service occupations instead of non-routine manual tasks.

Table 4. *Task employment shares changes in West Germany, 1991-2010.*

Panel A			
	COGNITIVE	MANUAL	
1991	0,498	0,502	
2010	0,564	0,436	
100 x change	**6,59**	**-6,59**	
Panel B			***Panel C***
	ROUTINE COGNITIVE	ROUTINE MANUAL	ROUTINE
1991	0,183	0,266	0,448
2010	0,204	0,221	0,425
100 x change	**2,12**	**-4,43**	**-2,31**
	NON-ROUTINE COGNITIVE	NON-ROUTINE MANUAL	NON-ROUTINE
1991	0,315	0,237	0,552
2010	0,360	0,215	0,575
100 x change	**4,48**	**-2,16**	**2,31**

Notes: my calculations on IAB administrative data.

I now look at the allocation of tasks and its changes among districts with different degrees of employment density. I begin by looking at the aggregate share and the related over time variations of routine tasks, non-routine cognitive and non-routine manual tasks. I report the results of this exercise in Table 5. As for the expansion of non-routine cognitive tasks, Panel A of Table 5 clearly shows that this increase is more pronounced among denser districts (in the case of the top-5 cities, 27 per cent higher than that observable in Panel B of Table 4, i.e. 5.70 vs. 4.48). Further, it comes out a certain degree of monotonicity - i.e. the higher (lower) the degree of employment density, the higher (lower) is the growth of non-routine cognitive tasks. This result is not surprising, being largely consistent with the empirical literature focused on the positive relationship between agglomeration economies and workers' skills and education. More interesting is the trend detected in Panel B, which points out that for routine tasks this linear relationship results completely reversed: moving from low to high-density districts, routine tasks shares contractions are increasingly more pronounced. As for non-routine manual tasks, differences between high and low density areas are smaller (Panel C). Still, it comes out that non-routine manual tasks tend to decrease more among districts with lower degrees of employment density, whereas their contraction results systematically less (more) pronounced than that of routine tasks among high (low) density districts.

Overall, the decomposition exercise of table 5 shows that tasks associated with high-skilled employment increase more in cities, while tasks that are mainly related to medium-skilled and low-skilled employment follow rather different patterns. In rural areas, the task composition of employment seems to follow a rather upgrading trend, with the bottom end of employment decreasing sensibly more than the middling part. In cities, the task composition change is not only more pronounced, but is also qualitatively different, oriented toward job-polarization trends: the increase of non-routine cognitive tasks mainly occurs at the expenses of routine tasks.

In Table 6, I decompose routine tasks share variations in a routine cognitive and a routine manual component. Not surprisingly, I find that routine-cognitive tasks are more concentrated in cities, whereas routine-manual ones exhibit higher shares in rural areas. As in Table 4, I find that the negative trend of routine tasks is entirely attributable to the contraction of routine-manual tasks, since routine-cognitive tasks slightly increase over time. However, it is worth noting that the growth of routine-cognitive tasks does not have a monotonic linear relationship with density. In particular, by comparing Table 5 with Table 6 (Panel A) it comes out that - even if both non-routine cognitive and routine-cognitive tasks expand more in districts above the median of employment density - non-routine cognitive tasks variations become increasingly larger in denser districts (5.25 to 5.70) whereas routine cognitive tasks variations become increasingly smaller (2.35 to 1.93). This decoupling is very interesting, pointing out that routine-cognitive tasks might be less complementary to cities than non-routine cognitive ones.

Moving to Panel B of Table 6, we can see that the monotonic trend detected in Panel B of Table 5 is almost entirely attributable to changes in routine manual tasks, which are traditionally more concentrated in the manufacturing sector. In particular, this raises some concerns about a possible role of faster structural change in agglomerated areas – i.e. routine manual tasks may decrease more in denser places because of a faster decline of manufacturing in cities. To explore the sectoral dimension, in Table 7 I repeat the decomposition of Table 6 by splitting the sample between the broad manufacturing sector (NACE D) and non-manufacturing activities (all the other sectors except NACE D).

Table 5. *Task employment shares changes by employment density quantiles, 1991-2010.*

EMPLOYMENT DENSITY	**Low density districts**			**High density districts**		
	Bottom 5%	**<=25p**	**<=50p**	**>50p**	**>=75p**	**Top 5 cities**
Panel A			NON-ROUTINE COGNITIVE			
1991	0,266	0,272	0,282	0,347	0,372	0,396
2010	0,302	0,308	0,321	0,400	0,425	0,453
100 x change	**3,57**	**3,61**	**3,90**	**5,25**	**5,27**	**5,70**
Panel *B*			ROUTINE			
1991	0,438	0,453	0,461	0,435	0,419	0,413
2010	0,430	0,442	0,444	0,405	0,386	0,377
100 x change	**-0,84**	**-1,15**	**-1,70**	**-3,02**	**-3,27**	**-3,53**
Panel C			NON-ROUTINE MANUAL			
1991	0,296	0,275	0,257	0,217	0,209	0,192
2010	0,269	0,250	0,235	0,195	0,189	0,170
100 x change	**-2,73**	**-2,46**	**-2,21**	**-2,23**	**-2,00**	**-2,18**

Notes: my calculations on IAB administrative data. Employment-weighted density quantiles are computed by averaging density across all years.

Table 6. *Routine tasks employment shares changes by employment density quantiles: decomposition into a manual and a cognitive component.*

EMPLOYMENT DENSITY	bottom 5%	<=25p	<=50p	>50p	>=75p	Top 5 cities
Panel A			ROUTINE COGNITIVE			
1991	0,155	0,159	0,165	0,200	0,215	0,230
2010	0,174	0,178	0,184	0,224	0,236	0,249
100 x change	**1,88**	**1,89**	**1,99**	**2,35**	**2,11**	**1,93**
Panel B			ROUTINE MANUAL			
1991	0,283	0,294	0,297	0,235	0,204	0,183
2010	0,256	0,264	0,260	0,182	0,150	0,128
100 x change	**-2,72**	**-3,04**	**-3,69**	**-5,37**	**-5,38**	**-5,46**

Notes: my calculations on IAB administrative data. Employment-weighted density quantiles are computed by averaging density across all years.

Table 7. *Routine tasks employment shares changes by employment density quantiles: decomposition into manual and cognitive components between manufacturing and non-manufacturing sectors.*

EMPLOYMENT DENSITY	**bottom 5%**	**<=25p**	**<=50p**	**>50p**	**>=75p**	**Top 5 cities**
			MANUFACTURING			
Panel A			ROUTINE COGNITIVE			
1991	0,131	0,135	0,139	0,157	0,170	0,183
2010	0,150	0,151	0,153	0,174	0,188	0,205
100 x change	**1,95**	**1,57**	**1,48**	**1,71**	**1,83**	**2,21**
Panel B			ROUTINE MANUAL			
1991	0,416	0,418	0,416	0,367	0,336	0,305
2010	0,390	0,389	0,386	0,319	0,281	0,239
100 x change	**-2,68**	**-2,88**	**-3,00**	**-4,74**	**-5,49**	**-6,52**
			NON-MANUFACTURING			
Panel C			ROUTINE COGNITIVE			
1991	0,174	0,182	0,191	0,228	0,237	0,251
2010	0,188	0,197	0,206	0,242	0,249	0,261
100 x change	**1,42**	**1,54**	**1,57**	**1,43**	**1,23**	**0,93**
Panel D			ROUTINE MANUAL			
1991	0,177	0,176	0,176	0,151	0,140	0,127
2010	0,172	0,175	0,170	0,130	0,114	0,099
100 x change	**-0,43**	**-0,19**	**-0,58**	**-2,05**	**-2,53**	**-2,78**

Notes: Our calculations on IAB administrative data. Employment-weighted density quantiles are computed by averaging density across all years.

The results in Table 7 characterize the trend detected in Tables 5 and 6 by highlighting two interesting facts. First, the monotonic relationship between employment density and the decline of routine-manual tasks applies in the case of the broad manufacturing sector (Panel B). Second, the slower growth of routine-cognitive tasks in denser areas stems from non-manufacturing sectors (Panel C). In other words, the negative relationship between employment density and routine-tasks employment shares variations applies especially in the manufacturing for routine-manual tasks, whereas in the case of routine-cognitive tasks it holds especially in non-manufacturing activities.

4. Possible channels of the contraction of routine tasks in cities

In this section, I provide descriptive evidences on four alternative possible channels of the contraction of routine tasks in cities. By exploiting the longitudinal dimension of IAB data, I begin by analyzing routine workers' flows across high and low density areas, and compare them with those of non-routine ones. Second, I address whether employment density increases the probability of routine workers to switch to non-routine occupations. Third, I assess to which extent my measure of routine tasks is related to a higher probability of joining unemployment for workers employed in cities. Forth, I investigate the existence of composition effects related to the entrance of younger cohorts in the labor market in cities.

4.1. Routine workers' spatial mobility

I exploit the longitudinal dimension of IAB data to address whether routine workers' spatial mobility may account for a higher contraction of routine tasks in denser areas. By using the transition matrix as in Table 8, reporting routine and non-routine workers' flows across high and low-density districts – i.e. above and below the median employment density -, I consider four time-periods between 1991 and 2010. In particular, for each time-period, I restrict my sample to workers observable both at the start and at the end of period. Hence, I distinguish between those that at the end of period are still employed in, respectively, a routine or in a non-routine intensive occupation (therefore, workers who within periods switched from a routine to a non-routine occupation - or vice-versa - are not considered in the matrix). As before, I define routine vs non-routine occupations those occupations for which more than 50% of tasks are routine or non-routine. In the first row of each Panel (HD), I consider all workers that at the start of period were employed in high-density districts. In particular, I report the fraction of those that, respectively, at the end of the period remained in a high-density district (HD - first column for routine workers, third column non-routine ones) or moved to a low-density one (LD - second column routine, fourth column non-routine). The second row of each Panel (LD) reports the same information for workers that at the start of period were employed in low-density districts. Note that I report absolute numbers in square brackets and, to facilitate the reading of the matrix, I highlight the fraction of movers in bold.

Table 8. *Transition matrix of routine and non-routine workers' flows between high and low density districts.*

		(1)	(2)	(3)	(4)
		ROUTINE		**NON-ROUTINE**	
Panel A	**1991-96**	**HD**	**LD**	**HD**	**LD**
	HD	0,947	**0,053**	0,930	**0,070**
		[633379]	**[35370]**	[868302]	**[64949]**
	LD	**0,036**	0,964	**0,067**	0,933
		[28147]	[747815]	**[55859]**	[773269]
Panel B	**1996-01**				
	HD	0,942	**0,058**	0,924	**0,076**
		[582733]	**[35731]**	[876216]	**[71737]**
	LD	**0,040**	0,960	**0,082**	0,918
		[31050]	[736408]	**[69107]**	[771256]
Panel C	**2001-06**				
	HD	0,946	**0,054**	0,927	**0,073**
		[576030]	**[33125]**	[928203]	**[72714]**
	LD	**0,040**	0,960	**0,080**	0,920
		[32173]	[764493]	**[69799]**	[804052]
Panel D	**2006-10**				
	HD	0,950	**0,050**	0,938	**0,062**
		[589561]	**[31222]**	[1009667]	**[66353]**
	LD	**0,034**	0,966	**0,070**	0,930
		[28206]	[801318]	**[66688]**	[887603]

Notes: IAB administrative data. HD=districts above median employment density, LD= districts below median employment density.

As for workers employed in routine-intensive occupations, Columns 1 and 2 clearly shows that the fraction of those moving from high to low-density districts is systematically higher than that of those moving in the opposite direction, and this difference holds also in absolute terms. In other words, workers that after 5 years are still employed in routine-intensive occupations result more likely to leave - rather than join – high-density districts, suggesting that a net outflow of routine workers from denser areas may be at work. For instance, in the period 1991-96 the share of routine workers in high-density areas moving to low-density ones amounts to 5.3%, while only 3.6% of routine workers move from low to high-density areas. On the contrary, moving to Columns 3 and 4 we can see that, in the case of non-routine workers, no clear systematical pattern emerges, whereas in three time-periods out of four the share of those moving to from low to high-density districts is slightly higher than that of those moving in the opposite direction.

4.2. Routine workers' transitions to non-routine occupations

I now investigate whether employment density increases the probability of workers employed in routine occupations to switch to non-routine jobs. As in the previous subsection, I take into account four time-periods, restricting my sample to workers employed in a routine-intensive occupation at the start of period and still observable in the same district at the end of period regardless of the occupation.[10] This choice is related to the fact that I want to investigate occupational mobility within-location, hence I neglect those individuals moving to other locations (that are

[10] Therefore, workers that have changed district at the end of period are not considered.

actually considered in the previous exercise). I pool these observations from the four time-periods, and I make use of a simple linear probability model in which the response variable equals one if the worker at the end of period is employed in a non-routine occupation and zero otherwise. To estimate the effect of density on routine to non-routine transitions, I regress this variable on a dummy variable taking the value of one if the worker at the start of period is located in a high-density district. In particular, I consider three alternative definitions of high-density district: 1) above the median employment density, 2) in the top quartile of employment density, 3) among the top-ten cities for employment density.[11] Regressions also includes a wide set of control variables (age, gender, university education and German nationality dummies, time-period dummies, broad economic sector and occupation dummies - both at the 1-digit level).

[11] In order of employment density, the top 10 cities are: Munich, Frankfurt, Stuggart, Düsserldorf, Nuremberg, Berlin, Mannheim, Köln, Essen and Hamburg.

Table 9. *Probability to switch to non-routine occupations*

	(1)	(2)	(3)
Density>50p =1	0.012***		
	(0.000)		
Density>75p =1		0.023***	
		(0.000)	
Top 10 city =1			0.028***
			(0.000)
Observations	5,493,193	5,493,193	5,493,193
R^2	0.021	0.022	0.022

Notes: Pooled OLS estimators, robust standard errors in parentheses. All regressions control for workers' age (continuous), gender, university education and German nationality dummies, and include an intercept, time-period dummies, broad economic sector and occupation dummies (both at the 1-digit level). *** p<0.01, ** p<0.05, * p<0.1.

The results of this exercise are summarized in Table 9. According to the first Column of Table 9, routine workers employed in districts above the median employment density have, conditional on observable characteristics, a 1.2% higher probability to switch to a non-routine job. If we consider that the fraction of switchers in the sample is 6.3%, this equals to a 19% increase of the probability of switching. Interestingly, this figure almost doubles for workers in districts in the top quartile of employment density (Column 2) and continues to grow up to 44% for those in a top-ten city for employment density (Column 3). In other words, my results point out that the denser is employment, the harder is to remain employed in routine-intensive occupations – suggesting that routine-workers' transitions to non-routine occupations represent an important channel of the contraction of routine tasks in denser places.

4.3. Routine tasks and unemployment in cities

In this subsection, I address whether a higher content of routine tasks in cities is related to a higher probability to become unemployed. Since IAB data provide information on individuals in receipt of unemployment benefits, I use this information to identify workers joining unemployment. I consider again four time-periods, but I restrict my sample to workers employed at the start of period and still observable - both among the employed or among the benefit receivers - at the end of period.[12] By doing so, I end up with more than 15 million observations. I define the dependent variable as being unemployed at the end of the period, i.e. 7.8% of the sample. Conditional on workers' start-of-period observable characteristics (regressions include age, gender, university education and German nationality dummies, time-period dummies, broad economic sector and occupation dummies - both at the 1-digit level), I regress the dependent variable on my (standardized) routine task measure. In a second step, I add its interaction with a dummy variable taking the value of one if at the start of period the worker is located in a top-ten city for employment density. The estimate in Column 1 of Table 10 points out that, conditional on my set of controls, workers at one (employment weighted) standard deviation of the routine-task measure have a 0.24 per cent higher probability to join unemployment relative to those at the mean. Though significant, this is objectively a rather small effect. In

[12] By definition, individuals cannot be in both groups in the same year. Note that, in principle, also those workers no longer observable at the end of period may have joined unemployment (or inactivity) during the reference period, though without receiving any benefit.

column 2, I add the interaction with the top-10 city dummy variable: the coefficient results close to zero and statistically non-significant.[13] However, we know that the routine task measure is composed by a routine-manual and a routine-cognitive component (section 2), and that the demand for routine-cognitive tasks increased over time (section 3). To explore the existence of differences in the predictions of both components, in Columns 3 to 6 I repeat regressions separately for routine-manual and routine-cognitive tasks.

[13] For sake of completeness, in the last row of Table 10 I report coefficients on the top-10 city dummy. These coefficients estimate the effect of being in a top-10 city on the probability to join unemployment for workers in occupations at the (employment-weighted) mean of the routine task measures. I do not comment these estimations because - as the total effect of being in a Top-10 city also depends on the value assumed by the routine-task measure - their interpretation is not straightforward.

Table 10. *10 x workers' probability to join unemployment as a function of routine tasks*

	(1)	(2)	(3)	(4)	(5)	(6)
Routine	0.024***	0.024***				
	(0.000)	(0.000)				
Routine*Top 10 city		0.001				
		(0.000)				
Routine-manual			0.144***	0.140***		
			(0.000)	(0.000)		
Routine-manual*Top 10 city				0.055***		
				(0.000)		
Routine-cognitive					-0.121***	-0.114***
					(0.000)	(0.000)
Routine-cognitive*Top 10 city						-0.044***
						(0.000)
Top 10 city=1		0.113***		0.133***		0.125***
		(0.000)		(0.000)		(0.000)
Observations	15,414,820	15,414,820	15,414,820	15,414,820	15,414,820	15,414,820
R^2	0.027	0.027	0.028	0.028	0.028	0.028

Notes: Coefficients are multiplied by 10. Pooled OLS estimators, robust standard errors in parentheses. All regressions control for workers' age (continuous), gender, university education and German nationality dummies, and include an intercept, time-period dummies, broad economic sector and occupation dummies (both at the 1-digit level). *** p<0.01, ** p<0.05, * p<0.1.

Interestingly, it comes out that the positive relationship between routine tasks and the probability to join unemployment is entirely driven by routine-manual tasks, since in the case of routine-cognitive tasks this relationship reverses. On the one hand, workers at one standard deviation of the routine-manual measure have a 1.4% higher probability to join unemployment relative to those at the mean (Column 3), and this figure grows up to 2% for those in a top-10 city (Column 4) – i.e. a 25% increase of the average probability to become unemployed. On the other hand, workers at one standard deviation of the routine-cognitive measure have 1.2% *lower* probability to join unemployment relatively to those at the mean (Column 5), whereas for those in a top-10 city this figure amounts to -1.6% (Column 6) – which equals to a 20% drop of the baseline probability. Overall, my results point out that the probability to join unemployment for workers employed in occupations with a high content of routine-manual tasks increases in cities, though the same does not apply in the case of workers employed in jobs with a high content of routine-cognitive tasks - for whom this probability, on the contrary, significantly decreases in cities.

4.4. Task composition changes by age groups

I conclude this section by addressing whether a faster decline of routine tasks among younger cohorts in cities may account, at least partially, for trends detected in Section 3. In particular, in Table 11 I report routine tasks employment share changes between 1991 and 2010 for three different age groups: 15 to 30 (Column 1), between 30 and 50 (Column 2), older than 50 (Column 3).

Table 11. *Routine task employment shares changes for different age cohorts: differences among top-10 cities for employment density and the rest of the sample.*

	(1) **Young**	(2) **Prime age**	(3) **Old**
Panel A		All sample	
1991	0,49	0,45	0,43
2010	0,43	0,39	0,42
100xChange	**-6,41**	**-5,75**	**-1,42**
Panel B		All sample except top 10 Cities	
1991	0,50	0,47	0,45
2010	0,45	0,43	0,45
100xChange	**-5,19**	**-4,79**	**-0,69**
Panel C		Top 10 Cities only	
1991	0,43	0,37	0,37
2010	0,33	0,28	0,32
100xChange	**-10,10**	**-8,89**	**-5,33**

Notes: Young: age<=30; Prime: age>30 & <50; Old: age>=50.

Table 11 clearly shows that, in comparison to the whole sample (Panel A), among all cohorts routine-tasks shares are lower in the top-10 cities (Panel C) and higher in the rest of the sample (Panel B). Further, routine-tasks shares are always higher among young workers, but contractions are systematically faster - both in the top-10 cities for employment density and in the rest of West Germany (Panel A). Nonetheless, Table 11 seems to suggest that changes in the occupational structure among younger workers are not an important channel of the overall contraction of routine tasks in cities. Both for young and prime-age workers, indeed, the percentage point reduction of routine tasks in the Top-10 cities almost doubles in comparison to the rest of West Germany, with no changes in relative terms between the two groups.

From Column 3 we can see that, though the overall reduction of routine tasks among old workers is negligible (Panel A), it is dramatically higher in cities in comparison to the rest of the sample. In other words, for elderly workers changes in the occupational structure of employment tend to depress routine tasks especially in cities. Overall, these results do not match with the idea that younger workers in cities may be more likely to undertake jobs intensive in non-routine tasks. If anything, they point out that, on the contrary, it is the elderly component of employment to suffer comparatively larger contractions of routine tasks in cities.

To recap, in this section I explored some possible channels of the higher contraction of routine tasks denser areas. Overall, my results suggest that routine workers' are more likely to leave denser places relative to non-routine ones, while those who stay in denser areas are more likely to switch to non-routine occupations. Interestingly, I find that only the manual component of routine tasks is associated to a higher probability to join unemployment in cities, while changes in the task composition of young workers seem not play an important role.

5. Agglomeration and the decline of Routine Tasks: causal impact or simple correlation?

In this section, I investigate whether a causal relationship between employment density and the decline of routine tasks applies. The mechanism I have in mind is simply based on differences in congestion costs and in returns to skills for different skill groups. On the one hand, an exogenous increase in agglomeration will enhance relatively more the productivity of non-routine cognitive tasks and, in turn, increase their relative demand (see Bacolod et al., 2009, and Andersson et al., 2014). On the other hand, rising congestion costs stemming from higher agglomeration will increase the relative opportunity-cost of using other type of tasks – i.e. tasks that do not benefit (or benefit relatively less) from agglomeration externalities - and the relative demand for these tasks may decrease.

However, the impact of agglomeration on non-routine manual tasks is ambiguous. On the one hand, the same mechanism that applies for routine workers might apply for non-routine manual workers- i.e. agglomeration might increase their relative costs with respect to other categories. On the other hand, there are reasons to think that the demand for these tasks may be positively correlated with agglomeration. Consider, as standard in the RRTC literature, personal services occupations. The demand for these occupations may increase in presence of consumption spillovers from high-income workers - more complementary to technology and mostly associated to non-routine cognitive tasks (see Mazzolari and Ragusa, 2013). Since high-skilled workers tend to concentrate in cities (e.g. because of a better matching with more productive firms, see Dauth et al., 2016), I expect cities to have a wider extent of consumption spillovers of the kind described by Mazzolari and Ragusa (2013). Besides personal service occupations, consider the importance, for large agglomerations, of road/buildings/infrastructures maintenance and construction occupations – i.e. occupations characterized by a high content of non-routine manual tasks.

In line with this thinking, a higher relative demand for non-routine manual tasks would not depend on changes in productivity differentials caused by agglomeration economies (i.e. agglomeration does not benefit the productivity of non-routine manual tasks by increasing their demand as it assumed for non-routine cognitive tasks), but on changes in consumption/demand patterns associated with the agglomeration phenomena. Since different forces are at work (e.g. rising congestion costs vs. consumption spillovers), the impact of agglomeration on non-routine manual tasks is ambiguous from a theoretical point of view, and the empirical analysis will allow identifying the prevailing force.

In this theoretical framework, it is the relative demand for routine tasks that is expected to shrink as a direct consequence of increasing agglomeration, and this would depend, conditional on technology, by agglomeration forces that casually drive the labor market composition in the space dimension. A challenging explanation would instead claim that agglomeration and contraction of routine employment are spuriously correlated, since it may be argued that both variables are jointly determined by technological progress, which may affect at the same time the level of agglomeration and the relative demand for different tasks.

My empirical analysis investigates whether the contraction of routine tasks is simply correlated with employment density, or whether density plays a causal role on the decline of routine employment for economic reasons attributable to agglomeration externalities (rather than to technology). In order to do this, I make use of the spatial approach developed in the RRTC literature (see Autor and Dorn, 2013, Autor et al., 2015). Furthermore, I address the endogeneity of employment density by following a long tradition in urban economics, which uses deep lags of population density as instrumental variable.

5.1. Untangling agglomeration and exposure to automation

My empirical analysis is based on two main pillars. The first pillar concerns the adoption in my analysis of the approach of Autor and Dorn (2013) and Autor et al. (2015). In these papers, the authors estimate the effect of exposure to automation on different local labor market outcomes. In particular, they use U.S. commuting zones (CZs) start-of-period routine employment shares to proxy for local exposure to automation. This approach builds on the idea that - for a given reduction in the cost of technology - the higher the routine employment shares in a CZ, the larger the adjustment in the employment composition. Autor and Dorn's (2013) empirical analysis shows that, over the period 1980-2005, CZs with higher degrees of exposure to automation have experienced a larger contraction of routine employment and a larger expansion of low-skilled service jobs.[14] In my analysis, where I focus on the effects of agglomeration on the contraction of routine tasks, I make use of the start of period routine-task share as a control variable. By using this strategy, I aim at taking into account the effect of RRTC – i.e. the main technological driver of the decline of routine employment and job polarization.

The second pillar needs to address endogeneity issues related to employment density, adopting a very established IV strategy that relies on deep lags of population density (among many others, see Ciccone and Hall, 1998, Combes et al., 2008, Combes et al., 2010, Mion and Naticchioni, 2009). The intuition is that population density in the past is correlated with present employment density (because of the long-lasting effects of urbanization patterns) but uncorrelated with time-varying cyclical-shocks that might simultaneously affect employment density and routine-tasks employment shares. For instance, a positive demand shock for knowledge-intensive goods in a given district may generate inflows of high-skilled (non-routine) workers. Accordingly, in that district we may have increasing employment density and declining routine-tasks shares. Similar mechanisms would apply in presence of time-varying productivity or technological shocks. Of course, this would bias my estimates. In my benchmark model, I instrument

[14] Accordingly, I expect this variable to significantly predict both the contraction of routine tasks and the expansion of non-routine manual tasks, a phenomenon that would stem from the reallocation of routine workers to low-skilled occupation - see the theoretical model of Autor and Dorn (2013).

employment density with information on population density in 1952 (i.e. the last year of the Marshall Plan) which is available for 319 districts. In all regressions, I pool four time-periods between 1991 and 2011 (i.e. 1991-1996, 1996-2001, 2001-2006, 2006-2010). My benchmark model estimates the following equation:

$$\Delta RSH_{dmt} = \alpha + \delta_{t_0} + \beta_1 Den_{d,t_0} + \beta_2 RSH_{d,t_0} + X'_{d,t_0} + \gamma_m + e_{dmt}, \qquad (2)$$

where ΔRSH_{dmt} is the variation of routine-tasks employment shares in district d of LLM m between t_0 and t_1, Den_{d,t_0} is district d start of period population density, RSH_{d,t_0} is district d start of period routine employment share and δ_{t_0} is a set of time-period dummies. Since I also include 107 LLM dummies γ_m, βs are identified within LLM variations as well as by exploiting time variations.

Table 12 reports the main results of this econometric model.[15] According to my benchmark OLS specification (Panel A, Column 1), the point estimate of population density is -0.933, significant at 1% level. To have an idea of the magnitude of the impact, one standard deviation increase in employment density predicts a 0.12 standard deviations negative change in routine tasks employment shares. In contrast, an increase of one standard deviation in the routine-tasks share at the beginning of the period significantly predicts a 28% standard deviations negative change in the response variable (second

[15] Unfortunately, I do not have 1952 population-density data for Berlin and the six districts of the Saarland. To maximize comparability between OLS and 2SLS estimates, I exclude these observations from OLS regressions – though estimates are substantially the same when considering all districts.

row of Column 1). In other words, the relative impact of employment density results to be lower in magnitude - i.e. approximately 40% than the effect of RRTC. To control for districts' industrial composition, in Column 2 I include the start of period manufacturing share. This covariate has a positive and significant coefficient, indicating that routine-tasks have been more resilient in districts' with higher shares of manufacturing employment, as one may expect. Further, whereas the coefficient of the routine-tasks share is sensitive to the inclusion of this control variable (increasing by 32%), the estimate on employment density does not substantially change.

To control for the socio-demographic composition of employment, In Column 3 I consider the district share of female employment and the ratio of graduate on non-graduate employment. Further, I include a potentially endogenous variable, the number of registered patents per capita, which I use to proxy for districts' propensity to innovate. I do this to rule out the possibility that a positive correlation between employment density and districts' propensity to introduce technological innovations is biasing my estimates.[16] According to Column 3, routine-tasks shares contracted slower in districts with high shares of female employment and faster in districts abundant in graduate employment, though both predictions are non-significant.

[16] The correlation coefficient between employment density and the number of registered patents per capita is indeed positive, though not high (13%). NUTS-3 level data on patents registrations are publicly available on the Eurostat website (http://ec.europa.eu/eurostat/Ib/regions/data/database).

Table 12. *Employment Density and Growth of Routine Tasks within Districts, 1991-2010 stacked first differences, OLS and 2SLS estimates. Dependent variable: 100 x routine tasks employment share change.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A		OLS			2SLS (1952 Population density)	
Employment density$_{-1}$	-0.933***	-0.921***	-0.923***	-0.967***	-0.915***	-0.978***
	(0.140)	(0.138)	(0.189)	(0.170)	(0.158)	(0.239)
Routine tasks share$_{-1}$	-6.901***	-9.404***	-10.558***	-7.013***	-9.387***	-10.578***
	(0.888)	(1.253)	(1.374)	(0.937)	(1.217)	(1.316)
Manufacturing/empl-$_{1}$		0.737**	1.022***		0.737**	1.016***
		(0.299)	(0.286)		(0.286)	(0.279)
Female/empl-$_{1}$			0.201			0.202
			(0.823)			(0.786)
Grad./non-grad empl$_{-1}$			-0.232			-0.137
			(0.513)			(0.555)
Patents /pop$_{-1}$			-3.498**			-3.654**
			(1.605)			(1.603)
R^2	0.475	0.478	0.483	0.475	0.478	0.483
Panel B			ROUTINE COGNITIVE COMPONENT			
Employment den.$_{-1}$	-0.267**	-0.261**	-0.327***	-0.268**	-0.244*	-0.283*
	(0.115)	(0.115)	(0.125)	(0.125)	(0.126)	(0.154)
R^2	0.456	0.458	0.463	0.456	0.458	0.463
Panel C			ROUTINE MANUAL COMPONENT			
Employment den.$_{-1}$	-0.666***	-0.659***	-0.597**	-0.699***	-0.671***	-0.696***
	(0.204)	(0.204)	(0.235)	(0.223)	(0.221)	(0.260)
R^2	0.496	0.496	0.503	0.496	0.496	0.503
WALD rk F				162.708	185.666	45.333

Notes: N=1276 (4 time periods x 319 districts). In panel B and C I repeat regressions of Panel A by splitting the response variable in a routine-cognitive and a routine-manual component. Robust standard errors clustered by district. All regressions include an intercept, time period dummies and local labor market dummies. Models are weighted by start of period district share of total employment. *** p<0.01, ** p<0.05, * p<0.1.

The estimate on the patents per capita variable, on the contrary, is significant at the 5% level, and the corresponding coefficient shows the expected sign. Still, it is worth noting that the estimate on employment density is extremely stable after the inclusion of the full set of controls.

The remaining columns of Table 12 display the 2SLS results obtained by using population density in 1952 as IV. Interestingly, findings are widely confirmed when addressing endogeneity, with no substantial deviations from OLS estimates. Moreover, the first-stage t-statistics always score above 6.[17]

Panel B and C refer to the same specification in equation (2), where the dependent variable has been replaced by changes in the shares of routine-cognitive and routine-manual tasks, respectively, to explore the possibility of some heterogeneity in the effects of agglomeration detected in Panel A. In particular, it comes out that estimates on the aggregate share of routine tasks (Panel A) are mainly driven by the routine-manual component (Panel C) – which accounts for about two thirds of the total effect in each specification. In contrast, the routine-cognitive component (Panel B) accounts for about one third of the overall effect in Panel A. Overall, these results suggest that increasing agglomeration mainly reduces the relative demand for routine-manual tasks, with a less pronounced impact on the demand for routine-cognitive tasks.

[17] In specification (4) and (5), the first-stage coefficient on the instrumental variable is positive with a t-statistic above 12. In specification (6), the first-stage t-statistic on the instrument scores above 6. Further, the Kleiberger-Paap rk LM statistics reported in Table 12 scores between 185 and 45, reassuring that the instrument is far from being weak.

In Table 13, I investigate the impact of agglomeration on the relative growth of non-routine manual tasks, i.e. by substituting the left hand side variable of equation (2) with changes of non-routine manual tasks employment shares.

Table 13. *Employment Density and Growth of Non-Routine Manual Tasks within Districts, 1991-2010 stacked first differences, OLS and 2SLS estimates. Dependent variable: 100 x non-routine manual tasks employment share change.*

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		2SLS (1952 Population density)		
***Employment density*$_{-1}$**	0.419**	0.402**	0.377	0.239	0.165	0.036
	(0.183)	(0.177)	(0.234)	(0.200)	(0.197)	(0.287)
***Routine tasks share*$_{-1}$**	3.515***	7.003***	8.215***	2.914***	6.281***	8.123***
	(0.866)	(1.454)	(1.546)	(0.886)	(1.392)	(1.489)
***Manufacturing/empl*-$_{1}$**		-1.027***	-0.621*		-1.045***	-0.711*
		(0.303)	(0.350)		(0.299)	(0.367)
***Female/empl*-$_{1}$**			2.488***			2.482***
			(0.878)			(0.871)
***Graduate/non-grad empl*$_{-1}$**			0.380			0.877
			(0.600)			(0.616)
R^2	0.388	0.394	0.400	0.387	0.393	0.398
Wald rk F				162.708	185.666	48.306

Notes: N=1276 (4 time periods x 319 districts). Robust standard errors clustered by district. All regressions include an intercept, time period dummies and local labor market dummies. Models are weighted by start of period district share of total employment. *** p<0.01, ** p<0.05, * p<0.1.

My benchmark OLS specification (Column 1) shows a significant positive correlation between employment density and the variations of non-routine manual tasks, as expected. Similarly, the start of period routine tasks shares (the proxy of exposure to automation) predicts a positive change in the response variable. This outcome is highly consistent with the findings of Autor and Dorn (2013) - i.e. employment tends to polarize when routine-replacing technical change is at work. Moreover, the impact of RRTC increases in magnitude when controlling for districts' sectoral and demographic composition (Columns 2 and 3) while at the same time the estimate on employment density slightly decreases, becoming non-significant in the most complete specification (Column 3). Interestingly, when accounting for endogeneity of employment density, across all specifications the impact of agglomeration is not statistically different from zero (Columns 4 to 6). In other words, the increase in the relative demand for non-routine manual tasks results to be driven exclusively by routine-replacing technical change (as in Autor and Dorn, 2013), with no evidence of a causal role played by agglomeration. This suggests that while for routine tasks a causal effect of agglomeration is at work, the same does not apply for non-routine manual tasks.

Overall, these results point out that increases in employment density reduce the relative demand for routine tasks, but have no clear effects towards non-routine manual tasks - as can be observed by comparing 2SLS estimates in Table 12 and 13. Further, they reveal that also in West Germany a close relationship between exposure to automation, higher contractions of routine employment and relative increase of non-routine manual tasks holds, as documented by Autor and Dorn (2013) in the case of the Unites States.

5.2. Robustness checks

5.2.1. Endogeneity of the routine-tasks share

A possible critic to my empirical strategy is that also my measure of exposure to automation might be endogenous. Indeed, unobservable cyclical-shocks may not only affect employment density, but also the start of period routine-tasks share. For this reason, the routine tasks share may not capture correctly the "long-run component of the industrial structure" that determines "exposure to automation" in this analysis (for further details, see Autor and Dorn, 2013). In this case, estimates on employment density might be biased. To address this bias, I follow as close as possible the instrumental variable strategy proposed by Autor and Dorn (2013). In particular, they instrument the CZ routine employment share with an interaction between the CZ industry composition in 1950 and the 1950 occupation composition of industries among those federate states not containing that CZ. Since IAB data are not available prior to 1975, I construct my instrumental variable with 1975 data, as follows:

$$\widetilde{RSH}_d = \sum_{i=1}^{I} E_{i,d,1975} \times R_{i,-d,1975} \ , \tag{3}$$

where $E_{i,j,1975}$ is the 1975 employment share of industry i in district d, and $R_{i,-d,1975}$ is the 1975 routine-tasks employment shares in industry i in all Western Germany states *except* the state in which district d is located. Though my instrument cannot go back in time as the one used by Autor and Dorn's (2013), it is important that it refers to a period prior the advent of the computer era (i.e. the 1980s') and 16 years prior the starting period of my empirical analysis (1991). Therefore, I assume that my instrument is not correlated with present cyclical spikes affecting the routine-tasks share and its subsequent variations.

Table 14. *Employment Density and Growth of Routine Tasks within Districts: 2SLS estimates with two endogenous variables and two instruments. Dependent variable: 100 x routine tasks employment share change.*

	(1)	(2)	(3)
Employment density$_{-1}$	-1.058***	-1.129***	-0.962***
	(0.184)	(0.192)	(0.269)
Routine tasks share$_{-1}$	-7.973***	-17.053***	-15.677***
	(1.353)	(4.331)	(3.511)
Manufacturing/empl-$_{1}$		2.102***	1.744***
		(0.788)	(0.574)
Female/empl-$_{1}$			-0.327
			(0.800)
Graduate/non-grad empl$_{-1}$			-0.804
			(0.827)
Patents /pop$_{-1}$			-3.718**
			(1.633)
R^2	0.474	0.462	0.477
Wald rk F	98.871	21.888	29.267

Notes: N=1276 (4 time periods x 319 districts). 2SLS estimates, 2 endogenous variables and 2 instruments. Employment density is instrumented with population density in 1952; the routine-tasks share is instrumented with the variable described in equation (3). Robust standard errors clustered by district. All regressions include an intercept, time period dummies and local labor market dummies. Models are weighted by start of period district share of total employment. *** p<0.01, ** p<0.05, * p<0.1.

MY 2SLS estimates with 2 endogenous variables and 2 instruments are reported in Table 14. According to the benchmark specification (Column 1), instrumenting for the start of period routine share does not change substantially my previous estimates on employment density.

More specifically, if compared with Column 1 of Table 12, both the coefficient on employment density and the coefficient on routine share slightly increase. Similarly to what found in previous models (Tables 12 and 13), after controlling for the industrial and demographic composition of employment the coefficient on the routine-tasks share grows in magnitude, whereas the coefficient on employment density is rather stable (Columns 2 and 3). We can also see that the estimate on the routine-tasks share grows more than in previous models. In the most complete specification (Column 3), one standard deviation increase in the routine-tasks share predicts a 0.65 standard deviations decrease in the dependent variable – an effect which is 50% higher than that estimated in Column 6 of Table 12. On the contrary, the effect of employment density is extremely close to that estimated in Table 12. In Column 6, one standard deviation increase in employment density explains a 12% standard deviations decrease in the response variable. These results suggest that the endogeneity of the routine-tasks share is not an important source of bias for my estimates on the effect of employment density.

5.2.2. Local Labor Markets evidences and alternative lags of population density

The second robustness check concerns a possible critic to my IV specification, i.e. the fact that population density used as instrument are rather recent

(1952), and hence there might still be some degree of persistency over time of the unobserved factors that may bias the estimates. For this reason, I carry out my regressions by aggregating districts in 108 local labor markets (LLMs). Using this level of analysis it is possible to use population density data from 1933 and 1910 – i.e. before the advent of WWII and WWI, respectively.[18] Because of the huge political breakdown for Germany due the WWI and especially WWII, the degree of exogeneity of these instruments is much stronger.

Another possible related critique that I address with this robustness check is that the use of districts as unit of analysis – though allowing for a more precise measurement of employment density – might be somehow misleading. Indeed - being shaped around historical and administrative reasons - it may be argued that districts do not represent economic units (or, in this case, local labor markets). Since the LLM level aggregation is based on information on workers' commuting flows across districts, it is supposed to consistently identify local labor markets in the space dimension (see Kosfeld and Werner, 2012).

I estimate a simple variant of equation (2), as follows:

$$\Delta RSH_{mt} = \alpha + \delta_{t_0} + \beta_1 Den_{m,t_0} + \beta_2 RSH_{m,t_0} + X'_{m,t_0} + e_{mt}, \tag{4}$$

where ΔRSH_{mt} is the variation of routine-tasks employment shares in LLM m between t_0 and t_1, Den_{m,t_0} is LLM m start of period population density,

[18] Population-density data in 1933 and 1910 are not available at the district level (i.e. NUTS-3). I thank IAB researchers Wolfgang Dauth and Annetkatrin Niebhur for providing me with lagged population density data.

RSH_{m,t_0} is LLM m start of period routine employment share and δ_{t_0} is a set of time-period dummies. I report results of this model in Table 15 (for sake of space, I only report benchmark and most complete specifications). In comparison to previous estimates, the OLS coefficient on employment density is still negative, though much bigger in magnitude with respect to the baseline specification (from 0.933 in column 1 of Table 12 to 5.232 in Table 15). Moving to column 2, the coefficient drops considerably after controlling for my full set of covariates. Nonetheless, the magnitude of the impact is highly comparable to previous estimates: the coefficient in Column 2 predicts a 10% standard deviation decrease in the response variable (-12% standard deviations in the in the baseline estimate of Table 12) for one standard deviation increase in employment density.

Results derived in 2SLS regressions are reported in Columns 3-6. The effects estimated using the most complete specifications in Columns 4 (IV population density lags in 1933) and 6 (in 1910) are slightly higher than the OLS estimates in Column 2, getting extremely close to the figures I estimate in previous subsections. According to Column 6 (the most complete specification in which I use 1910 lags of population density as IV), one standard deviation increase in employment density predicts a 12.5% standard deviations decrease in the dependent variable. In relative terms, the magnitude of this effect is basically the same derived with a different spatial breakdown (LLM vs districts) in Table 12.

Table 15. *Employment Density and Growth of Routine Tasks within Districts: OLS and 2SLS estimates with variables specified at the local labor market level. Dependent variable: 100 x routine tasks employment share change.*

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		2SLS (IV 1933)		2SLS (IV 1910)	
Employment density$_{-1}$	-5.232***	-2.787***	-4.875***	-3.906**	-4.733***	-3.689**
	(0.889)	(0.803)	(1.483)	(1.549)	(1.427)	(1.458)
Routine tasks share$_{-1}$	-1.710**	-6.683***	-1.469	-6.085***	-1.374	-6.201***
	(0.768)	(2.147)	(1.028)	(2.212)	(0.998)	(2.187)
Manufacturing/empl$_{-1}$		0.736		0.559		0.593
		(0.567)		(0.582)		(0.574)
Female/empl$_{-1}$		0.207		0.028		0.063
		(0.849)		(0.857)		(0.846)
Graduate/non-grad empl$_{-1}$		-2.921***		-2.401***		-2.502***
		(0.606)		(0.853)		(0.826)
Patents /pop$_{-1}$		-7.098		-14.607		-13.146
		(33.104)		(34.958)		(34.705)
R^2	0.563	0.590	0.562	0.588	0.562	0.589
Wald rk F			11.511	7.877	12.106	8.407

Notes: N=432 (4 time periods x 108 local labor markets). Robust standard errors clustered by local labor market. All regressions include an intercept and time period dummies. Models are weighted by start of period local labor market share of total employment. *** p<0.01, ** p<0.05, * p<0.1.

The consistency with previous results is really striking, and provides a higher degree of robustness - both with respect to the choice of the level of analysis (districts versus LLM) and to the choice of the instruments (1952 vs 1933 and 1910). Further, this allows me to claim that the baseline estimates provided in Table 12 can be considered as highly reliable.

6. Conclusions

The evidences provided in this chapter suggest that urban agglomeration phenomena may exacerbate the job polarization trends documented by the literature on technological change and employment polarization. I documented a strong monotonic relationship between increasing employment density and the contraction of routine tasks. Further, I provided descriptive evidence suggesting that routine workers are more likely to leave denser places, whereas those who stay in denser areas have higher probability to switch to non-routine occupations. In order to explain these outcomes, I postulate that since the benefit of locating economic activities in large agglomerations is more likely to be higher when production processes are intensive in non-routine cognitive tasks, activities that are intensive in other types of tasks may pay the expenses of higher congestion costs and become relatively less profitable. Since the impact of agglomeration on the demand for non-routine manual tasks is theoretically ambiguous, the most penalized activities are supposed to be those that are intensive in routine-tasks. Interestingly, OLS and 2SLS estimations show that - conditional on exposure to routine-replacing technical change - agglomeration strongly predicts a larger contraction of routine tasks, but has no significant impact on non-routine manual tasks. This outcome is largely consistent with the theoretical intuitions I put forward to explain the phenomenon documented in this study.

References

Acemoglu D. and Autor D. (2011), “Skills, tasks and technologies: Implications for Employment and Earnings.” Handbook of Labor Economics, 4, 1043–1171.

Andersson, M., Klaesson, J., Larsson, J. (2014) “The sources of the urban wage premium by worker skills: Spatial sorting or agglomeration economies?” Papers in Regional Science, 93(4), 727-747.

Antonczyk, D., B. Fitzenberger, and U. Leuschner (2009), “Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?” ZEW Discussion Papers 08-132, ZEW - Zentrum für Europäische Wirtschaftsforschung.

Autor D. and Dorn D. (2013), “The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market”, American Economic Review, 103, 1553–1597.

Autor, D., Dorn, D., Hanson, G. (2015) “Untangling Trade and Technology: Evidence from Local Labour Markets”, The Economic Journal, 125(May), 621-646.

Autor, D.H., Levy, F., Murnane, R. J. (2003), “The Skill Content of Recent Technological Change: An empirical exploration.” Quarterly Journal of Economics, 118, 1279–1333.

Bacolod, M., Blum, B.S., Strange, W. (2009), “Skills in the City”, Journal of Urban Economics, 65, 136–153.

Baum-Snow, N. and Ferreira, F. (2015), “Causal Inference in Regional and Urban Economics”, Handbook of Regional and Urban Economics, vol. 5A, 3-68.

Becker, S., Ekholm, K, Muendler, M. (2009), “Offshoring on the onshore composition of tasks and skills”, CEPR Discussion paper 7391, London.

Black, S. and Spitz-Oener, A. (2010) “Explaining Women’s Success: Technological Change and the Skill Content of Women’s Work”, The Review of Economics and Statistics, 92(1), 187-194.

Blien, U. and Dauth, W. (2016), “Job Polarization on Local Labor Markets?”, mimeo.

Ciccone, A. and Hall, R. E. (1996), "Productivity and the Density of Economic Activity," American Economic Review, 86, 54-70.

Combes, P., Duranton, G., Gobillon, L. (2008), “Spatial Wage Disparities: Sorting Matters!”, Journal of Urban Economics, 63, 723-742.

Combes, P., Duranton, G., Gobillon, L., Roux, S. (2010), “Estimating Agglomeration Effects with HWestory, Geology and Workers’ Fixed-effects.” In: E. L. Glaeser (ed.) The Economics of Agglomeration. Cambridge, MA: National Bureau of Economic Research.

Combes, P., Duranton, G., Gobillon, L. (2011), “The Identification of Agglomeration Economies”, Journal of Economic Geography, 11, 2, 253-266.

Combes, P. and Gobillon, L. (2015), “The Empirics of Agglomeration Economies”, Handbook of Regional and Urban Economics, vol. 5A, 257-348.

Dauth, W. (2014), “Job Polarization on Local Labor Markets”, IAB Discussion Paper 18/2014.

Dauth, W., Findeisen, S., Moretti, E., Suedekum, J. (2016), “Spatial Wage Disparities – Workers, Firms, and Assortative Matching”, mimeo.

Duranton, G. and Puga, D. (2004), Micro-foundations of Urban Agglomeration Economies. In: Henderson, V., Thisse, J.-F. (Eds.), Handbook of Urban and Regional Economics, North Holland.

Dustmann, C., Ludsteck J., Sch¨onberg, U. (2009), “Revisiting the German Wage Structure.” Quarterly Journal of Economics, 124, 843–881.

Glaeser, E. and Maré, D. (2001), “Cities and Skills”, Journal of Labor Economics, 19(2), 316-342.

Glaeser, E. And Resseger, M. G. (2010), “The Complementarity between Cities and Skills,” Journal of Regional Science, 50(1), 221–244.

Glaeser, E. and Saiz, A. (2004), “The Rise of the Skilled City”, Brookings-Wharton Papers on Urban Affairs, 1, 47-105.

Goos, M., Manning, A., Salomons, A. (2009), “Job Polarization in Europe” American Economic Review: Papers & Proceedings, 99(2), 58–63.

Goos, M., Manning, A., Salomons A. (2014), “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring.” American Economic Review, 104(8), 2509–2526.

Kosfeld, R. and Werner, A. (2012), “German Labour Markets. New Delineation after the Reforms of German Districts Boundaries 2007–2011”, Raumforschung und Raumordnung (Spatial Research and Planning), 70, 49-64.

Lindley, J. and Machin, S. (2014), “Spatial Changes in Labour Market Inequality.” Journal of Urban Economics, 79, 121-138.

Mazzolari, F. and Ragusa, G. (2013), “Spillovers from High-skilled Consumption towards Low-skilled Labor Markets”, The Review of Economics and Statistics, 95(1), 74-86.

Mion, G. and Naticchioni, P. (2009), “The Spatial Sorting and Matching of Skills and Firms.”, Canadian Journal of Economics, 42(1), 28-55.

Puga, D. (2010), “The Magnitude and Causes of Agglomeration Economies” Journal of Regional Science, 50(1), 203-219.

Rosenthal, S., Strange, W. (2004), Evidence on the Nature and Sources of Agglomeration Economies. In: Henderson, V., Thisse, J.-F. (Eds.), Handbook of Urban and Regional Economics, North Holland.

Spitz-Oener, A. (2006), “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure.” Journal of Labor Economics, 24(2), 235–270.

Agglomeration and the Decline of Routine Tasks

Appendix

Table 1. *Task measures of service occupations.*

SERVICE OCCUPATIONS	NRC	RCOG	RMAN	NRM
Cleaning and waste disposal workers	0.02	0.02	0.05	0.92
Housekeeping occupations	0.15	0.06	0.02	0.77
Cooks	0.16	0.04	0.06	0.74
Guard/watchmens	0.14	0.09	0.11	0.67
Hotel and guesthouse workers	0.26	0.10	0.02	0.62
Hairdressers/cosmeticians/personal hygiene technicians	0.34	0.06	0.01	0.59

Notes: service occupations selected among occupations for which more than 50% of tasks are non-routine manual tasks.

Table 2. *Occupation groups mean wage and educational attainment composition, 1991-2010. Focus on service occupations.*

Occupation group	Mean gross daily wage	% low educ	% med educ	% graduates
NRC >.5	180€	5.30	66.47	28.23
ROUTINE >.5	103€	17.01	82.24	0.75
NRM >.5	88€	22.14	76.53	1.32
SERVICE	**73€**	**35,58**	**63,03**	**1,39**

Notes: IAB administrative data, 95 million observations. Low-skilled: without a vocational training degree; medium-skilled: with a vocational training degree; high-skilled: with a degree from a University, or a University of Applied Sciences. The table refers to Table 3 of Chapter III by also considering service occupations.

Table 3. *Service occupations employment shares changes in West Germany, 1991-2010.*

	SERVICE OCCUPATIONS
1991	0,060
2010	0,071
100 x change	**1,18**

Notes: my calculations on IAB administrative data.

Table 4. *Service occupations employment shares changes by employment density quantiles, 1991-2010.*

EMPLOYMENT DENSITY	Low density districts			High density districts		
	bottom 5%	**<=25p**	**<=50p**	**>50p**	**>=75p**	**Top 5 cities**
			TOTAL			
1991	0,055	0,055	0,055	1991	1991	1991
2010	0,064	0,064	0,064	2010	2010	2010
100 x change	**0,91**	**0,69**	**0,92**	**1,47**	**1,70**	**1,47**
			MANUFACTURING			
1991	0,019	0,017	0,016	0,018	0,019	0,020
2010	0,014	0,012	0,011	0,011	0,012	0,014
100 x change	**-0,50**	**-0,49**	**-0,52**	**-0,66**	**-0,67**	**-0,66**
			NON MANUFACTURING			
1991	0,114	0,104	0,095	0,093	0,100	0,100
2010	0,123	0,109	0,102	0,104	0,112	0,110
100 x change	**0,88**	**0,47**	**0,77**	**1,02**	**1,18**	**0,95**

Notes: my calculations on IAB administrative data. Employment (weighted) density quantiles are computed by averaging density across all years. The table repeats results in Tables 5, 6 and 7 of Chapter III by considering service occupations.

Table 5. *Employment Density and Growth of Service occupations employment shares within Districts, 1991-2010 stacked first differences, OLS and 2SLS estimates. Dependent variable: 100 x non-routine manual tasks employment share change.*

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		2SLS (1952 Population density)		
Employment density-1	0.097	0.078	0.027	0.095	0.013	-0.068
	(0.183)	(0.172)	(0.180)	(0.253)	(0.233)	(0.273)
Routine tasks share-1	1.495*	5.469***	5.808***	1.487	5.270***	5.782***
	(0.807)	(1.122)	(1.292)	(0.917)	(1.069)	(1.233)
Manufact./empl-1		-1.170***	-1.182***		-1.175***	-1.207***
		(0.237)	(0.274)		(0.229)	(0.282)
Female/empl-1			0.118			0.116
			(0.678)			(0.649)
Graduate/non-grad empl-1			0.244			0.383
			(0.427)			(0.436)
Wald rk F				162.708	185.666	48.306
R^2	0.152	0.163	0.163	0.152	0.163	0.163

Notes: N=1276 (4 time periods x 319 districts). Robust standard errors clustered by district. All regressions include an intercept, time period dummies and local labor market dummies. Models weighted by start of period district share of total employment. The table repeats results in Table 13 of Chapter III by considering service occupations instead of non-routine manual tasks.

Conclusions

This doctoral dissertation addressed the routinization hypothesis by means of three separate contributions. In the first chapter, I presented the routinization hypothesis in the context of the wider empirical literature on the relationship between of technology and the labor market. The main conclusions drawn from Chapter I point out that, although over the last decades technological advancements did not exert an adverse effect on overall employment growth, the literature reaches a wide consensus about the existence of critical relative demand shifts caused by technical change. These labor demand adjustments are characterized, in turn, by a relative contraction in the demand for medium-skilled occupations and a relative expansion in the demand for low-skilled and high-skilled ones, resulting in wage polarization and employment polarization patterns. As far as medium-skilled jobs typically exhibit higher contents of routine-tasks, the literature shows that these shifts are largely consistent with the routinization hypothesis.

By focusing on the routinization hypothesis, in the second chapter I measured regional exposure to automation in Europe by using U.S. occupational tasks data (O*NET) and European employment data (EU-LFS). I showed that this variable is associated to more pronounced polarization patterns, as already found by the literature in the case of the United States. The empirical evidences I provide in the second Chapter also indicate that the effects of exposure to automation on the decline of routine employment are mainly related to the within-industries dimension, rather than to the between-industries one.

In the third Chapter, finally, I used IAB administrative data on West Germany in order to assess whether urban agglomeration phenomena may exacerbate the job polarization patterns documented by the literature on the routinization hypothesis. In particular, I measured the task content of occupations with BIBB/IAB German survey data, and matched this information into IAB data. Following this approach, I not only described a strong positive correlation between employment density and the contraction in routine tasks, but I also showed that the negative impact of agglomeration on the contraction of routine tasks is stable and significant - especially after taking into account both the effects of automation and the endogeneity of employment density.

List of References

Acemoglu, D. (2002) "Technical Change, Inequality, and the Labor Market", Journal of Economic Literature, 40, 7-72.

Acemoglu, D. and Autor, D. (2011) "Skill, Tasks and Technologies: Implications for Employment and Earnings", Hanbook of Labor Economics, vol. 4B (1043-1171).

Acemoglu, D. and Restrepo, P. (2017) "Robots and Jobs: evidences from U.S. labor markets", NBER Working Paper No. 23285.

Andersson, M., Klaesson, J., Larsson, J. (2014) "The sources of the urban wage premium by worker skills: Spatial sorting or agglomeration economies?" Papers in Regional Science, 93(4), 727-747.

Antonczyk, D., Fitzenberger, B., Leuschner, U. (2009) "Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?" ZEW Discussion Papers 08-132, ZEW - Zentrum für Europäische Wirtschaftsforschung.

Arntz, M., Gregory, T., Zierahn, U. (2016) "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris.

Autor, D. (2015) "Why Are There Still So Many Jobs? The History and Future of Workplace Automation", Journal of Economic Perspectives, 29(3), 3-30.

Autor, D. and Dorn, D. (2013) "The Growth of Low Skill Service Jobs and the Polarization of U.S. Labor Market", The American Economic Review, 103(5), 1553-1597.

Autor, D. and Dorn, D. (2009) "This job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure." The American Economic Rewiev, 99(2), 45-51.

Autor, D., Dorn, D., Hanson, G. (2015) "Untangling Trade and Technology: Evidence from Local Labor Markets*", Economic Journal*, 125(584), 621-646.

Autor D., Katz L., Kearney M. (2006) "The Polarization of U.S. Labor Market", The American Economic Review, 96(2), 184-194.

Autor, D., Katz, L., Kearney, M. (2008) "Trends in U.S. Wage Inequality: Revising the Revisionists", Review of Economics and Statistics, 90(2), 300-323.

Autor, D., Levy, F., Murnane, R. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration", The Quarterly Journal of Economics, 118(4), 1279-1333.

Bacolod, M., Blum, B.S., Strange, W. (2009) "Skills in the City", Journal of Urban Economics, 65, 136–153.

Baum-Snow, N. and Ferreira, F. (2015) "Causal Inference in Regional and Urban Economics", Handbook of Regional and Urban Economics, vol. 5A, 3-68.

Becker, S., Ekholm, K, Muendler, M. (2009) "Offshoring on the onshore composition of tasks and skills", CEPR Discussion paper 7391, London.

Black, S. and Spitz-Oener, A. (2010) "Explaining Women's Success: Technological Change and the Skill Content of Women's Work", The Review of Economics and Statistics, 92(1), 187-194.

Blien, U. and Ludewig, O. (2017) "Technological Progress and (Un)employment Development", IZA Discussion Paper Series 10472.

Bogliacino, F. and Pianta, M. (2010) "Innovation and Employment: A Reinvestigation Using Revised Pavitt Classes", Research Policy, 39(6), 799-809.

Bogliacino, F., Piva, M., Vivarelli, M. (2012) "R&D and Employment: An Application of LSDVC Estimator using European Micro-Data", Economic Letters, 116(1), 56-59.

Bogliacino, F. and Vivarelli, M. (2012) "The Job Creation Effect of R&D Expenditures", Australian Economic Papers, 51(2), 96-113.

Brynjolfsson, E. and McAfee, A. (2011) Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy. Digital Frontier Press.

Brynjolfsson, E. and McAfee, A. (2014) The Second Machine Age: Work, Progress and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Co. Press.

Card, D. and Lemieux, T. (2001) “Can Falling Supply Explain the Rising Return to College for Younger Men?”, The Quarterly Journal of Economics, 116(2), 705–46.

Cardona, M., Kretschmer, T., Strobel T. (2013) “ICT and Productivity: Conclusions from the Empirical Literature”, Information Economics and Policy, 25(3), 109-125.

Centeno, M. and Novo, A. (2009) “When Supply Meets Demand: Wage Inequality in Portugal”, IZA Working Papers, 4592.

Ciccone, A. and Hall, R. E. (1996), "Productivity and the Density of Economic Activity," American Economic Review, 86, 54-70.

Ciriaci, D., Moncada-Paternò-Castello, P., Voigt, P. (2016) “Innovation and job creation: A sustainable relation?” Eurasian Business Review, 6, 189-213.

Charnoz, P., Coudin, E., Gaini, M. (2011) “Wage Inequalities in France 1976-2004: A Quantile Regression Analysis”, INSEE Working Paper, 6.

Coad, A. and Rao, R. (2011) “The firm-level Employment Effects of Innovations in High-Tech US Manifacturing Industries”, Journal of Evolutionary Economics, Vol.21 (255-283).

Combes, P., Duranton, G., Gobillon, L. (2008) “Spatial Wage Disparities: Sorting Matters!”, Journal of Urban Economics, 63, 723-742.

Combes, P., Duranton, G., Gobillon, L., Roux, S. (2010) “Estimating Agglomeration Effects with HWestory, Geology and Workers’ Fixed-effects.” In: E. L. Glaeser (ed.) The Economics of Agglomeration. Cambridge, MA: National Bureau of Economic Research.

Combes, P., Duranton, G., Gobillon, L. (2011) “The Identification of Agglomeration Economies”, Journal of Economic Geography, 11(2), 253-266.

Combes, P. and Gobillon, L. (2015) “The Empirics of Agglomeration Economies”, Handbook of Regional and Urban Economics, vol. 5A, 257-348.

Cortes, M. (2016) “Where Have the Middle-Wage Workers Gone? A Study of Polarization using Panel Data”, Journal of Labor Economics, 34(1), p.t.1, 63-105.

Dauth, W. (2014) “Job Polarization on Local Labor Markets.”, IAB Discussion Paper 18/2014.

Duranton, G. and Puga, D. (2004) Micro-foundations of Urban Agglomeration Economies. In: Henderson, V., Thisse, J.-F. (Eds.), Handbook of Urban and Regional Economics, North Holland.

Dustmann, C., Ludsteck, J., Schönberg, U. (2009) "Revisiting the German Wage Structure", The Quarterly Journal of Economics, 124(2), 843-881.

Evangelista, R. and Vezzani, A. (2010) "The Economic Impact of Technological and Organizational Innovations. A firm-level Analisys", Research Policy, 39(10), 1253-1263.

EPSC (2016) "The Future of Work. Skills and Resilience for a World of Change", Issue 13.

Eurofound (2014) Drivers of Recent Job Polarization and Upgrading in Europe. European Jobs Monitor 2014, Publications Office of the European Union, Luxemburg.

Feldmann, H. (2013) "Technological unemployment in industrial countries", Journal of Evolutionary Economics, 23, 1099-1126.

Fernald, J. G. (2014) "Productivity and Potential Output Before, During and After the Great Recession", NBER Working Paper No 20248.

Firpo, S., Fortin, N., Lemieux, T. (2011) «Occupational Tasks and Changes in the Wage Structure», IZA Discussion Paper, 5542.

Frey, C.B. and Osborne, M.A. (2013) "The future of employment: how susceptible are jobs to computerisation?", Oxford University Working Paper, September 17, Oxford.

Glaeser, E. and Maré, D. (2001) "Cities and Skills", Journal of Labor Economics, 19(2), 316-342.

Glaeser, E. And Resseger, M. G. (2010) "The Complementarity between Cities and Skills," Journal of Regional Science, 50(1), 221–244.

Glaeser, E. and Saiz, A. (2004) "The Rise of the Skilled City", Brookings-Wharton Papers on Urban Affairs, 1, 47-105.

Goos, M. and Manning, A. (2007) "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", The Review of Economics and Statistics, 89, February, 118-133.

Goos, M., Manning, A., Salomons, A. (2009) "Job Polarization in Europe", The American Economic Review: Papers & Proceedings 2009, 99(2), 58-63.

Goos, M., Manning, A., Salomons, A. (2014) "Explaining Job Polarization: Routine Biased Technological Change and Offshoring", The American Economic Review, 104(8), 2509-2526.

Gregory, T., Salomons, A., Zierahn, U. (2016) "Racing With or Against the Machine? Evidence from Europe." ZEW Discussion Paper.

Hall B., Lotti F., Mairesse J. (2008) "Employment, Innovation and Productivity: Evidence from Italian Microdata", Industrial and Corporate Change, 17(4), 813-839.

Harrison, R., Jaumandreu, J., Mairesse, J. (2014) "Does Innovation Stimulate Employment? A firm-level Analisys Using Comparable Micro-data from Four European Countries", International Journal of Industrial Organization, 35, 29-43.

Heckman, J. and Mosso, S. (2014) "The Economics of Human Development and Social Mobility", Annual Review of Economics, Annual Reviews, 6(1), 689-733.

Hobsbawm, E. J. (1968) Industry and Empire: An Economic History of Britain since 1750. Penguin Books, Harmondsworth Middlesex.

Jeorgenson, D., Ho, M., Stiroh, K. (2007) "A Retrospective Look at the U.S. Productivity Growth Resurgence", The Journal of Economic Perspectives, 22(1), 3-24.

Izquierdo, M., Lacuesta, A. (2006) "Wage Inequality in Spain: Recent Developments", Banco de Espana Working Paper, 615.

Katz, L. and Murphy, K. (1992) "Changes in Relative Wages, 1963-87: Supply and Demand Factors", The Quarterly Journal of Economics, 107, 35-78.

Kelly, J. and Hamm, S. (2013) Smart Machines: IBM's Watson and the Era of Cognitive Computing, Columbia University Press, New York.

Keynes, J. M. (1963) Essays in Persuasion. New York: W. W. Norton & Co.

Kosfeld, R. and Werner, A. (2012) "German Labour Markets. New Delineation after the Reforms of German Districts Boundaries 2007–2011", Raumforschung und Raumordnung (Spatial Research and Planning), 70, 49-64.

Lachenmaier, S. and Rottmann, H. (2011) “Effects of Innovation on Employment: A Dynamic Panel Analisys”, International Journal of Industrial Organization, 29(2), 210-220.

Leontief, W. (1983) National Perspective: The Definition of Problems and Opportunities, in: National Academy of Engineering Symposium, The Long-Term Impact of Techonology on Employment and Unemployment, National Academy Press, Washington D.C.

Levy, F. and Murnane, R.J. (2004) The New Division of Labor: How Computers are Creating the Next Job Market. Princeton University Press.

Lindley, J. and Machin, S. (2014) “Spatial changes in labour market inequality.” *Journal of Urban Economics*, 79, 121-138.

Machin, S. (2011) “Changes in UK Wage Inequality Over the Last Forty Years”, in: Gregg P., Wadsworth J. (eds.), The Labour Market in Winter – The State of Working Britain. Oxford University Press.

Mazzolari, F. and Ragusa, G. (2013) “Spillovers from High-skilled Consumption towards Low-skilled Labor Markets.” *The Rewiev of Economics and Statistics*, 95 (1): 74-86.

Moore, G. (1965) "Cramming More Components onto Integrated Circuits", Electronics Magazine, 38(8), 114-117.

Murphy, K., Riddell, W., Romer, P. (1998) “Wages, Skills and Technology in the United States and Canada”, in: General Purpose Technologies. E. Helpman, MIT Press.

Naticchioni, P., Ragusa P., Massari, R. (2014) “Unconditional and Conditional Wage Polarization in Europe”, IZA Discussion Paper Series 8465.

Naticchioni P. and Ricci A. (2009), “Decreasing Wage Inequality in Italy: The Role of Supply and Demand for Education”, DSE-ISFOL Working Paper, No 9.

Naticchioni P. and Ricci A., Rustichelli E. (2008), “Wage Inequality, Employment Structure and Skill-Biased Change in Italy”, Labour, 22(1), 27-51.

Naticchioni P., Ricci, A., Rustichelli, E. (2010), "Far Away From a Skill-Biased change: Falling Educational Wage Premia in Italy", Applied Economics, 42(26), 3383–3400.

Pellegrino, G., Piva, M., Vivarelli, M. (2017) "Are Robots Stealing our Jobs?", IZA Discussion Paper Series 10540.

Piva M. and Vivarelli M. (2017) "Technological Change and Employment: Were Ricardo and Marx Right ?", IZA Discussion Paper Series 10471.

Puga, D. (2010). "The Magnitude and Causes of Agglomeration Economies", *Journal of Regional Science*, 50 (1): 203-219.

Ricardo, D. (1951) Principles of Political Economy, in: P. Sraffa (ed), The Works and Correspondence of David Ricardo. Cambridge: Cambridge University Press, vol. 1, third edn 1821.

Rifkin, J. (2014) The Zero Marginal Cost Society: The Internet of Things, the Collaborative Commons, and the Eclipse of Capitalism. St. Martin Griffin, New York.

Rifkin, J. (1995) The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era. Putnam Publishing Group, New York.

Rosenthal, S. and Strange W. (2004). "Evidence on the Nature and Sources of Agglomeration Economies." In: Henderson, V., Thisse, J.-F. (Eds.), *Handbook of Urban and Regional Economics*, Vol. 4, 2119-2171. North Holland.

Sabadash A. (2013) "ICT-induced Technological Progress and Employment: A Happy Marriage or a Dangerous Liason? A Literature Review", JRC-IPTS Working Papers, JRC76143, Institute for Prospective and Technological Studies, Joint Research Centre.

Samuelson, P., Koopmans, T., Stone, R. (1954) "Report of the Evaluative Committee for Econometrica." Econometrica, 22(2), 141-146.

Senftleben, C. and Wielandt, H. (2013). "The Polarization of Employment in German Local Labor Markets", SFB 649 Discussion Paper 2012-013.

Solow R. (1987) "We'd better watch out", The New York Times Book Review, July 12.

Spitz-Oener A. (2006) "Technical Change, Job Tasks and Rising Educational Demand: Looking Outside the Wage Structure", Journal of Labor Ecoonomics, 24(2), 235-270.

Vivarelli M. (2014), "Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature", Journal of Economic Issues, 48(1), 123-154.