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Structural Change and Employment Transformations

Doctoranda: Sudipa Sarkar

Directores: Dr. Rafael Muñoz de Bustillo Llorente

Dr. Enrique Fernandez Macias

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Thesis Supervisors: Dr. Rafael Muñoz de Bustillo Llorente and
Dr. Enrique Fernandez Macias

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Abstract

This thesis consists of an introduction, three self-contained essays of labour economics and a final chapter with the main conclusion. The first essay studies the association between technological change, employment polarization and over-education. It analyses the incidence of over-education and its change across skill-based and task-based job categories in four countries of Europe – Germany, Spain, Sweden and the United Kingdom. It also compares countries with different employment change patterns – mainly upgrading (rise in high-skill jobs) and polarizing (rise in low-skill and high-skill jobs at the expense of middle-skill jobs)– to establish a link between employment polarization and over-education. The analysis shows that countries with polarizing employment patterns have more incidence of over-education, which is particularly prevalent in low-skill jobs. The results remain unchanged in a job fixed effects regression.

The second essay investigates if job polarization has occurred in the labour market of India for a period spanning almost three decades, 1984 to 2012. It also analyses the implications of job polarization for increasing wage inequality in India. Using data from the National Sample Survey Organisation (NSSO), I find evidence of job polarization (employment growth in low- and high-skill jobs, and reduction in the middle) in urban India during the 1990s and the 2000s. However, the reduction in middle-skill jobs does not seem to be the consequence of only technological change and automation of routine jobs. Mechanisation along with the growing self-employment in India’s informal sector has contributed to the U-shaped pattern of employment change. Wage dynamics are consistent with the employment change during this period.

The final essay of the thesis explores the factors determining employment transitions of women in India. Using a nationally representative panel data set and correcting for selection bias due to initial employment and panel attrition, I show that women are not only participating less in the labour force, they are also dropping out of employment at an alarming rate. I find that an increase in income of other members of the household leads to lower entry and higher exit probabilities of women. Moreover, having a newborn child has a detrimental effect on women’s employment, indicating that provision of childcare facilities can be an important policy instrument in this context. I also find that the National Rural Employment Guarantee Scheme, a large public workfare program, has a significant effect on women’s labour force transition probabilities.

Resumen

La estructura de la tesis doctoral que aquí se presenta, está compuesta de varias partes, entre las debemos distinguir, el capítulo introductorio, tres ensayos independientes sobre economía laboral acompañados de un breve capítulo final que recoge las principales conclusiones de los ensayos.

En el primer trabajo, se investiga la asociación entre el cambio tecnológico, la polarización del empleo y la sobre-cualificación. Se analiza aquí la incidencia de la sobre-cualificación y su cambio, a través de categorías de empleos que han sido previamente agrupados de acuerdo a las habilidades exigidas en su ejecución y las tareas realizadas en cuatro países de Europa; Alemania, España, Suecia y el Reino Unido. También se compara estos países con diferentes patrones de cambio del empleo -principalmente de mejora estructural (aumento de los empleos de alta cualificación) y polarización (aumento de los empleos de baja cualificación y de alta cualificación a costa de los de cualificación intermedia) con la finalidad de establecer la posible existencia de un vínculo entre la polarización del empleo y la sobre-cualificación. Para ello, se utilizan datos de la Encuesta Europea de Población Activa para el período de 1999 a 2007. El análisis principal se realiza a nivel de *empleo*, donde el *empleo* se define como una combinación de ocupación e industria. Los principales resultados que se encuentran están relacionados con un patrón de cambio de polarización del empleo donde hay una mayor incidencia del sobre-cualificación, que afecta en mayor medida a los empleos de baja cualificación. Estos resultados se mantienen cuando se utilizan técnicas de regresión con efectos fijos.

En el segundo ensayo analizo los patrones de cambio en el empleo y los salarios en la India durante el periodo 1983-2011. La polarización del empleo y su efecto sobre la desigualdad de los ingresos ha sido estudiada en los países avanzados en los últimos años. Sin embargo, los países en desarrollo carecen de este tipo de análisis, ya que el cambio tecnológico ha sido percibido como un fenómeno propio de los países desarrollados. Recientemente el enfoque se ha centrado también en los países en desarrollo, especialmente en economías emergentes como Brasil, México, India y Rusia (Medina y Posso, 2010; Gimpelson y Kapeliushnikov, 2016). Este estudio contribuye a esta literatura mediante el análisis del cambio del empleo a través de las ocupaciones y los patrones simultáneamente al cambio salarial en la India. Utilizando datos de la Organización Nacional de Encuesta de Muestras y utilizando una metodología similar a la usada en el primer capítulo, se encuentra evidencia

de polarización en el empleo (crecimiento del empleo en empleos de baja y alta cualificación y reducción en el medio) en la India urbana durante los años noventa y primera década de siglo. Por otra parte, durante la década de los ochenta, hubo una mejora en el empleo. Los patrones de cambio en los salarios son consistentes con los patrones de cambio de empleo. Sin embargo, la reducción del peso de las ocupaciones rutinarias de cualificación intermedia parece ser resultado tanto del cambio tecnológico, como de la automatización de empleos rutinarios en la industria india. La mecanización, junto con el creciente empleo por cuenta propia en el sector informal de la economía india, ha contribuido a generar ese patrón de cambio en forma de U.

El capítulo final de la tesis investiga los factores que determinan las transiciones del trabajo femenino en la India. La desconcertante cuestión relacionada con la baja participación de la fuerza de trabajo, junto a un crecimiento económico sustancial, ha llevado a una mayor atención por parte de la literatura relacionada con este campo de estudio. Sin embargo, hasta el momento no se ha estudiado la dinámica del empleo en términos de entrada y salida del trabajo. En este trabajo, utilizando la base de datos de panel representativa a nivel nacional de la Encuesta de Desarrollo Humano de la India y corrigiendo mediante el sesgo de selección, se muestra cómo las mujeres no solo participan en menor medida en la fuerza de trabajo, sino también que su participación está cayendo a un ritmo alarmante. Entre los resultados más interesantes está el hecho de que el aumento de los ingresos de otros miembros del hogar, conduce a una menor entrada y mayores probabilidades de salida para las mujeres. Además, tener un hijo recién nacido tiene un efecto perjudicial en el empleo de las mujeres, reduciendo su probabilidad de entrada en el empleo en 1,7 puntos porcentuales y aumentando su salida en 3,5 puntos porcentuales. Este resultado indica que la provisión de servicios públicos para el cuidado de niños puede ser un instrumento de política laboral relevante en este contexto. Por último, se obtiene que el Esquema Nacional de Garantía del Empleo Rural -*National Rural Employment Guarantee Scheme*-, como programa de trabajo público, tiene un efecto significativo en las probabilidades de transición de la fuerza de trabajo de las mujeres.

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Chapter 1

Introduction

Labour market matching – the match between supply and demand for workers - has always been an important issue in the field of Labour Economics. The issue of labour market mismatch is particularly important as it has major consequences on the overall economy. It can contribute to unemployment and can also reduce productivity (Buchel, 2002; Shimer, 2007). In recent times finding the right skill for the right job is becoming more difficult as the nature of jobs is changing continuously and so is the demand for skills. Therefore, with faster economic and technological change the issue of job-skill mismatch has become more important. As pointed out by the existing literature, most of the new jobs the European economy is creating or expected to create over the next decade will require a high level of education and skills (Gallie et al., 1998; Hurley and Fernandez-Macias, 2008). In the supply side, the level of education is also increasing. The participation in tertiary education has been increasing since the 1970s, particularly in the developed countries (Freeman, 1975; Green, McIntosh and Vignoles, 1999; Tertiary Education Report EU-27, 2012). According to a fact book published in 2013 by the Organisation for Economic Co-operation and Development (OECD), tertiary educational level has increased considerably over the last 30 years. However, increasing levels of education does not imply a right balance between the demand and supply.

The key question here is whether this increase in educational attainment is demand driven or just the result of educational reform. It is important to know whether employers are seeking people with higher educational levels to do the same kind of jobs or the nature of the jobs has changed in a way that it requires more qualification. The impacts of demand driven and supply driven increases in higher education will be very different on the economy. In the absence of a commensurate rise in skilled job creation or job upgrading, the supply of highly educated workers will outpace the demand for such qualifications or skill levels in the labour market. A potential consequence of such phenomenon will be education- or skill-job mismatch, particularly over-education – a situation where worker has more education than what is required for his/her job (Freeman, 1975; Duncan and Hoffman, 1981; Alba-Ramirez, 1993).[1]

The objective of this thesis, which is part of an EU-funded training network, Eduworks, is primarily to study labour market mismatch from a job level perspective. Eduworks is a training network which aims to study the labour market matching process. The objective is to investigate to what extent individual skills match the demands of the jobs or the tasks, and what are the mechanisms causing skills mismatch in national and European labour market. The first essay of my thesis contributes to the broad objective of the project and investigates structural change and over-education in four countries of Europe using a job level approach. This approach has also been used in the analysis of the second essay which focuses on structural change by occupation and wage inequality in India.

The past few decades have also witnessed a big surge of technological change along with globalisation and increasing supply of education. Consequently labour markets have undergone significant structural change. This structural change has been studied by many labour economists and sociologists. According to the literature, some jobs or occupations are expanding while some are shrinking in terms of employment. These patterns have been termed as job polarization (expansion of high-skill and low-skill jobs while middle is shrinking), upgrading (monotonic expansion of low- to high-skill jobs) and mid-upgrading (increase in the middle-skill jobs) respectively in the literature (Autor, Levy and Murnane, 2003; Fernandez-Macias and Hurley, 2008; Goos, Manning and Salomons, 2009). The patterns have been different depending on the country and the period of study. Most of the studies have found job polarization in the USA and UK during the 1990s and this particular pattern (U-shaped) has received a lot of attention due to its major consequences (Wright and Dwyer, 2003: Acemoglu and Autor, 2010; Goos and Manning, 2007). The reason behind this as proposed in the literature has primarily been skill-biased technological change

[1] There are two types of education-job mismatch: vertical mismatch and horizontal mismatch. Vertical mismatch is a mismatch between the level of education of a worker and the level of education required for his/her job. Horizontal mismatch on the other hand is a mismatch between a worker’s field of study and the content of his/her job. In my thesis I focus only on the vertical mismatch.

(SBTC) along with routine-biased technological change (RBTC) which is replacing the routine jobs in the middle and enhancing the high skilled top tier jobs. However, the institutional setting, international trade and immigration have also been cited as important contributing factors.

Both job polarization and job-education mismatch, particularly over-education, have received increasing attention recently. However, these two phenomena can be linked in important ways. The first essay of my thesis in Chapter 2 aims to fill this gap in the literature by explicitly linking job polarization and over-education. [2] In this chapter, I investigate over-education across different quality jobs in four countries of Europe with different employment change patterns: Germany, Spain, Sweden and United Kingdom. As mentioned above, employment change and job-education mismatch have been studied by several researchers but none of them, so far, has linked the two to explore what is happening to job-education mismatch when structural change is unbalanced across skill levels. The question this paper seeks to address is what types of jobs are experiencing more over-education over time and how the patterns vary in countries with different labour market structures. Using data primarily from the European Labour Force Survey for the period from 1999 to 2007, and following the same methodological framework for four countries, this paper produces comparable cross-country results to answer this question.

The main analysis is performed at job level, where job is defined as a combination of occupation and industry. The job level approach was first introduced by Joseph Stiglitz in his Economic Report of the President in the year 1997. He constructed an occupation-by-sector matrix using the Current Population Survey data of 1994-96. The idea behind this was to observe the changes in each occupation across different industry sectors over time. The occupation-by-sector matrix makes it much easier to observe the changes by looking at each cell of the matrix. A similar approach has been adopted by many researchers while analysing occupational change in different countries (Hurley and Fernandez-Macias, 2008; Oesch and Rodriguez-Menes, 2011).

In the next step of the analysis the jobs in each country are grouped into three categories – *Low-skill*, *Middle-skill* and *High-skill* – using the median earnings of the jobs in each country. Jobs are also classified into three task-based categories – *Non-routine manual*, *Routine*, and *Analytical* jobs. Low-skill jobs are mostly interpersonal service jobs such as

[2] An article based on this essay has been published in the journal *Empirica*.

personal and protective service workers in hotels and restaurant industry which are also non-routine manual in nature. The middle-skill category consists of jobs such as *clerical*, *office assistants,* and *machine operators,* most of which are also categorised as routine jobs in the task-based categories. Professionals such as *teachers, doctors*, and *managers* fall into the high-skill job category and are often also categorised as analytical jobs. In the next step, I measure the percentage of over-educated workers using the realized matches approach. In this approach, a worker is identified as over-educated if s/he has more education than the modal education of the job s/he is doing. The job level approach is particularly useful in this context as it considers both occupation and industry while measuring modal level of education of a job. A particular occupation may have different educational or skill requirement depending on which industry it belongs to. Therefore, ignoring the industry information may over- or under-estimate the incidence of mismatch.

The empirical analysis in this paper first estimates the percentage of over-educated workers in each of the skill-based and task-based job categories to examine if the extent of over-education varies with the skill level or task content of jobs. Further, I estimate a job fixed-effects multivariate regression to investigate the association between over-education and job type. The results suggest a higher incidence of over-education in polarized countries – UK and to some extent in Spain compared to countries with a somewhat upgrading pattern of employment change – Germany and Sweden. It also reveals that in Spain and UK, over-education is prominent and increasing over time in the low-skill jobs which are mostly non-routine manual in nature, while Germany and Sweden have more over-educated workers in middle skilled routine and high skilled analytical jobs. The findings highlight the fact that as the middle-skill routine jobs decline in employment share and the education level increases in all the countries, relatively high educated workers opt for low-skill non-routine manual jobs. This happens in countries where employment in both high-skill and low-skill jobs increases at the cost of a reduction in middle-skill jobs. Consequently, incidence of over-education increases in these countries, particularly in low-paid non-routine manual jobs.

Job polarization and its effect on earnings inequality has been studied extensively in the developed countries in the past few decades. However, developing countries lack this kind of analysis as technological change has been perceived as a developed country phenomenon. But recently the focus has shifted to the developing countries, especially to the emerging economies like Brazil, Mexico, India and Russia (Medina and Posso, 2010; Gimpelson and

Kapeliushnikov, 2016). The existing literature provides evidence of the presence of technological change in India (Berman et al., 2005; Unni and Rani, 2004). Moreover, India is one of the largest emerging economies which has also experienced trade liberalisation in the early 1990s. It is, therefore, interesting to see if the labour market of India has undergone any structural change in the past few decades.

The second essay in Chapter 3 contributes to this literature by analysing employment change and concurrent wage change patterns in India.[3] The main objective is to investigate if job polarization has occurred in the labour market of India for a period spanning almost three decades, 1984 to 2012. It also analyses wage changes across the wage distribution in urban India during the same period. We use data from the Employment and Unemployment survey conducted by the National Sample Survey Organization (NSSO), Government of India. Data from several survey rounds have been used starting from 1983-84 to 2011-12. These surveys are nationally representative surveys, and collect socioeconomic and demographic information of households and individual members across all states except some remote and inaccessible pockets. On average, there are 125 to 136 thousand individuals in the working age population (15-65) in each round.

The methodology is quite similar to that of the first essay where occupations or jobs are the main unit of the analysis. Following the standard method I rank the jobs from lowest to highest skilled jobs using the mean wage of the initial year. Occupations in this data are coded following the detailed classification of occupation and thus, considering some of the industry variation. I, therefore, do not combine all the occupations with industry to define 'job' in this study. However, some big occupations (such as Clerk general, and Labourers) which do not consider industry variations are further broken by industry groups.

Results suggest that there has been job polarization (employment growth in low- and high-skill jobs, and reduction in the middle) in urban India during the 1990s and the 2000s. However, the 1980s experienced an employment upgrading with a monotonic expansion in employment from low to high-skill jobs. I find a reduction in the employment share in routine task intensive occupations during the last two decades which is consistent with the job polarisation literature. However, the reduction does not seem to be the result of only technological change and automation, although mechanisation also plays an important role.

[3] This essay has been published as a Warwick IER working paper and also currently under peer review in the journal *Development and Change*.

On the other hand, the increase in employment in both low-skill and high-skill occupations is more the result of growing self-employment in the informal sector in urban India. The wage change patterns are mostly consistent with the employment change patterns. Employment expansion in both low-skill and high-skill jobs may have contributed to the increasing earnings inequality in urban India. Therefore, the structural employment change across occupational skill distribution remains an important factor for understanding earnings inequality in India.

The third and the final essay in Chapter 5 delves into another key aspect of the labour market – the employment transition of women. This chapter investigates the factors determining employment transitions – entry into and exit from employment of women in India. As mentioned earlier, India is an emerging economy with a growth rate as high as 7 to 8% during the past decade. Despite its high economic growth, demographic dividend (high share of working age population), increasing educational level, decreasing gender gap in education, and decreasing fertility rate, female labour force participation has been declining in recent years. This apparently puzzling issue of declining labour force participation despite substantial economic growth in India has received increasing attention in the literature (Klasen and Pieters, 2015; Lahoti and Swaminathan, 2016; Siddiqui et al., 2017). However, no study so far has looked into the dynamics of employment in terms of entry and exit in this context.

Using nationally representative panel data from the India Human Development Survey (IHDS), I show that women are not only participating less in the labour force, but also dropping out at an alarming rate from employment. Using an endogenous switching model that corrects for selection bias due to initial employment and panel attrition, I investigate the determinants of women's entry into and exit from employment. However, the focus of this analysis is to contribute to the literature which has conjectured that women may drop out of the labour force as the socio-economic status of the household increases. This analysis provides evidence by analysing the employment transition of the same women in two time points.

The results suggest that the increase in income of other members of the household leads to lower entry and higher exit probabilities of women. This income effect persists even after controlling for the dynamics of asset holding of the household. Along with the effects of caste and religion, this result reveals the interplay between cultural and economic factors that are important in explaining the declining workforce participation of women in India. Also, having a newborn child has a detrimental effect on women's employment, indicating that provision of childcare facilities can be an important policy instrument in this context. I also explore the effects of education, marital status, household composition, presence of in-laws and regional characteristics. I find that while having other elderly members in the household plays as a hindrance for women in continuing in work, the presence of in-laws in the same house helps them in staying in the employment. National Rural Employment Guarantee Scheme, a large public workfare program, also has a significant role to play in women's employment transition.

This thesis sheds light on three important issues of labour economics in both developed and developing countries. While the first essay focuses on the labour markets of developed countries and provides a cross country comparison in the context of over-education and employment change across jobs, the last two essays focus on a developing country and provides some keys for the interpretation of recent developments of the labour market of India. The thesis highlights the fact that though in the era of globalisation mature of jobs and production process are changing in similar ways, country differences persist.

The findings of the three essays have some policy relevance. In the context of increasing supply of educated people in a labour market where the nature of jobs is rapidly changing, policy responses should help people gain the right skills to contribute in the new production processese. Though it seems that a developing country like India is following the footsteps of the developed world, it has very different problems to address, such as its informal sector and decreasing women's participation in the labour force. Policy should not only focus on bringing more women into the labour force but also to keep them in employment. The provision of child care seems to be an important policy measure in this context. Moreover, availability of work in the local labour market is also necessary to bring more women and to keep them in employment. However, as India is growing fast the use of machines and technology is slowly taking over its labour intensive production process. This process can lead to less employment growth and it can be safely assumed that women may be affected at least as much as men, if not more, by the lack of job opportunities.

Chapter 2

Employment Change and Over-Education in Germany, Spain, Sweden and UK

2.1 INTRODUCTION

Technological development in production process has been taking place since the late 1970s particularly in the developed countries. Consequently the labour market has experienced employment upgrading (monotonic employment growth from low- to high-skill jobs) or employment polarization (employment growth in low- and high-skill jobs, and reduction in the middle-skill jobs) depending on the nature of technological change – whether it has been skill-biased or task-biased (SBTC or TBTC).[4] Mostly an asymmetric polarization of employment change has been found in countries like USA and United Kingdom during the 1980s and the 1990s (Acemoglu, 1999; Autor, Katz and Kearney, 2006; Goos and Manning, 2007). This pattern has been linked to the displacement of routine task intensive jobs by task-biased technological change (Goos and Manning, 2007). On the other hand increasing supply of higher educated population in the absence of commensurate rise in quality job has

[4] SBTC predicts the use of computer-based technology to complement skilled jobs and thus to increase monotonically the demand for high-skill workers relative to low-skill workers. TBTC (which is also referred as RBTC, routine-biased technical change) on the other hand argues that use of computer-based technology is most likely to replace middle-skill jobs with routine tasks. According to the TBTC hypothesis, while machine can replace the methodical jobs, the non-routine jobs located in very bottom and top of the occupational hierarchy cannot be substituted by technology. For a vivid discussion on SBTC and TBTC please refer to Fernandez-Macias and Hurley (2016) for further reading.

resulted in high incidence of over-education in developed countries for the past few decades (Freeman, 1975; Alba-Ramirez, 1993; Quintini, 2011; Education Report EU-27, 2012).

This paper seeks to investigate two important issues in this context. First, it tries to explore the association between technological progress and over-education by investigating if incidence of over-education varies in jobs with different skill level and task intensity. Following similar methodology that has been used in the literature to study job polarization, I construct three skill based categories as *Low-skill*, *Middle-skill* and *High-skill jobs*, and three task based categories as *Non-routine manual*, *Routine*, and *Analytical jobs*.[5] Then I look at the incidence of over-education and its change in three skill-based job categories and three task-based job categories. Second, the study compares four countries of Europe with upgrading and polarizing employment structure to establish a link between job polarization and over-education. Using data primarily from the European Labour Force Survey for the period from 1999 to 2007, this paper compares four countries of Europe: Germany, Spain, Sweden and United Kingdom. This comparative analysis provides an insight on whether countries with different structure of employment change experience varying incidence of over-education across the occupational categories.

The empirical analysis in this paper first estimates the percentage of over-educated workers in each of the skill-based and task-based job categories to examine if the extent of over-education varies with skill level or task content of jobs. Further, I estimate a job fixed-effects multivariate regression to investigate the association between over-education and job type. Although we are unable to estimate a causal relationship, yet this regression is helpful in testing the robustness of the observed correlation after eliminating the partial effects of some other relevant factors. I find that over-education is lower in countries where technological change is more skill-biased leading to a job upgrading. In contrast, countries where technological change is task-biased have comparatively higher incidence of over-education. The results are quite consistent in both bi-variate and multi-variate analysis. They show that incidence of over-education is very different in countries with upgrading and polarizing employment patterns. Higher incidence of over-education is observed in low-skill and non-routine manual jobs in countries with polarizing employment pattern, i.e. in UK and Spain.

[5] Literature of polarization and technological change has interchangeably used the terms low-skill, low-paid or bad jobs and high-skill, high-paid or good jobs while explaining the structural change across the job or occupational hierarchy. These terms have also been used in this paper to refer job or occupational hierarchy.

Germany and Sweden, on the contrary, have more over-educated workers in middle-skill and routine intensive jobs.

This study contributes to two important streams of literature: job-education mismatch and job polarization. Various studies have focused on job-education or job-skill mismatch by analysing incidence, determinants, consequences, and returns to over-education and under-education (Alba-Ramirez, 1993; Sloane, Battu and Seaman, 1999; Baur, 2003; Green and Zhu, 2008). The literature has pointed out many negative effects of over-education on individual worker as well as on the overall economic productivity. [6] Over-educated workers are penalized as they earn less than what they would earn if they were matched.[7] These findings are supported by almost all the empirical studies based on advanced countries including the study countries Germany (Buchel, 2002), Spain (Alba-Ramirez, 1993), Sweden (Korpi and Tahlin, 2009; Nordin et al., 2010) and UK (Sloane et al., 1999).

A separate stream of literature has analysed technological change and job polarization (the U-shaped employment change pattern) since the 1980s (Acemoglu, 1999; Goos, Manning and Salomons, 2009; Oesch and Rodriguez-Menes, 2011; Fernandez-Macias, 2012; Goos, Manning and Salomons, 2014). Job polarization has been found in the labour market of Europe by Goos, Manning and Salomons (2009). However, Fernandez-Macias and Hurley (2008) and Oesch and Rodriguez-Menes (2011) show that there are variations across countries in Europe in terms of employment change pattern: not all countries experience the same polarized pattern in Europe. Most of the studies have found polarizing pattern in the USA and UK during the 1980s and the 1990s (Wright and Dwyer, 2003: Autor and Dorn, 2013; Acemoglu and Autor, 2010; Goos and Manning, 2007). However, countries like Germany, Netherland, Sweden, Spain and some other European and developed Asian countries are much debated in the literature: the pattern varies from upgrading, mid-upgrading to polarized upgrading depending on the job skill measure and period of study

[6] The concept of over-education was first explored by Richard Freeman in his book 'The Overeducated American' in 1976 (Freeman, 1976). In this book Freeman focuses on over education, the situation where worker's skill or education level exceeds the level of skills or education required by the employer to obtain or perform the job. There can also be a situation where workers' actual levels of skills or education fall short of the requirement. This situation is called under-education or under-skilling. Given the higher level of participation in tertiary education in developed countries, over-education has been a major concern for the past few decades.

[7] The literature (Duncan and Hoffman, 1981; Hartog and Oosterbeek, 1988; Green et al., 2002) on over-education has mushroomed with a little attention to the phenomenon of under-education. Nonetheless, many studies highlight the fact that under-education is a temporary phenomenon and can be overcome with experience while over-education can be a long term problem (Green and McIntosh, 2007).

(Spitz-Oener, 2006; Felsted et al., 2007; Tahlin, 2007; Bernerdi and Garrido, 2008; Dustmann et al. 2009).[8]

This paper tries to link both the issues – job polarization and over-education – prevalent in the advanced economies using data from four countries of Europe. As mentioned earlier, a few studies have provided insights on employment change, skills supply and technological progress (Spitz-Oener, 2006), and have also compared different countries of Europe in this context (Tahlin, 2007; Oesch and Rodriguez-Menes, 2011; Goos, Manning and Salomons, 2014). But linking job polarization and over-education has been relatively under researched. The distinctive feature of this study is that it analyses both these issues, and investigates if there is any association between the two. It also provides cross-country comparison by analysing four countries with different patterns of employment change.

The rest of the paper is organised as follows. Next section provides a review of the existing research on mismatch, paying special attention to the problem of measurement. Section 2.3 discusses the selection of countries and the data used in the. In section 2.4 I discuss about the methodology and empirical specifications. Section 2.5 discusses the results from the analysis and Section 2.6 concludes.

2.2 A REVIEW OF LITERATURE ON MISMATCH

The participation in higher education, particularly in tertiary education has been increasing in the developed (US and Europe) countries for the past few decades (Freeman, 1975; Green, McIntosh and Vignoles, 1999; Tertiary Education Report EU-27, 2012). The reason behind this rise has mostly been the governmental policies encouraging higher education participation by investing more in higher education and reforming the universities. As Freeman (1975) mentions "the proportion of GNP allocated to colleges and universities jumped from 0.8 percent to 2.2 percent between 1950 and 1970; college enrolments more than tripled; the number of BA graduates rose by 91 percent; master's and doctorate

[8] Bernerdi and Garrido (2008) and Oesch and Rodriguez-Menes (2011) find a polarizing employment structure in Spain unlike Fernandez-Macias and Hurley (2008). Tahlin (2007) and Dustmann et al. (2009) find an occupational upgrading in Germany while Spitz-Oener (2006) finds a job polarization for Germany. In a recent study Adermon and Gustavsson, (2015) find job polarization in Sweden during the 90s and the 2000s contradicting the findings of Fernandez-Macias and Hurley (2008) and Aberg (2004) who observe an occupational upgrading in Sweden. The common fact which has emerged from all of the studies is that there has been a massive job upgradation in advanced countries of Europe.

production more than tripled" in the US. According to a fact book published in 2013 by the Organisation for Economic Co-operation and Development (OECD), tertiary educational level has increased considerably over the last 30 years.

The concept of *over-education* was first explored by Richard Freeman in his book *The Overeducated American* in 1976 (Freeman, 1976). In this book Freeman focuses on over education, the situation where worker's skill or education level exceeds the level of skills or education required by the employer to obtain or perform the job. However, there can also be a situation where workers' actual levels of skills or education fall short of the requirement. This situation is called under-education or under-skilling. Given the higher level of participation in tertiary education in developed countries, over-education has been a major concern for the past decades. So the literature on over-education has mushroomed with a little attention to the phenomenon of under-education. Nonetheless, many of these studies highlight the fact that most of the arguments related to over-education are also applicable to under-education (Green, McIntosh and Vignoles, 1999).

2.2.1 Difference between skill mismatch and educational mismatch.

Educational mismatch and skill mismatch are sometimes treated as interchangeable terms in the literature. However there is evidence in the literature which suggests that both are not synonymous. Most of the growing literature on mismatch deals with *education* or *qualification mismatch* rather than *skill mismatch*. While the definition of education mismatch is straightforward dealing with the discrepancy between the level of formal education acquired by a worker and the level required to obtain the job, the concept of skill is much more complicated to define. Skill can be attributed as the observed (training, experience and knowledge) and unobserved characteristics (abilities or potentiality) of a worker. Defining skill mismatch is, therefore, difficult mostly because of a lack of suitable data to address it.[9] Although the concepts are related but they should be clearly distinguished

[9]There has been a couple of surveys very recently which provide information on individual's skill level. The Programme for International Assessment of Adult Competencies (PIAAC) and Adult Literacy and Lifeskills Survey (ALL) are among them. These data sets provide direct measures of key foundation skills as well as indirect measures of the use of certain generic skills at work. PIACC contains even more detailed level of information on the use of skills at work and aims to assess of what is known about skill mismatch using prior surveys of adult skills as well as to investigate the consequences of skill mismatch on labour market outcomes (e.g., earnings and training).

because they lead to different types of analyses and implications. According to Thurow (1975), over-educated workers are likely to under-utilise their skills. He argues that one plausible explanation behind the existence of over-education is employers use personal characteristics, such as education, as criteria in their hiring decisions. They use level of education as a proxy for skills and training of the employee. Hence, employers sometimes hire the most educated applicant considering that they have to invest less on his/her on-the-job training.

Another most reasonable statement on this phenomenon is given by Clogg and Shockey (1984), who conclude that the disparity between a worker's acquired schooling and the level of schooling traditionally required to obtain his or her job (educational mismatch), is a valid indicator of the under- or over-utilization of skills. Clogg and Shockey are not the only one to view educational mismatch this way. There are couple of more studies which corroborate to the same. According to Burris (1983), over-education is workers' "inability to exercise acquired skills on the job." Similarly, Kalleberg and Sorensen (1973:217) explain: "An increase in the educational attainments of Americans, coupled with a not-so-great increase in jobs which make use of these attainments, produces group of over trained workers who cannot find jobs which make full use of their abilities. Hence, they are likely to be 'underutilized'" (also see, Duncan and Hoffman 1981; Rumberger 1987; Sicherman 1991).

In late 90s the whole concept of educational mismatch and skill mismatch was viewed from a different perspective. In the study on graduate over-education in the UK, Chevalier (2000) brings the notion of *apparently* over-educated and *genuinely* over-educated.[10] He identifies the apparently over-educated workers as those who have more education level (observed) than required for their job but are less able in terms of unobserved skills, so reportedly satisfied with the match between their education and job. These are the workers who are more likely to receive in-service training to improve their skills and ability. On the other hand, the *genuinely* over-educated workers are those who are actually over-educated in terms of formal education and training, and so are under-utilising their skills (over-skilled). In line with the research of Chevalier, a recent study by Green and Zhu (2008) has

[10]Chevalier used the data of two cohort sample of UK graduates collected by a postal survey. The survey was organised by the University of Birmingham in the winter of 1996 among graduates from 30 higher education institutions covering the range of UK institutions. The survey asked questions regarding job satisfaction and Chevalier used this self-reported information to distinguish between *apparently* and *genuinely* over-educated graduates.

distinguished between *real* and *formal* over-qualification.[11] The categorisation is very much similar to the one adopted by Chevalier based on the occurrence of over-education and skill underutilisation. In the *real* over-education category, the workers are both over-educated and over-skilled, so underutilising their skills. But in the latter category, workers are over-educated but fully utilising their skills. It is, therefore, clear that over-education does not always lead to over-skilling. Allen and van der Velden have tried to explore the relationship between these two phenomena using the data from 11 European countries and Japan (2001). According to them, it is very important to make the distinction between the two concepts- educational mismatch and skill mismatch. The findings suggest that educational mismatch is neither a necessary nor a sufficient condition for skill mismatch. They estimate three earnings equations including educational mismatches and skill mismatches separately in first two models and then the third model combines both educational mismatches and skill mismatches. The findings suggest that both kinds of mismatches have a significant effect on wages, even when controlling for the other. However, about half of the effect of skill underutilisation disappears when educational mismatches are controlled in the regression. The magnitudes of adjusted R-square reveal that skill underutilisation accounts for a comparatively smaller wage variance than educational mismatches do. Skill underutilisation rather has stronger effects on job satisfaction and on-the-job search (Allen and van der Velden, 2001; Cedefop, 2010a). Using a cross sectional sample for Britain, Green and McIntosh (2007) have also investigated the correlation between educational mismatch and skill mismatch. They find a positive, significant but rather weak correlation (0.2) between over-education and over-skilling. The result is similar to that of Alen and van der Velden (2001) for Europe and Ryan and Sinning (2011) for the Australian labour market. Turning to the correlation between under-education and under-skilling, there is no relationship at all between under-education and under-skilling (Green and McIntosh, 2007). The reason behind this, as explained by Green and McIntosh, is under educated workers have acquired the skills to perform the job through some out-of-school training or years of experience.

[11] They used data drawn from the 2006 Skills Survey, along with three other surveys conducted in 1992 (Employment in Britain), 1997 (Skills Survey) and 2001 (Skills Survey) in the UK labour market. The 2006 survey covered workers aged between 20 and 60 years. The categorisation of *real* and *formal* over-educated workers are, although, based on similar definition as adopted by Chevalier (2003), the authors acknowledged that they used different terms in order to avoid the word 'apparent'. In addition to the *rea*l and *formal* over-education categories, this study has the third category called *skills underutilisation* (no over-education but underutilising skills).

2.2.2 Measurement of skill

Most of the studies measure educational mismatches by comparing the acquired level of education with the level of education considered most appropriate for the job. However, skill mismatches are mostly measured by worker's responses to the following statements – 'My current job offers me sufficient scope to use my knowledge and skills' and 'I would perform better in my current job if I possessed additional knowledge and skills'. The responses are, *Strongly agree*, *Agree, Disagree, Strongly disagree* (Green and McIntosh, 2007; Alen and van der Velden, 2001).

Ryan and Sinning (2011) use information on individual literacy and numeracy skills and the extent to which individuals report that they undertake tasks which require these skills in their jobs. Using these information they generate a measure of 'relative skill use'. This is a measure which reflects the skill requirements of workers' jobs relative to the skills that the worker possess. This measure allows to distinguish between 'over-skilled' workers (those with high levels of skills who report rarely undertaking tasks involving such skills) and 'under-skilled' workers (those with low levels of skills who report frequently undertaking tasks involving skills they do not seem to have). Desjardins and Rubenson (2011) use a similar method to measure skills. They use ALLS data where respondents are asked about the extent of use of a series of specific skills (e.g., literacy, numeracy, problem solving, teamwork, etc.) in their job. However, this method may be inadequate to assess all the specific skills through the survey instruments.

2.2.3 Measurement of mismatch: discussion of different approaches

Given the major consequences of educational mismatch, its measurement has become an important issue. According to the definition of over- or under-education, one needs to know the required level of education of a job and the actual level of education of the individual doing the job in order to measure mismatch. However, the level of education required for a job or occupation is not straightforward to measure. Therefore, most of the studies start by measuring the required level of education for a particular occupation or job. There are mainly three types of measurement approaches in the literature.

i. Job Analysis Approach (JA):

Under this approach, systematic evaluation of tasks under a certain occupation is done to assign a skill level to each occupation. Professional job analysts evaluate the job titles of the occupational classification and decide the required level of qualification and skill needed to perform the tasks under the job.[12] The workers doing that job with more or less level of qualification than the level required for that job, are considered as over- or under- qualified or educated. This approach is also called Objective measure. However, this measure does not consider the fact that there can be a distribution of educational requirements for different jobs under a broad occupational category. So assigning one single level of educational qualification to a particular occupation would lead to over or under estimation of mismatch. Also the changes in the tasks in an occupation due to technological changes over time may require different skills to perform the job. This phenomenon cannot be captured by this approach unless it is revised timely.

ii. Workers self-assessment Approach (WA):

Under this approach worker's self-assessment method is used to measure skill mismatch. Workers are asked different questions on the required level of education and skills for the particular job they are doing and whether it is different from their own level of education. Based on the responses given by them, the mismatch is calculated.[13] So this method is also called Subjective approach. This approach is particularly useful to measure skill mismatch as it allows to get necessary information on workers' skills and abilities; on the degree to which they are able to use their present skills and abilities in their job. This allows to control for differences in abilities across workers in the sample. However, this approach is not free of criticism as the results would vary depending upon the questions asked to the workers and the worker's own judgment.

iii. Realized Matches (RM):

[12] A well-known example is the Dictionary of Occupational Titles (DOT) which contains an indicator for educational requirements in the form of the General Educational Development (GED) scale. This scale runs from 1 to 7. These GED categories are then translated into school years equivalents (0 to 18) (cf. Eckaus, 1964, p.184). Following the OECD (2007a) job-analysis approach to measuring immigrants' over-education, Muñoz de Bustillo, R and Antón, J.-I. (2012) measure mismatch. They use both International Standard Classification of Occupation (ISCO) and educational levels (using ISCED taxonomy), and re-codify them into three categories of skills and educational attainments (low, intermediate and high), respectively.

[13]Direct questions on use of skill or required level of education are asked to the workers. For example: 'what is the level of schooling you think is necessary to perform this job?', 'are you satisfied in your current job?', 'do you use your skills and training in the current job?'

Realized matching approach, sometimes called as statistical or empirical approach, is useful when there is no direct question about the required level of education. This approach does consider the fact that there is a distribution of required level of education for a particular occupational group. So it calculates the required level of education using the central tendency of the distribution. The mean or the modal level of education is used as the required level and there is educational mismatch if the actual education of worker is greater than one standard deviation above or below the mean or mode. This approach has an a priori assumption of symmetry between over- and under-education. The critiques have suggested using mode rather than mean to estimate the required level of education given the asymmetry between over- and under- education if measured by mean level of education. Also, mode is less sensitive to outliers as well as technological changes (Sloane, 2003). However, this approach is suitable for measuring educational mismatch rather than measuring skill mismatch. Measurement of skill mismatch needs particular information on individual skills and abilities in their current job.

It has been a long debated issue in the literature that which of these three measures is superior for the measurement of educational and skill mismatch. According to Sloane (2003) *WA* suffers from the subjectivity problem; some individuals may easily overstate the requirements of their job to raise the status of their position, or they may simply reproduce actual hiring standards. This causes problems if actual schooling levels in the labour force increase over time, and employers adjust hiring standards but the jobs themselves have not changed. Both *JA* and *WA* approaches refer to the level of education and do not consider the type of education. A worker may be properly matched in terms of the level of education he has received but the type of education is completely different than the one required by the job.[14] While Van der Velden and van Smoorenburg (1997) favour WA approach compared to *JA* approach, some others (Hartog and Oosterbeek, 1998; Sloane, 2003) have criticised *WA* approach suggesting that it may lead to an upward bias. Hartog (2000) and Halaby

[14]This situation is called *Horizontal mismatch* in the literature (Robst, 2007a; Nordin, Perrson and Rooth, 2010). Horizontal skill mismatch is a situation in which the level of education or skill of the worker matches the required level but the type of education or skill differs from the type required. For example, in a job the level of education required is 'graduation' and a person having graduation in literature may apply and is eligible to get the job but the type of activity under the job might require graduation in Economics. Therefore, there will be mismatch in the type of education or skill not in the level of education or skill. The mismatch between the level of education required for a job and the level of education of the worker holding the job is termed as *Vertical mismatch*.

(1994) identify some major disadvantages of JA approach except the one mentioned earlier. Hartog (2000) points out that updates are infrequent and sometimes not so accurate because they are costly. Another disadvantage, specifically made by Halaby (1994), is no consensus on the conversion of the General Educational Development (GED) scale to years of schooling. On the other hand, *RM* assumes symmetry between over-education and under-education which is a rare phenomenon in reality and therefore may lead to biased estimates. The *RM* approach also consists of the realised equilibrium of the demand and supply of labour market; it is therefore not an appropriate measure of demand side. Particularly because, the changes in labour supply will affect the threshold level of education in a particular job. Therefore, Sloane (2003) and Hartog (2000) consider *JA* as the superior method comparing the merits of the three measures. But as the *JA* measures are available only for some specific years, so *WA* measure has been used widely due to the availability of the information. In absence of data related to *JA* and *WA* approaches, *RM* approach has been adopted in some studies.

2.2.4 Existing research on mismatch

The research on over-education that has followed the footsteps of Duncan and Hoffman's study on 'The incidence and wage effects of over-education' has mainly focused on three topics. First, measuring the incidence of over (under) –education; second, its determinants at the individual level, and third, looking at the consequences of educational mismatch particularly estimating the wage equation proposed by Duncan and Hoffman in order to obtain separate estimates of returns to required education, surplus education and under-education.

2.2.5 Incidence of educational mismatch and skill mismatch

All the three alternative approaches have been used by researchers in this field to measure educational mismatch. Rumberger (1981) uses the *JA* approach to estimate the rising incidence of over education in the US labour market during the 1970s. The results of this study revealed that the incidence of over-education increased between 1960 and 1976. Rumberger (1987) also estimates the over-education using both subjective and objective approach and finds very low incidence of over-education (27 %) using subjective measure as compared to 57% of over-educated workers using *JA* or objective approach in the US labour market. Duncan and Hoffman (1981) use Panel Study of Income Dynamics (PSID) data from US labour market to estimate the incidence of over-education and its effect on wage. The authors use subjective or workers self-assessment approach and found 42% of US workers to be over-educated. On the other contrary, using *RM* approach or statistical approach Verdugo and Verdugo (1989) estimate the incidence of over-education as low as 10.9% using the data of 1980 from the US labour market. The findings from the research studies based on the European countries reveal that Netherland in 1982 had experienced 16% of workers over-educated while measured using *WA* or subjective approach and *RM* approach (Hartog and Oosterbeek, 1988; Groot, 1993). The incidence of over-education went down in 1994 to 15.9% (measured by *JA* approach), 11.85% while measured by *RM* approach and 11.15% while measured by *WA* approach (Groot and Maassen van den Brink, 2000)[15]. Alba-Ramirez (1993) employs the *WA* approach and measures educational mismatch using the data from Spanish Labour Force Survey in the year 1985. The percentage of workers who reported to have more education than required for the job was 17% and percentage of workers with less education than necessary for the job was 23%. However, Portugal during the same period had experienced a lower level of incidence of over education (5%), as estimated by *JA* approach (Cardosso, 2007).[16] The percentage increased drastically to 33% in 1991 using the same approach (Kiker et el., 1997).[17] The incidence of over-education in Germany was quiet closer to that in Spain. Bauer (2002) estimates 11.50% over-educated workers using *RM* approach during the year 1984-98. Using the data from Social Change and Economic Life Initiative (SCELI) survey from the year 1986-87, Sloane et al.(1999) estimate the educational mismatch for the UK using the *WA* or subjective approach. The findings suggest that 30.63% were overeducated, 17.21% undereducated and the majority (52.16%) had the required level of education (Sloane, Battu and Seaman, 1999). Dolton and Vingoles (2000) also found 30% over-educated graduate

[15] Another study by Alen and van der Velden (2001) estimate the incidence of over-education in Netherland during the year 1998 as 14% using *WA* approach.

[16] The data set used for this study comes from the survey annually done by the Ministry of Employment of Portugal to gather Quadros de Pessoal (personal information). It covers the population of firms in manufacturing and services in private sector and all their personnel, approximately 2 million workers. The sample for this study is restricted to the workers holding a high school degree or a university degree.

[17] Kiker et al. measure mismatch using both *JA* and *RM* approaches. The *RM* approach estimated 9.40% over-educated workers using mean measure and 25.50% over-educated workers using mode measure in Portugal. The data used in this study comes from the Personnel Records (Quadros de Pessoal) collected by the Portuguese Ministry of Labour.

workers in UK by using the same subjective approach and data from National Survey of Graduates Diplomates (carried out during 1980 and 1986). According to Green and Zhu (2008), the incidence of over-education (measured by *WA* approach) in UK has shown an increasing trend for both men and women starting from 26.4% (28.4% for women) in 1992 to 37.3% (37.7% for women) in 2006.The incidence of over-education in Northern Ireland during 1999-00 was 20% to 24% (McGuiness, 2003). The data used for this study was collected during a telephone survey of 1997/98 applicants to the Premiere programme conducted during July and August 2000[18]. A more recent study by Galasi (2008) using the data from European Social Survey finds that overall 33% of European workers were over-educated and 59% were under-educated.[19] The survey was carried out from 2004 to 2006 in 25 European countries among which 20 countries are the members of EU and 2 are from European Economic Area. Remaining 3 countries are Switzerland, Turkey and Ukraine. This study shows that the incidence of over-education varies substantially between countries with the percentage of over-educated workers as low as 14.7% in the Netherland and as high as 79% in Estonia. Overall, workers in the European countries are less likely to be over educated than in the United States. The average percentage of over-educated workers among studies for the United States is 26.3%, while among European studies this is 21.5% (Groot and van der Brink, 2000). The scenario is quiet similar for the incidence of under-education.

According to Chevalier (2003) and Green and Zhu (2008), the incidence of over-education is over-estimated unless the distinction is made between *apparent* or *formal* and *genuine* or *real* over-education. These studies consider the fact that workers, even with similar qualifications are not homogeneous in their ability or endowment of skills. This heterogeneity in ability has led to an over-estimation of the extent and effect of over-education on earnings in previous research. The estimated (using *JA* and *W*A approach) employed graduates not in a graduate job was 18% among which only 6% was *genuinely* over-educated and 12% was *apparently* over-educated in UK during 1996 (Chevalier, 2003).[20] However, Green and Zhu (2008) also estimate the percentage of graduates not in a

[18] The Premiere programme is a training programme of Ireland which was established during the late 1980s and provides training to around 250 graduates annually. The programme lasts 35 weeks during which time participants take a number of business courses to improve their skills and productivity.

[19]The estimates are based on the subjective measurement approach. The survey asks questions on the perceived required level of education ‘if someone was applying nowadays for the job you do now, would they need any education or vocational schooling beyond compulsory education?’, and ‘about how many years of education or vocational schooling beyond compulsory education would they need?’

[20] Chevalier (2003) in his paper uses three definitions of over-education and estimates the same using all three definitions. The findings suggest, the JA or expert measure and subjective measure on satisfaction result in

graduate jobs using *WA* approach and found 33% of men and 32% of women graduates are over-educated in 2006. The decomposition of over-education into *real* and *formal* over-education confirms that 23% of the over-educated graduate men (24% for women) experienced *formal* over-education and remaining 10% experienced *real* over-education (8% for women).

2.2.6 Factors contributing to mismatch

The situation of education-occupation mismatch is primarily a consequence of wide access to higher education during late 70s in the USA and 80s and beginning of the 90s in the European countries particularly in the UK. The higher education participation doubled in the period of five years increasing straight from 15% in 1988 to 30% in 1992 in Britain (Chevalier and Lindley, 2009). This led to students with lower ability to have access to higher education and some of them ended up acquiring less skills than a traditional student acquires during his degree. Besides, the increased participation in higher education also created some pressure on the Universities leading to poor quality education in some cases (Mason, 1999). Thus, graduates, even with similar qualifications are not homogeneous in their endowment of skills.

There are several studies which have analysed the individual level factors which are associated with the mismatch in the labour market. The results vary depending on the specification they use to estimate the association of different factors. Generally a probit model or a binary choice model has been estimated to analyse the determinants of educational and skill mismatch (Green and McIntosh, 2007). Some of the studies estimate multinomial logit model (Allen and Vries, 2004; Chevalier and Lindley, 2009) to distinguish between more than two categories of mismatch. The findings are more or less consistent and suggest that female workers are more likely to be over-educated than their male counterparts. This is mainly because men are considered as the primary income earner of the family and women who choose to work are compelled to make a choice in a place where man's career prospect is high. This may restrict them and force them to choose any job irrespective of their education and skill level (Frank, 1978). The same is applied to those who have children and thus, need more time to take care of them. These workers generally

the lowest over-education rate (around 18%), whereas the measure based on subjective responses on educational requirement generates a higher level of over-education (33%).

prefer a job with less responsibility and with a more flexible working time schedule. Green and McIntosh (2007) find that individuals with children are around 6 percentage points more likely to work in jobs for which they are over-educated than those who are childless. Their explanation is that the presence of children may restrict parents' mobility in the labour market because of preference to particular schools or institutions.[21] Younger workers are more likely to be over educated than their older counterparts since they lack the required experience compared to the older workers. This is consistent with the fact that workers are more likely to be over educated in their first job. There are also some job level characteristics which seem to be associated with the mismatch. Individuals in part time or shift jobs are more likely to be over educated. Some studies have found that the incidence of over-education is higher among immigrants from non-English-speaking countries (Green, Kler & Leeves, 2007; Lindley and Lenton, 2006). Immigrant workers have worse job matches than nationals. In a study on immigration in EU countries, Muñoz de Bustillo and Anton (2012) show that the incidence of over-qualification is higher among migrants than among nationals, for both men and women. Similar to the immigrants, the incidence of over-education is higher for non-white members of the native-born population. Another very important factor to determine mismatch is ability of a worker. The studies with suitable data to capture ability have found significant negative relationship between ability and over-education (Chevalier and Lindley, 2009; Green and McIntosh, 2007). Green and McIntosh (2007) use maths qualification as the proxy of ability that is valued in the labour market. They find that ability is associated with a lower likelihood of being over-educated and a greater likelihood of being under-educated. Among the macro level factors, while the growth rate of labour force is positively associated with incidence of mismatch, rate of unemployment is negatively associated with returns to required education (Groot and Van der Brink, 2000).

2.2.7 Consequences of mismatch

Mismatch in the labour market has serious consequences on the whole economy. Both the educational and skill mismatch, although different from each other, have important

[21] Green and McIntosh, however, investigate the fact that whether or not women are more affected by the presence of children. They test this hypothesis by including an interaction term between gender and number of children and find that the impact of children on the probability of being over-educated is 60% higher for women than men; the coefficient is not statistically significant.

consequences on the economy, implying a significant loss of well-being. There has been a handful of studies which have focused on the consequences of over- or under-education and over- or under-skilling. The literature suggests that the impacts of over-education are likely to be non-trivial and it may potentially be costly to individuals and firms, as well as the economy as a whole. It has effects on job satisfaction, productivity and wage (Tsang, 1987; Green and Zhu, 2008). Most of the studies find that educational mismatch has relevant impacts on wage, job satisfaction, absenteeism, shrinking and turnover. All these factors in turn affect the productivity which is not only important for the firm but also for the whole economy.

Researchers have measured the impacts of mismatch on productivity using two approaches: human capital theory and job satisfaction approach. According to the human capital theory, level of formal education and training both enhance the level of skill of a worker and make him more productive. Based on the differences in productivity workers may earn different wages. Using the human capital theory, Rumbergar (1987) has shown that years of over-education has positive returns on earnings but the return is lower than that of years of required education. Therefore, over-education is not utterly unproductive but at the same time it hinders the full use of skills and knowledge of the worker. Most of the other studies (Duncan and Hoffman, 1981; Hartog and Oosterbeek, 1988; Verdugo and Verdugo, 1989; Sicherman, 1991) also highlight the fact that in a particular job over-educated workers earn more than their co-workers with just the required level of education for that job but less than if they were matched. Similarly, the under-educated workers earn less than their co-workers with the required level of education for that particular job but more than if they were matched. Over-educated workers, as a result of skill underutilisation, are dissatisfied with their current jobs and try to look for other jobs which are more suitable for their abilities (Alen and van der Velden, 2001). This may lead to higher cost burden on firm’s side and for these reasons firms are less willing to hire the over- educated workers (Buchel, 2002). Workers’ lack of job satisfaction not only leads to on-the-job-search but also is related to firm’s output. There has been an extensive research on the impact of over-education on productivity (Rumberger, 1987; Tsang, 1987; Tsang, Rumberger and Levin, 1991; Buchel, 2002). Underutilisation of skills also implies underutilisation of resources (Tsang, 1987). Using firm-level production data and individual-level data for the employees of Bell (22 companies of Bell from the USA) for the period 1981-82, Tsang (1987) finds out that a firm which does not fully utilize the educational skills of its workers suffers a loss in output. The study has found that over-education is negatively and significantly related to firm's output. The negative effect of over-education on firm output is quite strong: a one-year increase in over-education is associated with an 8.35% drop in firm's output for the Bell companies. Therefore, the effects of over-education are likely to be non-trivial and the phenomenon may potentially be costly to individuals and firms, as well as the economy as a whole (McGuiness, 2006).[22]

2.2.8 Returns to over-education, under-education and adequate education

Estimating returns to over (under) –education and required education has been one of the broad issues in the literature since 1981. Duncan and Hoffman (1981) first estimated the wage effect of over and under education separately along with required level of education. Using the PSID data of USA from the year 1976 they decomposed the actual level of schooling of an individual into the level of schooling required for his/her job and surplus or deficit schooling. They included the decomposed years of schooling variables in the wage equation (which is a standard Mincerian earning equation) and estimated it for race-sex combination (white and black male and, white and black female) separately. The estimated findings suggest that the return to surplus education is positive and significant for all the four groups, while the estimated return to deficit schooling is negative, though significant only for a men (white and black). Although, the wage effect is positive for surplus schooling, the estimated coefficient is approximately half as large as the coefficient on required years of education. According to their estimation, one additional year of surplus schooling increases earnings of white men by 2.9%, whereas, one additional year of required schooling increases the earnings by 6.3%. In line with the research of Duncan and Hoffman (1981), most of the recent studies have found positive return to education for the overeducated as compared to secondary high school diploma holders (Brynin and Longhi, 2009; Cainarca and Sgobbi, 2009; Franzini and Raitano, 2012), while the overeducated earn on an average 18% less than individuals working in jobs for which they have an appropriate level of education (Green and McIntosh, 2007; Sloane, 2003; Leuven and Oosterbeek, 2011). The only exception is Verdugo and Verdugo (1989), who estimate the effect of surplus schooling

[22]McGuiness clearly concluded in his paper that "Over-education incurs significant wage costs on the individual and productivity costs on the economy that may well rise if higher education participation continues to expand without a corresponding increase in the number of graduate jobs." (McGuiness (2007), p.147)

on earnings using a random sample of white men. Their analysis has shown a negative coefficient of over-education dummy implying that over-educated workers earn less than their properly matched and under-educated counterparts. This finding of Verdugo and Verdugo (VV) has been extensively criticised by Cohn (1992) and Gill and Solberg (1992). They point out that the returns to over-education in VV's model is negative as they control for years of completed education (single year increment) in their regression; this is not clearly explained in VV's paper leading to incorrect impression. In their next article (Verdugo and Verdugo, 1992), VV reply to the points made by Cohn and Grill et al. and explain that their results differ from previous studies for several reasons (e.g. use of dichotomous variable, controlling for completed education and based on the measurement of over-education using *RM* approach). Given the fact that most of the studies have used information from supply side of the labour market, it is necessary to address mismatch considering both the demand and supply sides of the labour market. This will enable us to understand better the variety of factors which may have impact on educational and skills mismatch.

2.3 BACKGROUND

This section provides the basis of the later analysis of over-education across the skill and task-based job categories. I firstly discuss the reason of selecting the four countries based on the literature of employment change and then analyse the employment change from the data used in this study.

2.3.1 Selection of countries

The analysis has been done taking the sample of four countries – Germany, Spain, Sweden and United Kingdom for the years from 1999 to 2007. The reason for choosing these countries is mostly because they represent different socio-economic regimes of Europe and also experience different patterns in employment change and in distribution of household income during this period (Esteban, Gradin and Ray, 2007). As mentioned earlier, unlike Goos, Manning and Salomons (2009), some studies have established the fact that not all European countries have experienced job polarization during the last two decades

(Fernandez-Macias and Hurley, 2008; Oesch & Rodriguez Menes, 2011; Fernandez-Macias, 2012).

The common consensus is that high-skill analytical jobs (also termed as 'good jobs') expanded strongly during the last few decades. However, the expansion of low-skill interpersonal service jobs (also termed as 'bad jobs') has been moderate relative to middle-skill routine jobs in some countries such as Spain and UK (Goos and Manning, 2007; Felsted et al., 2007; Bernardi and Garrido, 2008; Oesch and Rodriguez-Menes, 2011). Also, geographically these countries are from different regions of Europe (west, north and south) with different socio -economic institutions. Germany is considered as a country of 'Conservative continental regime', while United Kingdom represents the 'Liberal regime', Sweden is part of 'Nordic regime' and Spain represents the 'Mediterranean regime' (Hall and Soskice, 2001).

2.3.2 Data

The data I use for this study come from JOBS project of European Foundation for the Improvement of Living and Working Conditions.[23] The JOBS data set has been constructed from individual level survey data from different sources, mainly from the European Labour Force Survey (ELFS), the European Structure of Earnings Survey (ESES, 2002) and the European Survey on Income and Living Conditions (ESILC, 2005). This data set is prepared to conduct the analysis at 'job' level where 'job' is defined as the combination of occupation and industry.[24] The occupation classification follows the International Standard Classification of Occupation (ISCO hereafter) and the industry classification follows the European Industrial Activity Classification (NACE hereafter). Defining jobs using both occupation and industry allows considering the variation under each occupation and industry at 2 digit level. Besides, as the analysis will be performed at job level, the occupation-industry combination will provide with more observations than using only

[23] The JOBS project is carried out by a team at the European Foundation for the Improvement of Living and Working Conditions (Eurofound). One of the objectives of this project is to construct data sets suitable to conduct analysis at 'job' level. For more details on the JOBS project and database see Fernandez-Macias, E., Hurley, J., & Storrie, D. (2012). *Transformation of the Employment Structure in the EU and USA, 1995-2007*. Palgrave Macmillan.

[24] The words job and occupation have been interchangeably used throughout the paper.

occupation at its 2 digit level.[25] For this analysis I use data from four countries covering the period from 1999 to 2007, as this is the period when all the four countries went through a recovery cycle. Also, there was no change in the occupational and industry classification for this period; categorisation of occupation and industry has used the same ISCO codes of 1988 and NACE codes from revision 1.1 for this period. Since the whole analysis is performed at occupation and industry (job) level, it is necessary to have same classification of occupation and industry.

2.3.3 Employment change trends

The change in employment is analysed in accordance with the related literature by looking at the percentage change in relative employment or employment share in the wage or skill terciles of jobs as mentioned above (Oesch and Rodriguez-Menes, 2011; Goos, Manning and Salomons, 2014; Kupets, 2016). To group the jobs into low-skill, middle-skill and high-skill jobs, I use median earnings as a proxy of the job skill. In the literature, average earnings and education of job have been extensively used as the proxy of job's skill to study job polarization (Wright and Dwyer, 2003; Autor and Dorn, 2013; Goos, Manning and Salomons, 2009; Fernandez-Macias, 2012).

In this paper I use the median earnings of the year 2002 to rank order the jobs from low skill (paid) to high skill (paid) jobs.[26] The jobs are then grouped into three equally weighted terciles in the beginning of the period 1999. Therefore, the bottom tercile consists of approximately 33% of the total employment with the lowest median earnings and the highest tercile holds 33% of the employment with the highest median earnings in each country. Three biggest jobs (as presented in appendix Table 2.A2) are quite similar in all the four countries. The lowest tercile has *Personal and protective service workers* in Hotel and restaurant industry and *Models, salespersons and demonstrators* in retail industry. *Office*

[25] After dropping small cells jobs, the final sample consists of around 1100 jobs in Germany, 970 jobs in Spain, 680 to 930 jobs in Sweden and almost 1050 jobs in UK across the years. However, the balanced panel has 847 jobs in Germany, 723 jobs in Spain, 540 jobs in Sweden and 785 jobs in the United Kingdom.

[26] The 2002 ESES was used for estimating median hourly wages for each job in each country. But this survey does not cover the public sector and does not provide a two-digit disaggregation of the manufacturing sector, so the European Survey on Income and Living Conditions data from the year 2005 has been used to complement. A detailed explanation of the JOBS data and the *Job-level* approach has been provided by Fernandez-Macias (2012).

clerks in Public administration and defence industry and in Health industry and *Extraction and building trade workers* in Construction are in the middle tercile. The high-skill jobs in tercile 3 have *Teaching professionals, health and life science professionals and associate professionals in* Education and Health industry.

Table 2.1: Classification of skill-based and task-based job categories

Skill-based job categories (based on median earnings of jobs of the year 2002)[∂]	
Low-skill	Jobs with the lowest median
Middle-skill	Jobs with the average median earnings
High-skill	Jobs with the highest median earnings
Task-based job categories (based on major task contents of ISCO 2 digit occupations)[α]	
Non-routine manual	Non-methodical, flexible use of brain, eyes, hands and legs.
Routine (manual and cognitive)	Repetitive works which involve systematic physical movement, use of fingers and hands. Calculating, bookkeeping, correcting texts/data, and measuring following a well-defined method.
Analytical	Analysing, interpreting, thinking creatively, guiding, directing, and establishing relationship.

[∂] The median earnings of a job has been estimated using European Structure of Earnings Survey, 2002 and European Survey on Income and Living Conditions, 2005. Jobs are then grouped into three equally weighted terciles based on the median earnings with approximately 33% of total employment in each of the three categories.
[α] Grouping ISCO 2 digit occupations into these three task-based categories has been done following the task intensity index calculated by Goos et al. (2014).

If earning is the proxy of one's skill level, then employment change across the wage terciles should reflect on the SBTC hypothesis. According to this hypothesis, employment will grow monotonically from low skilled to high skilled jobs. To distinguish the two hypothesis of technological progress: SBTC and TBTC, I also create three task-based job categories. The ISCO two digit occupations are grouped into three task-based categories following Goos et al. (2014): i) *Non-routine manual occupations*, ii) *Routine occupations* and iii) *Analytical* occupations as presented in the Table 2.1.[27]

Table 2.2 presents the percentage point changes in employment share across the three skill-based and three task-based job categories for the period 1999 to 2007. Clearly, the *high-skill jobs* as well as *analytical occupations* have expanded in all the four countries during this period. However, the share of *low-skill jobs* has increased only in the United Kingdom where a sharp decrease in the employment share of *middle-skill jobs* is also observed. Germany and Spain have similarities in terms of the decrease in employment share in both *low-skill* and *middle-skill* jobs. On the other hand, the employment share change in Sweden is consistent with the SBTC hypothesis – showing monotonic increase towards the *high skilled* jobs. The routinization hypothesis seems to hold for Spain and United Kingdom – employment shares have increased in both *non-routine manual* and *analytical occupations*, and declined in *routine occupations*. The results are consistent with Oesch and Rodriguez-Menes (2011) where they use the same countries (except Sweden) and almost same period to study employment change.

This analysis suggests a clear pattern of employment polarization in United Kingdom and to some extent in Spain during this period. However, the increase in employment share only in the high-skill and analytical jobs in Germany and Sweden imply a pattern of employment upgrading during this period. This differing pattern of employment change is the key reference point for the analysis of over-education and to investigate the association of job polarization and incidence of over-education.

[27] Routine occupations include both routine manual and routine cognitive occupations. A table with two digit ISCO codes under each of these task-based categories is presented in Appendix Table 2.A3.

Table 2.1 Change in employment share across wage/skill terciles and task-based categories, 1999-2007

	Germany			Spain			Sweden			UK		
	1999	2007	1999-2007	1999	2007	1999-2007	1999	2007	1999-2007	1999	2007	1999-2007
Change by wage/skill terciles												
Low-skill (tercile 1)	33.61	33.51	-0.10	35.71	35.17	-0.54	33.32	27.99	-5.34	33.38	35.32	1.95
Middle-skill (tercile 2)	33.78	28.49	-5.29	31.07	30.61	-0.46	35.86	35.62	-0.24	33.82	31.35	-2.47
High-skill (tercile 3)	32.61	38.00	5.39	33.22	34.22	1.00	30.81	36.39	5.58	32.81	33.33	0.52
Change by task-based categories												
Non-routine manual	40.02	38.75	-1.27	50.69	52.23	1.54	39.75	39.65	-0.10	37.19	40.62	3.43
Routine cognitive and manual	19.95	18.55	-1.40	18.95	15.24	-3.71	18.29	14.92	-3.37	22.89	16.91	-5.97
Non-routine analytical and interactive	40.03	42.70	2.67	30.36	32.53	2.17	41.96	45.44	3.47	39.92	42.46	2.54

Note: Jobs are grouped into *Low-skill*, *Middle-skill* and *High-skill* jobs based on the median earnings of jobs in the year 2002. The task based job categories – *Non-routine manual*, *Routine* and *Analytical* – are based on the routine task intensity index measured by Goos et al. (2014).

Source: Author's calculation from JOBS database (Eurofound).

2.4 EMPIRICAL MODEL

The first step of studying over-education is the measurement of job-education mismatch which, as we have seen in section 2.2 is an important issue in the literature of mismatch or over-education.

In this study incidence of job-education mismatch is measured using the statistical approach. This approach is in line with the objective of this study since the required level of education can be defined in terms of the mean or mode at both occupation and industry level. This will consider the possibility that occupation with the same title may have different requirements in different industries. Under this approach, mode has been suggested over mean as a better measure for required education by many researchers (Kiker et al., 1997). The argument they make is that mode is less sensitive to outliers and technological change. Besides, there is no rationale behind the arbitrary choice of one standard deviation, which is the standard measure for comparison with respect to mean. A caveat of using RM approach is that it defines the required education from the demand and supply interaction.

It can also suffer from the small cell jobs problem which can result in inconsistent estimations. This latter problem can be tackled by using a pooled sample of different years. Therefore, I use pooled data for nine years (1999 to 2007) to estimate the modal level of education for each job.[28] In this case the main assumption one would make is that the required education level for a particular job is fixed over time. This assumption is plausible as the level of education for a job does not change within a short span of time. To check whether this is true, I measure the modal education of each job in each year and see that more than 70 to 85% of the jobs in four countries have the same modal education level in 1999 and 2007. Therefore I use the pooled data to measure modal education level for each job where education can take values from 1 (ISCED 0-2), 2 (ISCED 3-4) and 3 (ISCED 5-6).[29] The workers are then categorised as over and under educated if they have more or less education than the modal education level of the job.

[28] The period 1999 to 2007 is used for the job-education mismatch analysis as the data before 1999 have some fluctuations in the education variable.

[29] The JOBS data also have detailed education variable taking 1 to 6 values of International Standard Classification of Education (ISCED). The 6 levels are: Level 1 - Primary education or first stage of basic; Level 2 - Lower secondary or second stage of basic education, Level 3 - (Upper) secondary education; Level 4 - Post-secondary non-tertiary education; Level 5 - First stage of tertiary education; Level 6 - Second stage of tertiary education. However, the broad three level education variable is used for the analysis since there are few observations (or no observation for some years) in the ISCED-1, ISCED-4 and ISCED-6. The whole

2.4.1 Regression specifications

In this section I discuss the regression specification used to investigate how the incidence of over-education varies across the job and occupational categories based on job skills and task content after controlling for several job characteristics. I estimate a linear regression with and without job fixed effects separately for each country. The regression analysis is aimed to investigate the partial correlation between incidence of over-education and job categories while controlling for other observable factors. Since there may be some unobserved or omitted variables which are correlated with both the job categories and over-education, therefore this regression may not indicate a causal relationship between the dependent and independent variables. However, it is still useful to estimate a multivariate regression and examine how far the relationship observed in bivariate analysis is robust to potentially confounding factors. The basic specification is of the following form:

$$Overed_{jt} = \alpha + \theta_t + \boldsymbol{X}_{jt}\,\beta + \gamma\, category_j + u_{jt} \qquad (1)$$

Where the subscript *j* refers to a job and *t* refers to time which takes the values 1 to 9 for the years 1999– 2007. The dependent variable is the share of overeducated in each job. The observable explanatory variables are included in the vector $\boldsymbol{X}_{jt}$. In our analysis, the explanatory variables considered are composition of gender, age, nationality, level of education, employment type (salaried or self-employed) and type of work (full/part time) in each job. The corresponding coefficient vector is denoted by β. These variables are discussed in more details while presenting the results of the regression in the next section. Time fixed effects (θ_t) are included to capture the change in over-education over time. To see how the incidence of over education varies with the job skills, and the task based occupation categories, I estimate two separate models. In the first model, the term $category_j$ includes dummy variables to reflect the skill-based job types while in the second model it is replaced by the task-based job categories.

In addition to the pooled regression specified above, I also estimate job fixed effects regression to investigate the temporal changes in over-education across the job types. The rationale for including job fixed effects is twofold. First, if the job fixed effects are not

analysis has also been done using the detailed education variable and the results are almost similar to that of the broad education variable.

controlled, then comparison across jobs may underestimate or overestimate the extent of over-education for a particular job category. For example, the high-skill jobs may have lower level of over-educated workers because they have the highest levels of educational requirements. Hence the regression estimate may show a negative relationship between skill ranking and over-education, even though that may not be a particularly interesting finding. Instead it may be more relevant to analyse how the extent of over-education changes over time for these different types of jobs. Second, in addition to the observable variables included in $\boldsymbol{X}_{jt}$, there may be some unobservable characteristics at the job level which can be correlated with the dependent as well as independent variables.[30] Thus it is important to control for job specific unobserved heterogeneity and exploit the within-job variation to investigate the association between job's skills and the extent of mismatch. Having repeated observations on each job for the years 1999 to 2007 enables me to control for job fixed effects (σ_j) in the next specification which is given below:

$$Overed_{jt} = \varphi + \sigma_j + \pi_t + \boldsymbol{X}_{jt} \in + \delta \ category_j \ t + \varepsilon_{jt} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (2)$$

Since the skill ranking of jobs based on its median wage (or the task categories) does not change over time hence $category_j$ does not have temporal variation and is not separately identified in this job fixed effects regression. Instead, I look at how over-education changes over time depending on the job skills, by interacting the wage tercile dummies (or dummies for task-based categories, in separate regressions) with a linear time trend.

It should be noted that the dependent variable, share of over educated workers, is bounded by 0 and 1. Besides, the share of over educated, under educated and perfectly matched workers in a job must add up to 1. Therefore, while analysing the relationship between share of over educated workers and other factors, one needs to consider the other categories as well. Therefore, an ideal econometric model in this framework would be fractional multinomial logit as suggested by Papke and Wooldridge (1996). However, I present the main results using linear models since the inclusion of fixed effects is more straightforward in linear regression as compared to non-linear models such as fractional multinomial logit. Besides, instead of predicted probabilities, we are interested in estimating the marginal

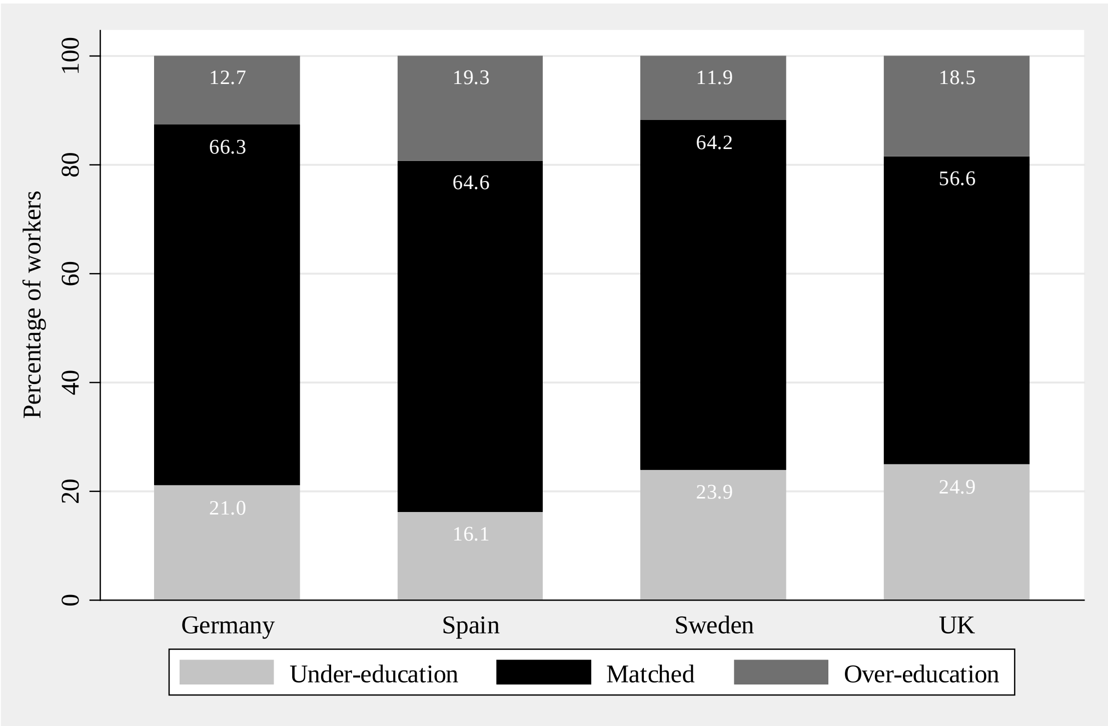
[30] Some jobs are very different in terms of the technology used or the tasks performed under them to produce output.

effects which are easier to estimate from a linear model. Nevertheless, the results remain unchanged even in a fractional multinomial logit model and are shown in the Appendix.

2.5 RESULTS

This section presents the results from the empirical analysis of over education. I begin with a descriptive analysis that compares the incidence of job-education mismatch in the four countries during the period under consideration. Then it shows how over education has changed across job skill and job-tasks. In the later part of the section, results from regressions, with and without job fixed effects, are presented.

Figure 2.1: Average level of mismatch during the period 1999 to 2007



Note: A worker is overeducated, matched or undereducated when her/his own level of education is, respectively, higher, equal or lower than the one required for her/his job.

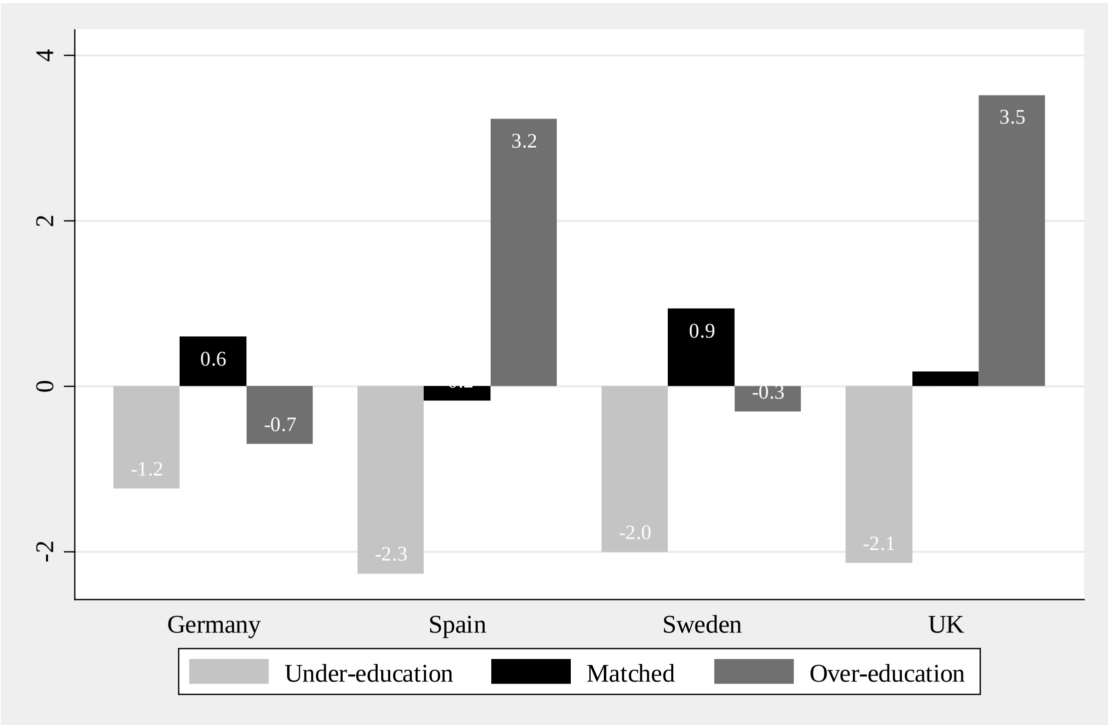
Source: Author's own calculation from the JOBS database.

2.5.1 Incidence of job-education mismatch

Figure 2.1 presents the average percentage of under educated, over educated and matched workers for the whole period of study (1999 to 2007) in each country, measured at the job level with the RM approach as explained in previous section.

As it is evident from the figure, majority of the workers are matched in terms of educational level in all the four countries. Spain and United Kingdom have the highest level of over education (19% approximately) followed by Germany and Sweden with almost 12% over educated workers. Incidence of under-education lies between 21 to 25% in all the countries except Spain where incidence of under-education is as low as 16%. Overall, UK is a country with maximum level of average mismatch during the period of 1999 to 2007. The estimates are quiet consistent with that of the figures of the Council of the European Union report, 2013.

Figure 2.2: Yearly relative change in percentage of over educated, matched and under educated workers between the years 1999 and 2007



Note: A worker is overeducated, matched or undereducated when her/his own level of education is, respectively, higher, equal or lower than the one required for her/his job.

Source: Author's own calculation from the JOBS database.

However, Figure 2.1 does not tell us the changes in these three categories over the year. Figure 2.2 depicts the relative change in percentage share of over educated, under educated and matched workers between the years 1999 and 2007. Clearly, Spain and UK have experienced substantial rate of increase in the absolute number of over educated workers during this period. The incidence of under education has a negative rate of growth in all the countries. UK is the country with highest rate of growth in over-educated workers followed by Spain.

One might argue that the educational distribution of the respective country will have influence on its over-education. Table 2.3 presents the changes between the year 1999 and 2007 in all the control variables used in the regression. It shows that all the countries have nearly half of the labour market population holding medium level of education except Spain. Spain has almost equal share of workers (around 40%) with low (primary and elementary) and high (tertiary) levels of education; workers with medium level of education have the lowest share in Spain. In spite of the similar pattern in employment change pattern and in incidence of over-education, Spain and UK have very different educational distribution in their respective labour markets. However, both the countries have experienced an increase in the share of medium and high level of education during this period. This increase along with the decrease in middle skilled routine jobs may have contributed to the incidence of over-education in the low-skill jobs. Germany and Sweden show very similar educational distribution in their labour markets during this period. Both the countries have nearly 60 percent of employed population with medium level of education.

Among all other job level characteristics, Spain has the lowest share of female workers and highest share of young workers (in the age group 15 to 39) employed in these jobs as compared to other three countries. Sweden is the country with highest share of aged population (almost 20 percent in age group 55 and above) employed. Though the average share of immigrants is high in Germany during this period (8.6%), Spain and UK have experienced huge increase in the share of immigrants in 2007 as compared to 1999 in their respective workforce. This can be another reason behind the increase in low-skill non-routine manual jobs and the high incidence of over-education in these jobs in Spain and UK.

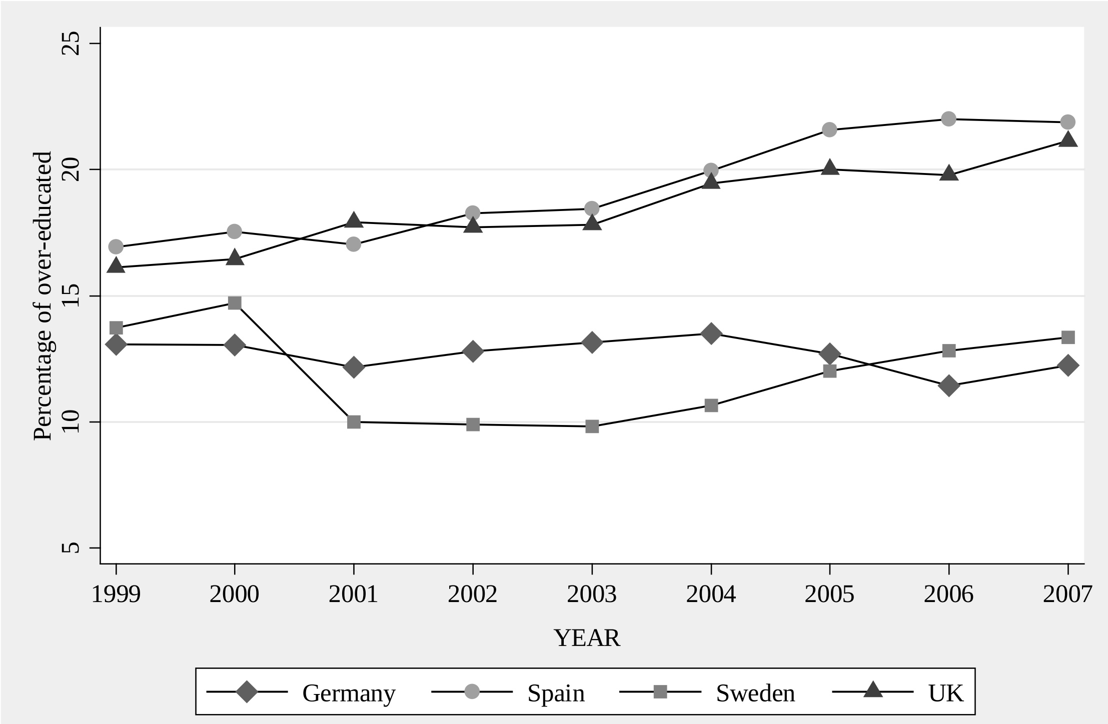
Table 2.2 Changes in job characteristics between the year 1999 and 2007

	Germany			Spain			Sweden			United Kingdom		
	1999	2007	change	1999	2007	change	1999	2007	change	1999	2007	change
Percentage of workers –												
Over-educated	13.1	12.2	-0.9	16.9	21.9	5.0	13.7	13.4	-0.3	16.1	21.1	5.0
Male	65.4	64.6	-0.8	72.8	66.9	-5.9	63.8	64.1	0.3	65.8	66.6	0.8
Female	34.6	35.4	0.8	27.2	33.1	5.9	36.2	35.9	-0.3	34.2	33.4	-0.8
Age group 15-24 yrs.	7.6	8.6	1.0	11.1	8.6	-2.5	7.4	9.5	2.1	13.4	11.3	-2.1
25- 39 yrs.	40.3	31.1	-9.2	45.7	45.4	-0.3	37.0	32.2	-4.8	40.8	33.7	-7.1
40-54 yrs.	37.7	44.1	6.4	33.7	34.4	0.7	38.3	36.5	-1.8	32.3	36.3	4.0
55-64 yrs.	13.2	14.5	1.3	8.9	11.0	2.1	16.3	20.0	3.7	11.4	16.0	4.6
65 and above	1.2	1.8	0.6	0.6	0.6	0.0	0.9	1.9	1.0	2.0	2.7	0.7
Low education	18.6	15.9	-2.7	44.1	37.0	-7.1	24.0	17.5	-6.5	33.5	24.7	-8.8
Medium education	55.6	59.2	3.6	20.6	22.6	2.0	49.0	57.8	8.8	40.6	45.9	5.3
High education	25.9	25.0	-0.9	35.3	40.4	5.1	27.0	24.7	-2.3	26.0	29.4	3.4
Native	91.9	91.3	-0.6	98.3	91.9	-6.4	96.3	96.0	-0.3	98.0	93.3	-4.7
Migrant	8.1	8.7	0.6	1.7	8.1	6.4	3.7	4.0	0.3	2.0	6.7	4.7
Employee	89.9	89.6	-0.3	86.8	86.0	-0.8	88.4	88.4	0.0	90.8	89.2	-1.6
Self-employed	9.6	9.7	0.1	12.3	13.1	0.8	11.2	11.3	0.1	8.7	10.4	1.7
Family workers	0.5	0.7	0.2	0.9	0.9	0.0	0.5	0.3	-0.2	0.5	0.4	-0.1
Fill time	84.7	78.8	-5.9	93.6	91.5	-2.1	83.5	82.8	-0.7	82.7	82.9	0.2
Part time	15.3	21.2	5.9	6.4	8.5	2.1	16.5	17.3	0.8	17.3	17.1	-0.2

Source: Author's own calculation from the JOBS database.

As the main focus of this paper is to study over-education, I present the incidence of over-education across the years in the next figure (Figure 2.3). It gives a similar picture of highest incidence of over-education in Spain and UK throughout the years. The increasing incidence of over-education in Spain and UK is clearer from this figure as it increases from around 16 percent in 1999 to over 20 percent in 2007.

Figure 2.3: Incidence of over-education across the years in four countries



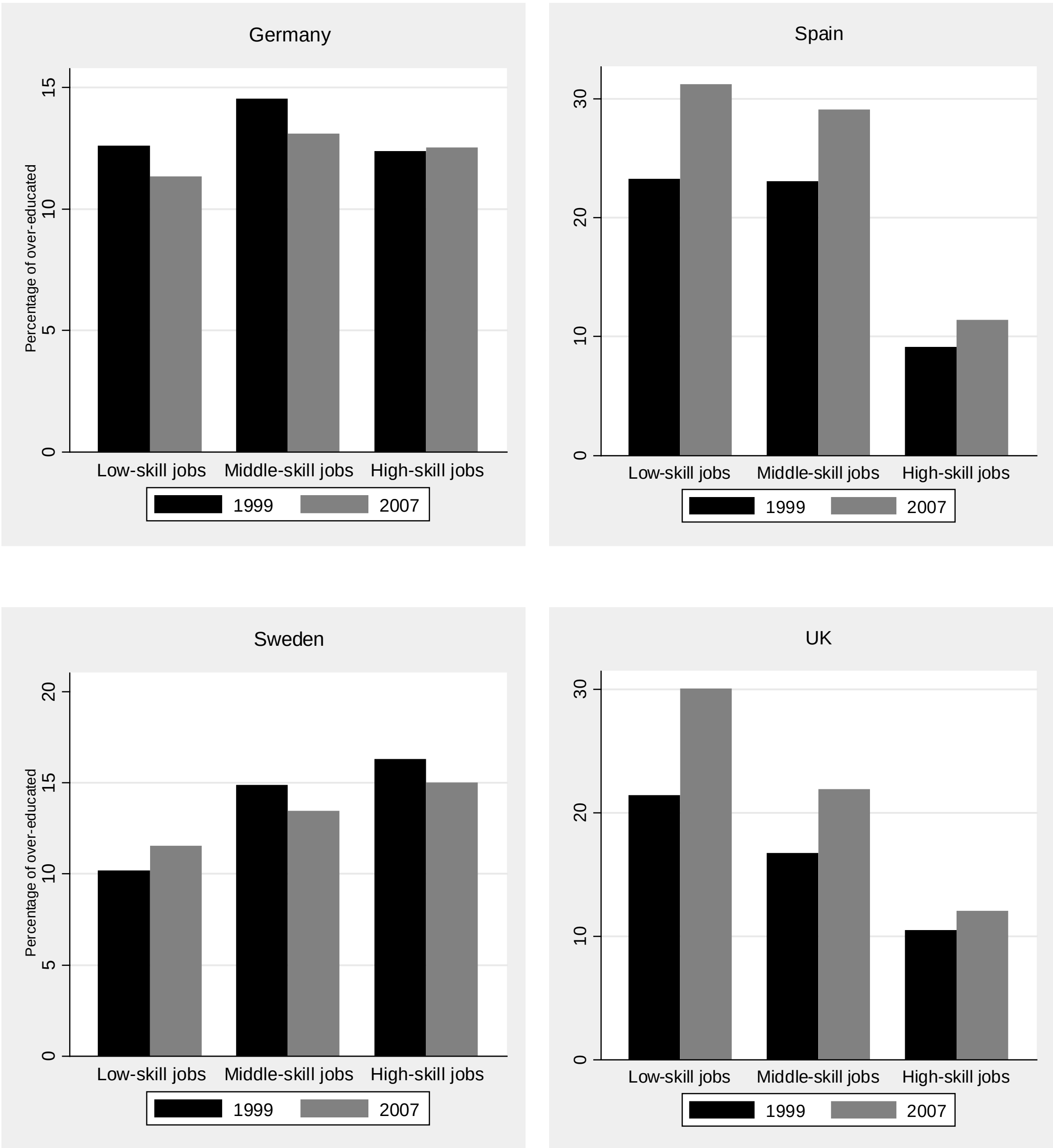
Note: A worker is overeducated, matched or undereducated when her/his own level of education is, respectively, higher, equal or lower than the one required for her/his job.

Source: Author’s own calculation from the JOBS database.

2.5.2 Incidence of over-education across skill-based and task-based job categories

One of the main objectives of this paper is to investigate if there is any association between technological change and the incidence of over-education. To investigate this I look at the percentage of over-educated workers across skill-based and task-based job categories. Figure 2.4 and Figure 2.5 present the average level of over-education across job types for the year 1999 and 2007. The figures show high incidence of over-education among workers in *low-skill* jobs and *non-routine manual* jobs in Spain and UK. On the other hand, Germany and Sweden have more over-educated workers in *middle-skill* and *high-skill* jobs (Figure 4), and in *analytical* jobs (Figure 5). As shown earlier, employment has expanded during this period in the non-routine manual jobs which are mostly interpersonal service jobs in both Spain and UK. Whereas, some routine jobs like office clerks and office assistants have declined in both the countries during the same time. The decline in employment in middle skilled routine (clerical and office assistant) jobs might force middle skilled workers to take employment in the low skill interpersonal services. This situation can result in creating more over-educated workers in the low skill jobs in Spain and UK.

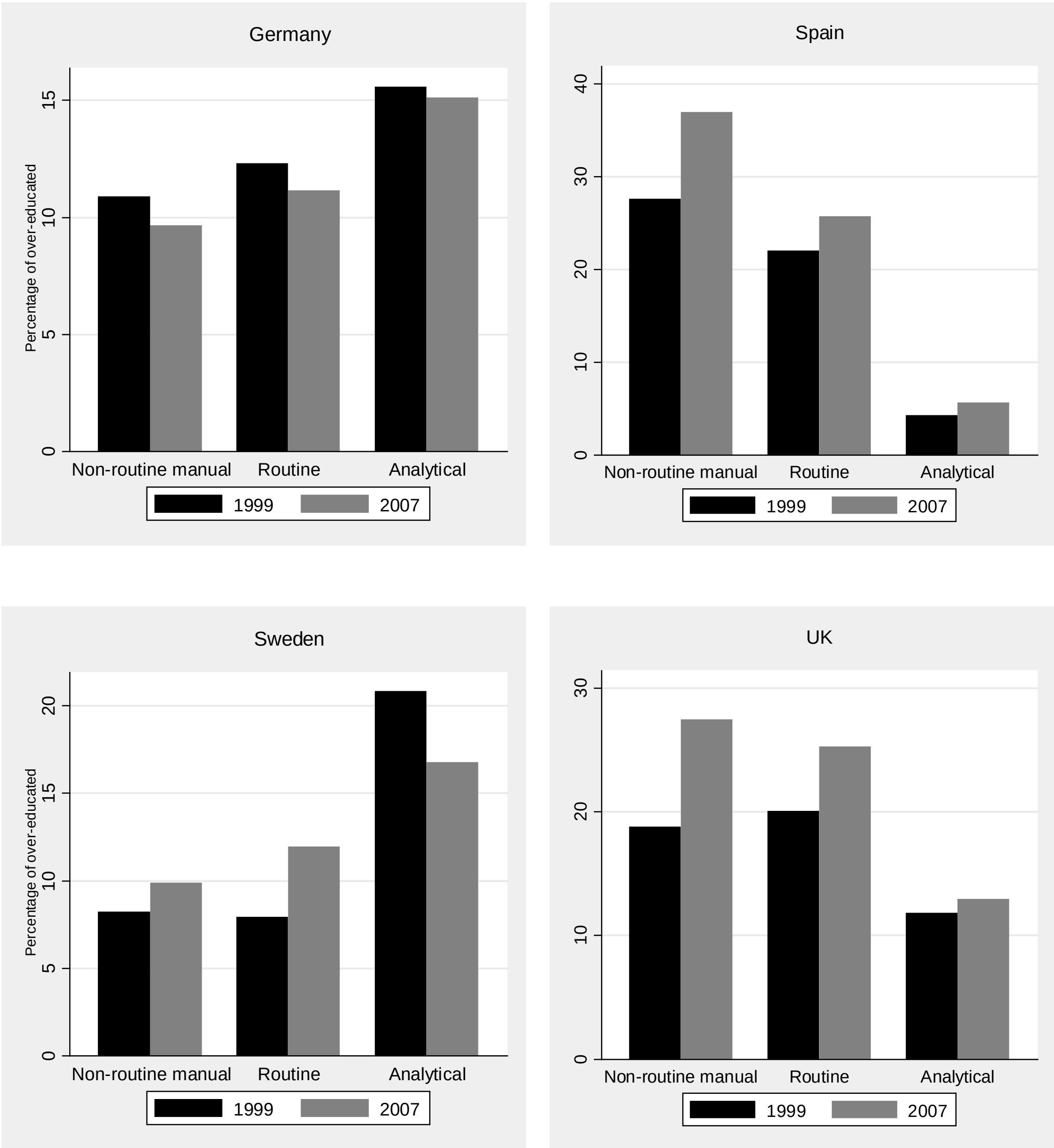
Figure 2.4 Percentage of over educated workers across skill-based job categories in 1999 and 2007



Note: A worker is overeducated, matched or undereducated when her/his own level of education is, respectively, higher, equal or lower than the one required for her/his job. Jobs are grouped into *Low-skill*, *Middle-skill* and *High-skill* jobs based on the median earnings of jobs in the year 2002.

Source: Author's own calculation from the JOBS database.

Figure 2.5 Percentage of over educated workers across task-based job categories in 1999 and 2007



Note: A worker is overeducated, matched or undereducated when her/his own level of education is, respectively, higher, equal or lower than the one required for her/his job. The task-based job categories – *Non-routine manual*, *Routine* and *Analytical* – are based on the routine task intensity index measured by Goos et al. (2014). The two digit International Standard Classification of Occupations, 1988 have been grouped into these three task-based categories.

Source: Author's own calculation from the JOBS database.

However, so far these arguments are based on one to one association between different type of jobs and incidence of over-education without looking at any other job characteristics. It might be possible that certain jobs are associated with more over-education because they have different gender composition or age composition or more immigrants; to investigate these possibilities I estimate multivariate regression models in the next section.

2.5.3 Regression results

The results of the pooled and job fixed effects regressions are presented respectively in Table 2.4 and 2.5 for each of the four countries.[31] The results vary across countries as well as between the two specifications. The regression equations include skill-based and task-based job categories in separate models, along with other explanatory factors. To account for any association between gender composition of employees and the extent of over-education, I include the share of female workers in a job as an explanatory variable in the regression. Similarly, there is evidence in the literature (Sanroma, 2008; Fernández and Ortega, 2008; Dell'Aringa and Pagani, 2011) that in some countries, migrants and self-employed workers are more likely to be overeducated than natives and salaried employees respectively. Concentration of migrants or self-employed in certain jobs may again lead to more over-education in those jobs although it is not entirely attributable to the job skill or its task content. Therefore, share of migrants and share of self-employed workers are also controlled in the regression. Since the incidence of over-education in a job is a function of the educational composition of that job, I include share of workers with high, medium and low levels of education. This analysis also controls for the type of employment by including the share of full time workers in the job. Time fixed effects are also included in the regression.

The results from the pooled regressions reported in Table 2.4 show that *middle-skill* jobs have significantly higher share of over-educated workers as compared to *low-skill* jobs in Germany and Sweden. Similarly, *analytical* jobs have significantly higher incidence of over-education as compared to *non-routine manual* jobs in both Germany and Sweden. On the contrary, Spain and UK have less share of over-educated workers in *middle-skill* and *high-skill* jobs as compared to *low-skill* jobs; the differences are significant except the one of middle-skill jobs in Spain. The results for task-based categories also show similar trends

[31] A summary table showing mean and standard deviation of dependent and all the explanatory variables are presented in Appendix Table 2.A1.

for Spain and UK. The results are consistent with the descriptive results discussed in the earlier section.

Table 2.3 Results from pooled regressions (dependent variable: share of over-educated workers)

	Germany		Spain		Sweden		UK	
VARIABLES	Skill-based	Task-based	Skill-based	Task-based	Skill-based	Task-based	Skill-based	Task-based
Female	0.065***	0.048***	-0.120***	-0.057***	0.001	0.007	-0.025	0.016
	(0.017)	(0.018)	(0.022)	(0.018)	(0.018)	(0.019)	(0.020)	(0.023)
25- 39 yrs.	-0.111***	-0.126***	0.011	0.041	0.031	0.006	-0.040	-0.056*
	(0.039)	(0.040)	(0.034)	(0.031)	(0.037)	(0.037)	(0.032)	(0.032)
40-54 yrs.	-0.123***	-0.146***	-0.022	0.013	0.010	-0.022	-0.090***	-0.102***
	(0.039)	(0.040)	(0.034)	(0.031)	(0.032)	(0.031)	(0.033)	(0.032)
55-64 yrs.	-0.102**	-0.116**	-0.052	0.004	0.027	-0.000	-0.038	-0.040
	(0.045)	(0.047)	(0.038)	(0.033)	(0.035)	(0.035)	(0.041)	(0.041)
65 and above	-0.136**	-0.118	-0.053	0.064	0.121*	0.118*	-0.147**	-0.143**
	(0.069)	(0.083)	(0.085)	(0.083)	(0.066)	(0.071)	(0.059)	(0.059)
Migrants	-0.043	-0.029	0.081**	0.020	-0.051	-0.044	0.014	0.048
	(0.032)	(0.034)	(0.037)	(0.035)	(0.040)	(0.040)	(0.057)	(0.053)
Medium education	0.014	-0.002	0.259***	0.360***	0.049**	0.029	-0.036	-0.055**
	(0.024)	(0.025)	(0.035)	(0.038)	(0.021)	(0.019)	(0.026)	(0.026)
High education	0.113***	-0.006	-0.078***	0.206***	0.153***	0.074**	-0.046	-0.002
	(0.035)	(0.036)	(0.027)	(0.036)	(0.037)	(0.037)	(0.031)	(0.032)
Self-employed	0.144***	0.110***	0.092***	0.283***	0.084***	0.045	-0.030	0.031
	(0.028)	(0.031)	(0.033)	(0.037)	(0.029)	(0.028)	(0.030)	(0.032)
Family workers	-0.026	0.011	-0.099	-0.076	0.023	0.013	0.052	0.086
	(0.069)	(0.081)	(0.104)	(0.095)	(0.074)	(0.075)	(0.130)	(0.133)
Full time	0.003	-0.015	-0.087**	-0.035	-0.037	-0.048*	0.009	0.011
	(0.027)	(0.027)	(0.039)	(0.032)	(0.027)	(0.027)	(0.032)	(0.032)
Mid-skill jobs	0.015*		-0.018		0.021*		-0.065***	
	(0.008)		(0.017)		(0.012)		(0.017)	
High-skill jobs	-0.039**		-0.135***		-0.004		-0.142***	
	(0.016)		(0.023)		(0.017)		(0.021)	
Routine cognitive		0.007		-0.118***		0.002		-0.029
		(0.010)		(0.019)		(0.012)		(0.018)
Analytical		0.045***		-0.402***		0.052***		-0.129***
		(0.016)		(0.027)		(0.016)		(0.019)
Constant	0.173***	0.224***	0.318***	0.199***	0.071*	0.120***	0.314***	0.289***
	(0.047)	(0.048)	(0.046)	(0.038)	(0.037)	(0.037)	(0.042)	(0.043)
Observations	7,622	7,424	6,504	6,369	4,854	4,764	7,091	6,876
R-squared	0.062	0.055	0.219	0.400	0.062	0.068	0.089	0.084

Robust standard errors clustered at the job level are in the parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: Reference categories are: Share of male, share of workers of age group 15- 24 years, share of native workers, share of workers with low level education, share of employees, share of part time workers, dummy for low-skill jobs and dummy for non-routine manual jobs. Time fixed effects are included in all the regressions but not reported in table.

Jobs are grouped into *Low-skill*, *Mid-skill* and *High-skill* jobs based on the median earnings of jobs in the year 2002. The task based job categories – *Non-routine manual*, *Routine* and *Analytical* – are based on the routine task intensity index measured by Goos et al. (2014).

The pooled regression does not take into account the fact that *high-skill* jobs or *analytical* jobs can be high skilled by nature and so will require high level of education. This can make these jobs less prone to incidence of over-education. Controlling for job-fixed effects in the model would allow it to exploit temporal variation in over-education within a job. I, therefore, estimate the job fixed effects regression allowing the time variable to vary across skill terciles and task-based occupation categories (results presented in Table 2.5). It gives the average change in over education across the skill-based and task-based job categories during this period after controlling for job fixed effects along with all other explanatory factors mentioned earlier. The main results are basically the same as we have seen in Table 2.5, except for Sweden where the differences become insignificant after controlling for job-fixed effects. The negative and significant coefficients of middle-skill and high-skill as well as routine cognitive and analytical jobs in the UK and Spain confirm that incidence of over-education is not only highest in low-skill and non-routine manual jobs but also increasing significantly over time in these jobs compared to their counterparts. Though, the coefficient is not significant for middle-skill jobs in Spain.

Among other factors, higher share of female workers is significantly associated with higher share of over educated workers in Germany, but it has a negative association with the share of over educated workers in Spain. However the coefficients are not significant once the job fixed effects are controlled in the second specification. This may imply gender specific job segregation across countries.

I also find that the share of self-employed has significant positive association with the share of over-educated workers in all the countries except UK; though the significance disappears in Sweden once the job fixed effects are controlled. Dolton (2001) finds similar result for UK in his study on over-education of graduate labour market. In his individual

Table 2.4 Results from job fixed effects regressions (dependent variable: share of over-educated workers)

	Germany		Spain		Sweden		UK	
VARIABLES	Skill-based	Task-based	Skill-based	Task-based	Skill-based	Task-based	Skill-based	Task-based
Female	-0.014	-0.018	0.000	-0.000	-0.031*	-0.030*	-0.013	-0.015
	(0.012)	(0.013)	(0.015)	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)
25- 39 yrs.	-0.004	-0.001	0.001	0.002	0.024	0.028	-0.001	-0.003
	(0.015)	(0.015)	(0.023)	(0.023)	(0.026)	(0.027)	(0.020)	(0.020)
40-54 yrs.	0.007	0.011	0.007	0.008	0.033	0.037	-0.003	-0.010
	(0.016)	(0.016)	(0.022)	(0.022)	(0.026)	(0.027)	(0.020)	(0.020)
55-64 yrs.	0.008	0.014	0.005	0.008	0.043	0.046	0.017	0.012
	(0.021)	(0.022)	(0.024)	(0.025)	(0.031)	(0.031)	(0.024)	(0.025)
65 and above	-0.062***	-0.050*	0.004	0.008	0.101***	0.113***	-0.073	-0.068
	(0.024)	(0.027)	(0.045)	(0.046)	(0.036)	(0.036)	(0.049)	(0.050)
Migrants	0.000	0.002	0.024	0.018	-0.009	-0.010	0.023	0.033
	(0.013)	(0.013)	(0.021)	(0.021)	(0.035)	(0.036)	(0.027)	(0.027)
Medium education	0.091***	0.093***	0.592***	0.583***	0.108***	0.107***	0.304***	0.288***
	(0.023)	(0.024)	(0.036)	(0.037)	(0.025)	(0.025)	(0.031)	(0.032)
High education	0.738***	0.724***	0.699***	0.696***	0.776***	0.774***	0.721***	0.729***
	(0.037)	(0.039)	(0.035)	(0.035)	(0.044)	(0.044)	(0.040)	(0.042)
Self-employed	0.056**	0.057**	0.044**	0.043*	-0.003	-0.002	-0.000	-0.004
	(0.024)	(0.025)	(0.022)	(0.022)	(0.019)	(0.019)	(0.023)	(0.024)
Family workers	-0.017	-0.018	0.128	0.124	-0.058	-0.061	0.087	0.083
	(0.032)	(0.034)	(0.088)	(0.086)	(0.073)	(0.073)	(0.077)	(0.078)
Full time	-0.012	-0.018	-0.026	-0.030	0.026*	0.025*	-0.017	-0.015
	(0.013)	(0.013)	(0.021)	(0.021)	(0.014)	(0.014)	(0.020)	(0.021)
	(0.004)	(0.004)	(0.008)	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)
Time*Mid-skill jobs	0.000		-0.001		-0.001		-0.004***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Time*High-skill jobs	0.002**		-0.005***		0.001		-0.005***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Time*Routine cognitive		0.001		-0.007***		0.000		-0.003**
		(0.001)		(0.001)		(0.001)		(0.001)
Time*Analytical		0.002**		-0.007***		-0.001		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Constant	-0.103***	-0.100***	-0.182***	-0.178***	-0.163***	-0.167***	-0.129***	-0.121***
	(0.022)	(0.023)	(0.031)	(0.032)	(0.036)	(0.037)	(0.033)	(0.034)
Observations	7,622	7,424	6,504	6,369	4,854	4,764	7,091	6,876
R-squared	0.624	0.607	0.597	0.595	0.620	0.620	0.459	0.469
Number of jobs	847	825	723	708	540	530	790	766

Robust standard errors clustered at the job level are in the parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: Reference categories are: Share of male, share of workers of age group 15- 24 years, share of native workers, share of workers with low level education, share of employees, share of part time workers, dummy for low-skill jobs and dummy for non-routine manual jobs. Time fixed effects are included in all the regressions but not reported in table. Jobs are grouped into *Low-skill, Middle-skill* and *High-skill* jobs based on the median earnings of jobs in the year 2002. The task based job categories – *Non-routine manual*, *Routine* and *Analytical* – are based on the routine task intensity index measured by Goos et al. (2014).

level analysis he finds no effect of self-employment status on being over-educated for graduate workers while controlling for other factors like occupational classification.

The increase in share of older workers is mostly associated with a decrease in share of over educated workers. Having more migrants in a job increases the incidence of over education only in Spain; the difference becomes insignificant once job-fixed effects are controlled. There is evidence in the literature which shows that migrants are more likely to be over educated. The argument is that migrants coming from a different country face difficulties in finding a proper job mostly because of the lower value on their qualification put by the local employer, and the language and cultural difference with the country they come from; hence they take up jobs which require lower education than their own education (Piracha and Vadean, 2012). But this hypothesis again varies across countries as immigration to a particular country depends on the institutions, language and culture of that country.

2.6 CONCLUSION

This paper investigates if the incidence of over-education is associated with technological progress and the concurrent structural change in employment. Using data from European Labour Force Survey, this paper comparatively analyses the incidence of over-education in two sets of countries with different patterns in employment change: countries with employment polarization – Spain and UK, and countries with employment upgrading – Germany and Sweden. The results suggest that as the middle-skill routine jobs decline in its employment share and the education level increases in all the countries, relatively high educated workers opt for low-skill manual jobs. This happens in countries where employment in both high-skill and low-skill jobs increases at the cost of reduction in middle-skill jobs which are mostly routine intensive. Consequently, incidence of over-education seems to be increasing in these countries, particularly in low-skill non-routine manual jobs.

The paper finds high and increasing incidence of over-education in low-skill jobs which are mostly non-routine manual by nature (personal and protective service jobs, sales and service elementary jobs etc.) in Spain and UK. Whereas, Germany and Sweden have higher incidence of over-education in middle-skill (mostly clerical) and high-skill (professional and managerial) jobs. This has serious implication to the society as over-education has wage penalty as well as negative effect on one's productivity. SBTC and TBTC are not only leading to increasing wage inequality by destroying the middle class but also affecting the productivity of some workers by pushing them into jobs which require lower education than their own. The policy response should be to help people gain the skills that technology complements, and not those that technology can emulate easily. These skills are not only difficult for technology to replace, but also for formal education system to provide, leaving many workers unprepared for the modern labour market.

2.7 APPENDIX

Table 2.A1 Summary statistics

	Germany		Spain		Sweden		UK	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd
Share of over-educated	0.127	0.163	0.193	0.233	0.119	0.176	0.185	0.217
Male share	0.649	0.285	0.691	0.290	0.637	0.302	0.664	0.303
Female share	0.351	0.285	0.309	0.290	0.363	0.302	0.336	0.303
Share in 15-24 yrs. age group	0.082	0.104	0.101	0.141	0.088	0.131	0.122	0.145
Share in 25-39 yrs. age group	0.359	0.168	0.452	0.221	0.345	0.198	0.368	0.196
Share in 40-54 yrs. age group	0.416	0.168	0.340	0.205	0.368	0.197	0.349	0.190
Share in 55-64 yrs. age group	0.130	0.114	0.101	0.125	0.184	0.154	0.140	0.139
Share in 65 & above age group	0.014	0.042	0.006	0.030	0.014	0.057	0.022	0.061
Share of national workers	0.914	0.112	0.955	0.103	0.960	0.076	0.962	0.080
Share of migrants	0.086	0.112	0.045	0.103	0.040	0.076	0.038	0.080
Share of low educated workers	0.167	0.174	0.402	0.322	0.205	0.204	0.280	0.239
Share of medium educated workers	0.578	0.230	0.213	0.184	0.560	0.245	0.445	0.225
Share of high educated workers	0.255	0.270	0.385	0.335	0.235	0.284	0.274	0.279
Share of employees	0.900	0.193	0.862	0.238	0.890	0.200	0.898	0.176
Share of self-employed	0.094	0.189	0.129	0.234	0.106	0.195	0.098	0.172
Share of family workers	0.006	0.035	0.009	0.036	0.004	0.034	0.004	0.024
Share of part-time workers	0.183	0.211	0.072	0.133	0.160	0.189	0.170	0.208
Share of full-time workers	0.817	0.211	0.928	0.133	0.840	0.189	0.830	0.208
time1	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.314
time2	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.314
time3	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.314
time4	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.314
time5	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.314
time6	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.315
time7	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.315
time8	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.315
time9	0.111	0.314	0.111	0.314	0.111	0.314	0.111	0.315
Share in low-skill jobs	0.364	0.481	0.282	0.450	0.352	0.478	0.270	0.444
Share in mid-skill jobs	0.294	0.456	0.275	0.447	0.278	0.448	0.429	0.495
Share in high-skill jobs	0.342	0.475	0.443	0.497	0.370	0.483	0.301	0.459
Share in non-routine manual job	0.372	0.483	0.388	0.487	0.345	0.476	0.383	0.486
Share in routine jobs	0.212	0.409	0.203	0.403	0.208	0.406	0.209	0.407
Share in analytical jobs	0.416	0.493	0.408	0.492	0.447	0.497	0.408	0.491
Observation	7,622		6,504		4,860		7,091	

Note: A worker is overeducated when her/his own level of education is higher than the one required for her/his job. Jobs are grouped into *Low-skill*, *Mid-skill* and *High-skill* jobs based on the median earnings of jobs in the year 2002. The task based job categories – *Non-routine manual*, *Routine* and *Analytical* – are based on the routine task intensity index measured by Goos et al. (2014).

Table 2.A2: Three biggest jobs from each of the skill-based job categories

Job code	Occupation (ISCO-2 digit)	Industry (NACE 2 digit)
Low-skill (Tercile 1)		
5155	Personal and protective services workers	Hotels and restaurants
5185	Personal and protective services workers	Health and social work
5252	Models, salespersons and demonstrators	Retail trade, except of motor vehicles and motorcycles
Middle-skill (Tercile 2)		
4175	Office clerks	Public administration and defence
4185	Office clerks	Health and social work
7145	Extraction and building trades workers	Construction
High-skill (Tercile 3)		
2380	Teaching professionals	Education
2285	Life science and health professionals	Health and social work
3285	Life science and health associate professionals	Health and social work

Note: These are the biggest jobs common in all the four countries which belong to the same tercile of wage rankings.

Table 2.A3: Occupations in task-based categories

Occupation titles under broad category	ISCO-1988 2 digit codes	Routine Task Intensity Index
1. Non-routine manual		
Personal and protective services workers	51	−0.60
Models, salespersons and demonstrators	52	0.05
Extraction and building trades workers	71	−0.19
Metal, machinery and related trades workers	72	0.46
Drivers and mobile plant operators	83	−1.50
Sales and services elementary occupations	91	0.03
Agricultural, fishery and related labourers	92	n.a.
Labourers in mining, construction, manufacturing and transport	93	0.45
2. Routine (cognitive and manual)		
Office clerks	41	2.24
Customer services clerks	42	1.41
Skilled agricultural and fishery worker	61	n.a.
Other craft and related trades workers	74	1.24
Stationary plant and related operators	81	0.32
Machine operators and assemblers	82	0.49
3. Analytical		
Corporate managers	12	−0.75
Managers of small enterprises	13	−1.52
Physical, mathematical and engineering	21	−0.82
Life science and health professionals	22	−1.00
Teaching professionals	23	n.a.
Other professionals	24	−0.73
Physical and engineering science associate professional	31	−0.40
Life science and health associate professional	32	−0.33
Teaching associate professionals	33	n.a.
Other associate professionals	34	−0.44

Note: The Routine Task Intensity Index is calculated by Goos et al. (2014).

Table 2.A4: Marginal effects on the share of over-educated workers estimated from fractional multinomial logit

	Germany		Spain		Sweden		UK	
VARIABLES	Skill-based	task-based	Skill-based	task-based	Skill-based	task-based	Skill-based	task-based
Female	0.068***	0.049***	-0.110***	-0.050***	0.003	0.011	-0.022	0.018
	(0.016)	(0.018)	(0.023)	(0.019)	(0.018)	(0.019)	(0.019)	(0.022)
25- 39 yrs.	-0.104***	-0.115***	0.021	0.040	0.042	0.013	-0.033	-0.047*
	(0.034)	(0.034)	(0.033)	(0.030)	(0.039)	(0.039)	(0.029)	(0.028)
40-54 yrs.	-0.122***	-0.139***	0.002	0.026	0.022	-0.016	-0.077***	-0.088***
	(0.034)	(0.034)	(0.030)	(0.029)	(0.036)	(0.035)	(0.030)	(0.029)
55-64 yrs.	-0.100**	-0.107**	-0.018	0.023	0.037	0.004	-0.022	-0.023
	(0.041)	(0.042)	(0.037)	(0.033)	(0.039)	(0.039)	(0.036)	(0.036)
65 and above	-0.132**	-0.111	-0.023	0.192*	0.102*	0.091*	-0.133**	-0.124**
	(0.067)	(0.073)	(0.120)	(0.103)	(0.053)	(0.055)	(0.062)	(0.060)
Migrants	-0.054	-0.041	0.076**	0.016	-0.070	-0.058	0.034	0.069
	(0.036)	(0.038)	(0.031)	(0.030)	(0.057)	(0.056)	(0.052)	(0.048)
Medium education	-0.017	-0.040	0.303***	0.340***	0.022	-0.008	-0.027	-0.045*
	(0.026)	(0.026)	(0.029)	(0.032)	(0.026)	(0.024)	(0.024)	(0.023)
High education	0.081**	-0.036	-0.142***	0.131***	0.107***	0.026	-0.044	0.012
	(0.033)	(0.035)	(0.032)	(0.037)	(0.033)	(0.033)	(0.032)	(0.034)
Self-employed	0.124***	0.090***	0.099***	0.339***	0.074***	0.040*	-0.030	0.038
	(0.020)	(0.022)	(0.030)	(0.040)	(0.023)	(0.023)	(0.030)	(0.035)
Family workers	-0.027	0.013	-0.078	-0.141	0.041	0.028	0.080	0.105
	(0.067)	(0.076)	(0.111)	(0.114)	(0.066)	(0.067)	(0.116)	(0.122)
Full time	0.003	-0.016	-0.076**	-0.030	-0.038	-0.048*	0.009	0.015
	(0.026)	(0.025)	(0.037)	(0.033)	(0.026)	(0.026)	(0.029)	(0.029)
Mid-skill jobs	0.015*		-0.016		0.025*		-0.055***	
	(0.008)		(0.013)		(0.013)		(0.014)	
High-skill jobs	-0.037**		-0.137***		0.004		-0.148***	
	(0.017)		(0.023)		(0.018)		(0.022)	
Routine		0.012		-0.081***		0.005		-0.027*
		(0.011)		(0.014)		(0.015)		(0.016)
Analytical		0.048***		-0.431***		0.060***		-0.140***
		(0.015)		(0.031)		(0.016)		(0.021)
Observations	7,622	7,424	6,504	6,369	4,854	4,764	7,091	6,876

Robust standard errors clustered at the job level are in the parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: Reference categories are: Share of male, share of workers of age group 15- 24 years, share of native workers, share of workers with low level education, share of employees, share of part time workers, dummy for low-skill jobs and dummy for non-routine manual jobs. Time fixed effects are included in all the regressions but not reported in table.

Chapter 3

Employment Change in Occupations in Urban India: Implications for Wage Inequality

3.1 INTRODUCTION

Over the last two decades employment in middle-skilled jobs has been squeezing in many developed countries particularly in the USA and UK (Acemoglu and Autor, 2011; Goos, Manning and Salomons, 2009). For the overall labour force, the employment change from the end of the 1980s to the end of the 2000s is characterized by a U-shape pattern, i.e. employment increases in the high-skill jobs at the top and at the bottom but hardly at all in the middle of the skill distribution. This U-shaped pattern of employment change is termed as 'job polarization' by labour economists. Job polarization has often coincided with wage polarization – a decrease in wages in middle-skill jobs and an increase in wages in low-skill services and high-skill professional and managerial jobs (Acemoglu and Autor, 2011).

The main reason behind job polarization as discussed in the literature is continual technological progress which favours the high-skill workers in professional, managerial and technical jobs consequently raising their demand as well as their wages but adversely affects the middle-skill workers in clerical and production jobs. Clerical and production jobs are mostly routine and automated and thus easy for technology to emulate, consequently declining the employment share and wages. However, low-skill jobs which are heavily manual and require flexible use of brain, eyes, hands and legs and therefore hard to be replaced by technology, increase its employment share and returns over time (Acemoglu and Autor, 2011; Goos and Manning, 2007).[32] Most of the developed countries and some transition countries have been studied for the evidence of job polarization (Goos and Manning, 2007; Autor, Katz, and Kearney, 2006; Kupets, 2016).[33] However, developing countries still lack this kind of studies which is very interesting from the perspectives of both policymakers and academics.[34]

Our article contributes to this literature by analysing employment change and concurrent wage change patterns in India, which to our knowledge is the first investigation to focus on this increasingly important research area using Indian data. India is one of the largest emerging economies in the world with almost one-fifth of world's total population. Besides, the country has experienced a series of events starting from the 1950s right after its independence; among them the most important is the economic liberalisation in the 1990s. Trade liberalization in India culminated in the drastic tariff reductions on imports during the 90s. According to the prediction of Stolper–Samuelson (SS) theorem, economic liberalisation would raise the demand for and returns to the abundant factor of production—that is, unskilled labour in India like most less developed countries (LDC). On the contrary, Acemoglu (2003) describes how after trade liberalization in LDCs, increased capital goods imports can lead to a higher demand for skilled workers. In this context it is worth investigating if employment polarization has happened in India and how much it has contributed to the growing wage inequality in urban India.

Using detailed data on labour market activities from the household level survey of National Sample Survey Organisation (NSSO) for three subsequent decades starting from 1983-84 to 2011-12, this study tries to answer three questions: i) what is the pattern of employment change in the urban labour market of India– Polarized, upgrading or downgrading during

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[32] Some other studies find evidence that trade liberalisation has led to the decline in the middle skilled routine jobs in developed countries by shifting these jobs to China's manufacturing sector (Keller and Utar, 2016). Immigration has also been cited as an important factor behind polarization in USA as the immigrants supply low-skilled labour and thus are raising the employment share of low-skilled jobs (Wright and Dwyer, 2003; Oesch and Rodriguez-Menes, 2011).

[33] The patterns of employment change, though, varies depending on country and period of study. Some recent papers (Oesch and Rodriguez-Menes, 2011, Fernandez-Macias, 2012) have argued that in Europe polarization is just one pattern among at least three different types – polarization (a U-shaped pattern), upgrading (a monotonically upward rising pattern) and mid-upgrading (an inverted U-shaped pattern). But if the patterns are aggregated at the EU level, a pattern of asymmetric polarization is observed.

[34] Medina and Posso (2010) have analysed the labour markets of Brazil, Colombia and Mexico, and have found evidence of job polarization in Colombia and Mexico but not in Brazil. Gimpelson and Kapeliushnikov (2016) have found an upgrading employment change pattern in Russia.

the periods 1983 to 1993(1980s), 1993 to 2005 (1990s) and 2005 to 2012 (2000s)? ii) Does the pattern vary before and after economic liberalisation in India? iii) What is the implication of this employment change in explaining wage inequality in urban India?

Our main findings can be summarized as follows: I find evidence of job polarization in urban India during the post-reform period. Between 2005 and 2012 the shares of employment in low- and high-paid jobs increased respectively by 5 and 8 percentage points, and the share of employment in middle-paid jobs decreased by 13 percentage points. Job polarisation occurred primarily in the 1990s and 2000s, whereas in the 1980s changes in the composition of employment were more consistent with general upskilling. An important question which researchers seek to answer is whether technological change has been purely skill-biased, raising demand for skilled versus unskilled workers, or it has been task-biased changing the relative demand for workers according to their skills to perform routine tasks, causing job polarisation.[35]

Our findings suggest that while routine occupations are shrinking during this period in urban India, the reduction does not seem to be the consequence of only task-biased technological change or automation. Unlike the developed countries, the decline in routine manual occupations in India seems to be more of a result of mechanisation in manufacturing industry while increase in non-routine occupations is a result of growing informal sector during the 90s and 2000s. Moreover, this process has led to subsequent reallocation between sectors. A shift-share analysis confirms this pattern by providing evidence of industrial shift as the main driver behind the decline in employment share in routine manual jobs during 1983 to 2012.Second, I also find wage polarization consistent with employment polarization particularly strong in the 1990s. These changes in the employment structure and in average earnings by occupation can explain the increase in earnings inequality that has taken place in urban India.

The rest of the article is organised as follows. Next section provides the background of this study followed by a discussion of earlier research in section 3.3. I present the data in section 4 and discuss the methodology used for the analysis in section 3.5. Section 3.6 discusses the results and section 3.7 concludes.

[35] For a vivid understanding of skill-biased technological change (SBTC) and task-biased technological change (TBTC) refer to Acemoglu and Autor (2011) and Fernandez-Macias and Hurley (2016).

3.2 BACKGROUND: URBANISATION IN INDIA

The Indian economy is going through a rapid process of urbanisation. Though the percentage of population living in urban cities is around 30 percent today, it has increased from less than 20 percent of its overall population in 1951. Number of people residing in urban areas has also increased from 25.8 million in 1901 to 285.3 million in 2001. There has been continual concentration of population in class I towns over the years (Datta, 2006).[36] According to the census 2011, urbanisation in India has been faster than it was expected. Urbanisation in India is perceived as a positive factor in the overall development as 62% of total GDP is attributable to urban sector (Bhagat 2011). Besides the employment in rural area is mostly dependent on agriculture (almost 3/4th of the rural employment) and the growth in real GDP has been consistently low in agriculture (Table 3.1 and Table 3.2).

Table 3.1: Growth in Real GDP (in %) per Annum

Period	Agriculture	Industry	Services	GDP
1950s	2.7	5.6	3.9	3.6
1960s	2.5	6.3	4.8	4
1970s	1.3	3.6	4.4	2.9
1980s	4.4	5.9	6.5	5.6
1990s	3.2	5.7	7.3	5.8
2000s	2.5	7.7	8.6	7.2
2011-12 to 2015-16 (NS)	1.7	5.5	8.9	6.5

Source: Estimated by Mahendra Dev (2016) for 2011-12 to 2015-16 based on Central Statistical Organization data.

Though employment in agriculture has declined substantially in both rural and urban location during 1983 to 2004-05, a large proportion of population (70%) is still employed in the agriculture in rural India. We, therefore, focus only on urban India for this study as the objective of this article is to analyse the employment change in different occupations, and 60 to 80 percent (in Table 3.1) of the workers in rural India are concentrated in only two occupations– *Cultivators* and *Agricultural labourers*. Given the thin employment in non-agricultural sector in rural India I limit this analysis only to the urban labour market.

[36] Class I towns in India are the ones which have a population of 100,000 or more (Census, 2011).

Table 3.2: Distribution of Workers across Broad Industry Sectors in Rural and Urban India: 1984 to 2012

	1983-'84 (%)		1993-'94(%)		2004-'05(%)		2011-'12(%)	
Industries	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
A-Agriculture, Hhunting, forestry	79.3	11.8	76.3	10.0	70.1	7.1	62.0	5.5
B-Fishing	0.4	0.4	0.4	0.4	0.4	0.3	0.4	0.4
C-Mining & quarrying	0.6	1.2	0.7	1.2	0.6	0.8	0.5	0.8
D-Manufacturing	6.9	26.8	7.7	25.6	8.2	23.8	8.5	23.3
E-Electricity, gas and water supply	0.2	1.0	0.2	1.1	0.2	0.7	0.2	0.8
F-Construction	2.0	5.0	2.7	6.8	5.5	8.5	11.4	9.7
G-Wholesale and retail trade	3.3	15.8	4.1	17.4	5.3	19.8	6.1	19.9
H-Hotels and restaurant	0.5	2.5	0.5	2.4	0.7	3.2	0.9	3.8
I-Transport, storage	1.3	8.9	1.7	8.5	2.8	9.2	3.3	8.8
J-Financial intermediary	0.1	1.6	0.2	2.2	0.3	2.2	0.4	2.6
K-Real estate, renting and business activities	0.1	1.3	0.1	1.5	0.3	3.3	0.5	5.2
L- Public administration	1.4	9.4	1.4	8.6	1.0	5.6	0.9	4.4
M-Education	1.3	4.0	1.3	4.2	1.8	5.1	2.3	5.6
N-Health and Social work	0.3	1.9	0.3	1.6	0.4	1.9	0.5	2.3
O-Other service sectors	2.4	8.5	2.4	8.6	2.5	8.5	2.1	7.2
Total	100	100	100	100	100	100	100	100

Source*:* Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status

3.3 A REVIEW OF EARLIER RESEARCH IN INDIA

Recent research documents that technological change has become a global phenomenon. In that regard, Berman, Somanathan and Tan (2005), and Unni and Rani (2004) investigate if skill-biased technological change (SBTC) was present in Indian labour market during the 80s and the 90s. They find that SBTC did in fact arrive in India in the 1990s. Using panel data from the Annual Survey of Industry (ASI) they show that while the 1980s was a period of falling skills demand, the 1990s showed generally rising demand for skills. According to them at least half of this increase in demand can be explained by two related factors – (1) increased output, and (2) SBTC. However, both the studies focus on the industries in India and do not answer the question of how the employment in specific jobs or occupations has been affected by SBTC (Berman, Somanathan and Tan, 2005; Unni and Rani, 2004).

In the New Industrial Policy of 1991 Government of India had announced to establish a National Renewal Fund (NRF). The objective of this fund was to provide safety net to the workers who were likely to be affected by the technological progress and modernisation in Indian industries. This again implies the presence of technological-upgradation in India during the 1990s. However, this policy was later abolished in 2000 due to its inadequate functioning of re-training and rehabilitation of jobless workers. Nagaraj (2004) in his study on organised manufacturing sector shows that 15 percent of workforce in this sector lost their jobs between the year 1995 and 2000-'01. He explains this job-loss as a result of NRF, a lack of labour law enforcement and introduction of information technology. The paper also highlights on how the extent of job losses are not reflected at the aggregate level as some other jobs are created at the same time particularly in the informal sector during late 90s and early 2000s. These jobs, as mentioned in this article, are mostly auxiliary services like transport, security, cleaning, and providing food which are non-routine manual works and require low skill.

In line with this literature, Ramaswamy and Agarwal (2013) and Mehrotra et al. (2014) discuss how non-agricultural industry sector, especially manufacturing, should expand more to absorb the low skilled young labour force in India in the near future. The World Development Report 2016 on "Digital Dividends" published by the World Bank analyses employment trends in both developed and developing countries in order to see displacement or automation of jobs by growing technological adoption. According to the report, the average decline in the share of routine employment has been 0.39 percentage points a year or 7.8 percentage points for the period since 1995. But the pace of labour market polarization is much slower than what is observed in developed countries (World Development Report 2016). The report also analyses the occupational employment change in India and finds polarizing employment trends for the period from 1995 to 2012.

Though very little research has so far focused on employment change and job polarization, there is a vast literature on economic liberalisation and wage inequality in developing countries particularly in urban India (Azam, 2012; Basu, 2006; Chamarbagwala, 2006; Milner et al. 2005; Kijima, 2004; Banerjee and Piketty, 2005; Bhalotra, 2002). All of these studies have analysed the periods of the 1980s or 1990s focusing on trade liberalisation. Acemoglu (2003) explains how after trade liberalization in LDCs, increased imports of capital goods can lead to a higher demand for skilled workers as a result of technological progress. This hypothesis is supported by Attanasio, Goldberg and Pavcnik (2004) for

Colombia and by Harrison and Hanson (1999) for the case of Mexico. Gorg and Strobl (2002) find an increase in the relative wages of skilled labour in Ghana which according to them is a result of SBTC brought by imports of technology-intensive capital goods. However, Pavcnik (2003) rejects the SBTC hypothesis for Chilean plants.

With a particular focus on globalisation and inequality in India, Basu (2006) in his article has pointed out the negative and positive effects of globalisation. According to his findings while the positive effects are enjoyed by the skilled end of the labour market which has access to technology, the negative effects are borne by the unskilled and illiterate section of the labour market. He argues that as the market opens up suddenly and fully, the prices of goods in poor countries will converge more rapidly toward prices in industrialized countries than the latter converge toward the former since a large share of the world's GDP comes from the industrialized countries (Basu, 2006). While he discusses whether technology favours skilled employment, his article does not really go into the details of employment change in different occupations as a result of technological progress.

Since the start of the economic reform in 1991, there have been serious concerns regarding the increasing income inequality in India. Kijima (2005) studies the reasons behind increasing wage inequality in urban India during the period from 1983 to 1999. This study found that: (1) Wage inequality in urban India started increasing before 1991; (2) The increase in wage inequality was mainly attributable to increases in the returns to skills; (3) The accelerating skill premium was due to increases in the demand for skilled labour. According to this article, the causes of wage inequality in urban India differed between the periods of 1980s and 1990s. He analyses the increasing wage inequality from the perspective of human capital (schooling and working experience) but ignores the occupational change and its impact on wages.

Milner et al. (2005), on the other hand, explore the roles of trade and technological change behind the rising wage inequality observed in Indian manufacturing following the 1991 trade policy reforms. Assuming endogeneity of price and technological change, they find that the rise in inequality post-reform is due only to technological change, and not price changes. Their results confirm the findings of Berman, Somanathan and Tan (2005), who argue that a part of the increase in the relative demand for skilled workers is due to SBTC. This finding is again demonstrated by Chamarbagwala (2006) who finds that increase in relative demand for skilled workers contributed to India's widening skill wage gap and narrowing gender wage differential during the two decades (80s and 90s) that coincide with the economic liberalization in the country (Chamarbagwala, 2006). According to this article the increase in demand for skilled labour was mostly due to skill upgrading within industries.

In a recent study Azam (2012) examines changes in the wage structure in urban India during the time periods 1983 to 2004-05 across the entire wage distribution using the Machado and Mata (2005) decomposition approach. He also breaks the two decades in two parts: 1983–1994 and 1993–2005 in order to capture any possible changes before and after economic liberalisation. He shows that real wages increased throughout the wage distribution during 1983–1993 and the increase was larger at higher quantiles; however, it increased more in the bottom and top end as compared to the middle of the wage distribution during 1993–2004 for male workers. But his paper does not explain the reason of this U-shaped wage change pattern during the latter period. While all these studies discuss skill-biased technological change and the composition of the workforce, they do not delve into analysing the change in employment across different occupations or jobs and its implications for wage inequality. This study substantially contributes to this debate of trade liberalisation, technological change and increasing wage inequality in urban India by providing a detailed analysis from an occupational perspective.

3.4 DATA

We use data from the Employment and Unemployment survey conducted by the National Sample Survey Organization (NSSO), Government of India. There are several rounds of Employment and Unemployment surveys in recent times conducted in almost every year, though the thick surveys are conducted once in every five years and are called quinquennial rounds. For this study I mainly use four quinquennial rounds of data from the year 1983-’84 (38^{th} round), 1993-’94 (50^{th} round), 2004-’05 (61^{st} round) and 2011-’12 (68^{th} round) as our main objective is to analyse the long run changes in employment (preferably at 10 years interval). However, to see some trends across the years, I also use the intermediate rounds from the year 1987-’88 (43^{rd} round), 1999-’00 (55^{th} round) and 2007-’08 (64^{th} round).

For simplicity, I will refer to the rounds by the initial year of the surveys, 1984, 1994, 2005 and 2012. Our main sample, thus, consists of four rounds of cross sectional survey data spanning over a period of almost three decades (28 years). This time period enables us to capture the trend in our results before (1984-1994), immediately after (1994- 2005) and decade after (2005- 2012) the trade liberalisation which was initiated in 1991.The Employment and Unemployment Survey design follows a stratified multi-stage random sampling and all units are assigned with adjusted sampling weights.[37]

The surveys collect socioeconomic and demographic information of households and individual members across all states except some remote and inaccessible pockets. Apart from the demographic characteristics, the surveys collect information on individual occupation, education, industry of employment, status of employment along with last weekly earnings. Moreover, the sample of the survey is representative at national level and therefore, provides a picture of overall labour market in urban India. On an average, there are 125 to 136 thousand individuals in the working age population (15-65) in each round with information on demographic characteristics. It is worth mentioning that the sampling strategies and questionnaires are quite similar across rounds and therefore, comparable.

3.5 METHODOLOGY

3.5.1 Occupational skill level

Defining occupational skill based on the complexity of the jobs or skill requirement to perform the job is one of the most important issues in studying employment change. The literature has grouped low-, middle-, and high-skill occupations in different ways and arrived mostly at the same results. Some studies have ranked them by initial average earnings or average education (e.g. Autor, Katz, and Kearney, 2006; Goos and Manning, 2007). [38] Alternatively, it has grouped managerial, professional, and technical occupations as *high-skill* or *non-routine cognitive*; sales, clerical, production, and operative occupations as *middle-skill* or *routine manual and cognitive*; and service and elementary occupations as *low-skill* or *non-routine manual* occupations (e.g. Acemoglu and Autor, 2010; Cortes, 2012; Jaimovich and Siu, 2012).[39]

[37] All the results reported in this paper are estimated using proper sampling weights.

[38] Mean earnings and median earnings have been used to proxy the skill level and rank the jobs in the literature. Our results are consistent using both mean and median earnings to define the skill ranking.

[39] Though these classifications are based on the tasks performed in occupations of USA using International Standard Classification (1988) codes but it has been widely used in other countries including some developing countries like Ukraine (Kupets, 2016) and in Latin America. The actual intensity of different tasks in each

However, some studies have used surveys like Dictionary of Occupational Titles (DOT) and its successor Occupational Information Network (O*NET) to measure the tasks and skill content of each occupation or job (Autor, Levy and Murnane, 2003). The occupations are then grouped into *non-routine manual, routine manual, routine cognitive* and *non-routine cognitive* occupations based on their task content.

We follow both the methods to group the occupations. First, I use the mean earnings of each occupation in 1983 to rank them from lowest to highest skilled occupation and also by grouping the broad categories into non-routine manual, routine manual, routine cognitive and non-routine cognitive occupations (the classification is presented in Appendix Table 3.A1). I have total 390 occupations coded following the National Classification of Occupation (NCO) version 1968 in 1983 among which we drop extremely small cells and also merge some of them with the closest big cell occupations.[40] I also use broad industry groups to break some extremely big cell occupations which do not consider industry variation in the classification (like clerk, general; Labourers; Merchants and Shop salesperson). [41] This process leaves us with 287 occupations in urban India with wage data in 1983.[42] The occupations are then ranked based on the mean wage of each occupation. I then create skill percentiles (quintiles) where each percentile contains approximately 1 percentage (20 percentage) of total employed population in urban India in 1983.

We perform this analysis using NCO 1968 only to the data till 2005 since the occupational classification follows the same version, NCO 1968, until 2005. The surveys afterwards have used the latest version of classification, NCO 2004. A concordance between these two is

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detailed occupation may vary if measured, unavailability of this kind of information does not allow us to categorise them based on the actual task intensity. This is a caveat of the analysis based on this categorization.

[40] There are a total of 450 occupation codes at 3 digit level in NCO 1968 classification. I have 390 occupations in the dataset of 1983. Some occupations are extremely small in terms of number of sample persons. So I drop the ones with less than 10 observations, merge some small cell occupations with the closest possible big cell ones and also desegregate some by broad industry. This exercise leaves us with approximately 280 occupations.

[41] NSSO uses National Industry Classification (NIC) codes to classify the industry and National Classification of Occupation (NCO) to classify the occupations of the respondents. Though three different versions of NIC have been used to classify industries in the three periods used in this study, the same version (NCO 1968) has been used to classify the occupations in all the study years (Table 1). So, while it is convenient to rank the occupations using 3 digit NCO 1968 classification alone, combining NCO and NIC at detailed level will make it difficult to use the same ranking across the years.

[42]Wage data are not available for self-employed workers. We, therefore, proxy the skill level of self-employed occupations using the median daily wage of same occupations in casual wage or regular salaried employment.

available at 3 digit NCO 1968 to 4 digit NCO 2004 level. However, the occupations in the survey data are coded at 3 digit level in all the survey rounds. A concordance from around 400 occupations in NCO 1968 to 113 occupations in NCO 2004 can make the results unreliable. We, therefore, use the old classification (NCO 1968) for all the rounds until the year 2005 and convert the latest version of occupational classification (NCO 2004) into old version for the year 2012. The conversion is performed at 3 digit NCO 2004 to 2 digit NCO 1968 following the concordance table. In this way I convert 113 occupational codes of NCO 2004 into some 93 occupational codes of the old version. These 3.2 digit occupation codes combined with 1 digit industry codes are ranked based on the mean earnings of the year 2005 to create the skill percentiles and quintiles for the period 2005 to 2012.

3.5.2 Regression analysis

Once the skill percentiles and occupation groups are created I look at the changes in employment share and changes in the wages for three periods: 1984 to 1994 (Period 1), 1994 to 2005 (Period 2) and 2005 to 2012 (Period 3). Such strategy allows us to see the decadal change in employment with the 1991 trade liberalisation in the middle. One of our objectives is to model the relationship between employment change and occupational skill for three subsequent periods. This relationship can be modelled in various ways, there are multiple econometric techniques that can be applied. Although the simplest method could be estimating a linear regression equation, it does not capture any potential non-linearity in the relationship between the outcome and the explanatory variables. Therefore, use of non-parametric technique is preferred over the traditional parametric models, because it does not require any assumption about the functional form of the expected value of the dependent variable.

Local polynomial smoothing method is one of the better performing methods for non-parametric analysis than other estimators as it has lowest bias and variance. Mean smoothing and locally weighted scatterplot smoothing (LOWESS) are special cases of polynomial smoothing. Most of the studies have used LOWESS to plot the smooth graph of employment change across skill percentile (Acemoglu and Autor, 2011; Autor and Dorn, 2013). For this analysis, I also use the LOWESS smoothing method.[43]

[43] For a detailed discussion on local polynomial smoothing, please refer to Fan and Gijbels (1996).

3.5.3 *Shift-share analysis*

In order to decompose the change in employment share into between-industry and within-industry components, I use shift-share analysis following Acemoglu and Autor (2011).

$\Delta E_{jt} = \Delta E_t^B + \Delta E_t^W$ ………………….. (1)

Where, ΔE_{jt} is the total change in employment share in job *j* in time interval *t* and

$$\Delta E_t^B = \sum_k \Delta E_{kt}\, \gamma_{jk} = between\ industry\ change.$$

$$\Delta E_t^W = \sum_k \Delta\, \gamma_{jkt} E_k = within\ industry\ change$$

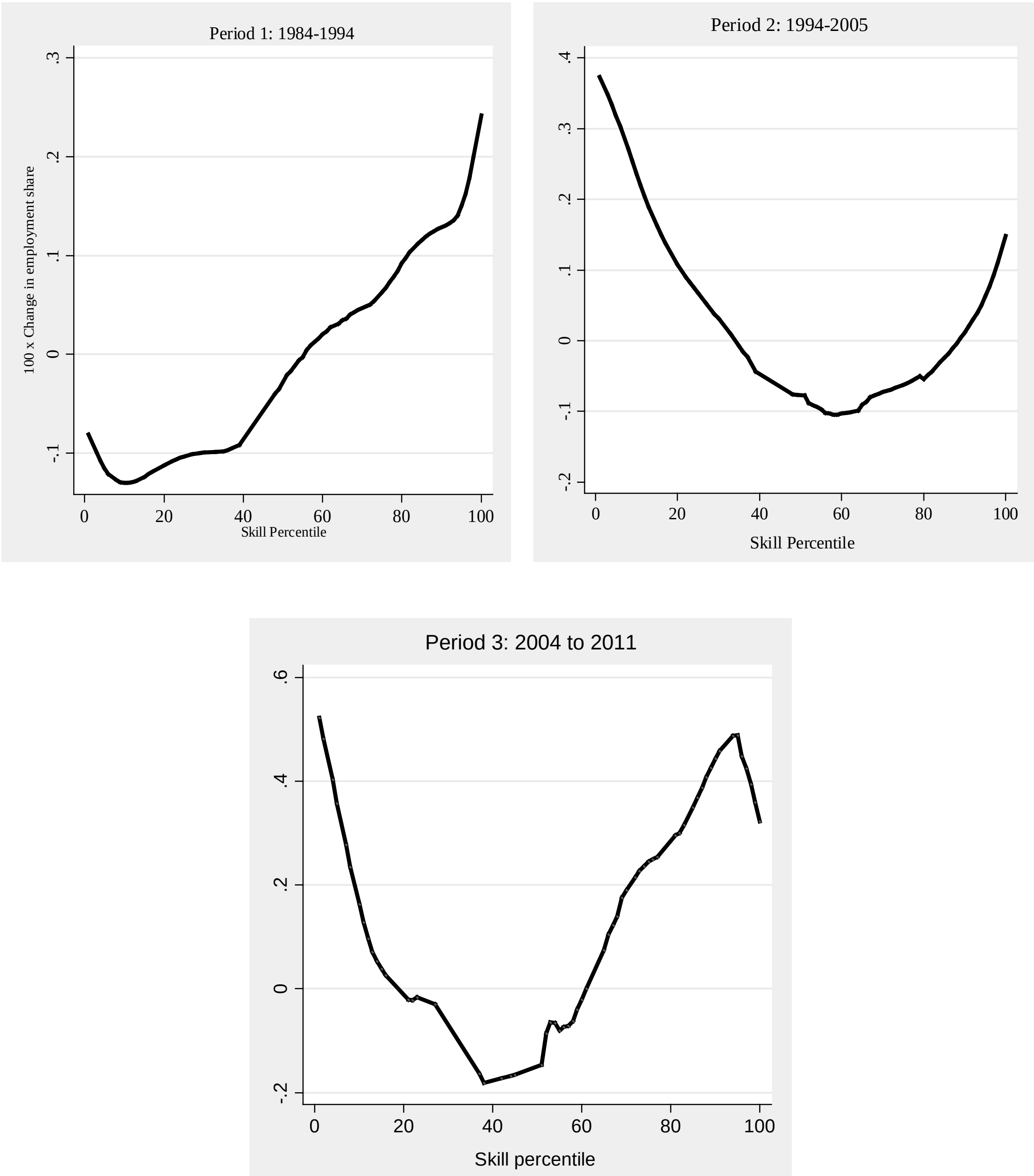
This analysis will enable us to understand to what extent the changes in employment share in broad occupations and four task-based occupation categories are attributable to changes in industry shift (ΔE_t^B) and to changes in the occupational shift with industry (ΔE_t^W). This decomposition exercise is implemented using ten broad occupational categories based on NCO 68 and 10 broad industry categories based on NIC 98. The results discussed in the next section are presented in Table 3.3.

3.6. EMPERICAL RESULTS

3.6.1. *Employment change*

We find evidence of employment polarization in urban India post-liberalisation. Figure 3.1 and Figure 3.2 plot the percentage change in employment share during the three periods by occupational skill percentile and quintiles. As mentioned earlier occupational skill is measured using mean wage of the year 1983 (using 3 digit occupation) and mean wage of

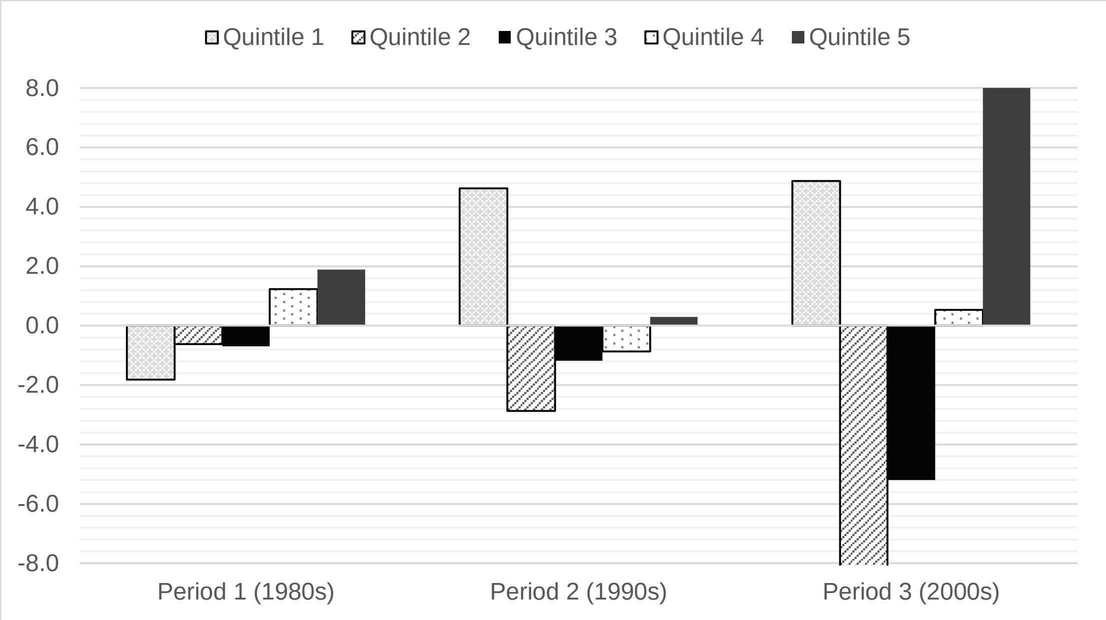
Figure 3.1 Smoothed Changes in Employment Share by Occupational Skill Percentile



Note: Occupational skill percentile is created by dividing 281 occupations into approximately 100 equally weighted groups in 1983 based on the mean earnings of the same year for the period 1983 to 2005. For period 3 (2005 to 2012), NCO 2004 3 digit occupational codes are matched to NCO 1968 codes at to 2 digit level and then the combination of occupation and broad industry has been grouped into percentile using mean wage of the year 2005.

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Figure 3.2 Changes in Employment Share (in %) across Occupational Skill Quintiles



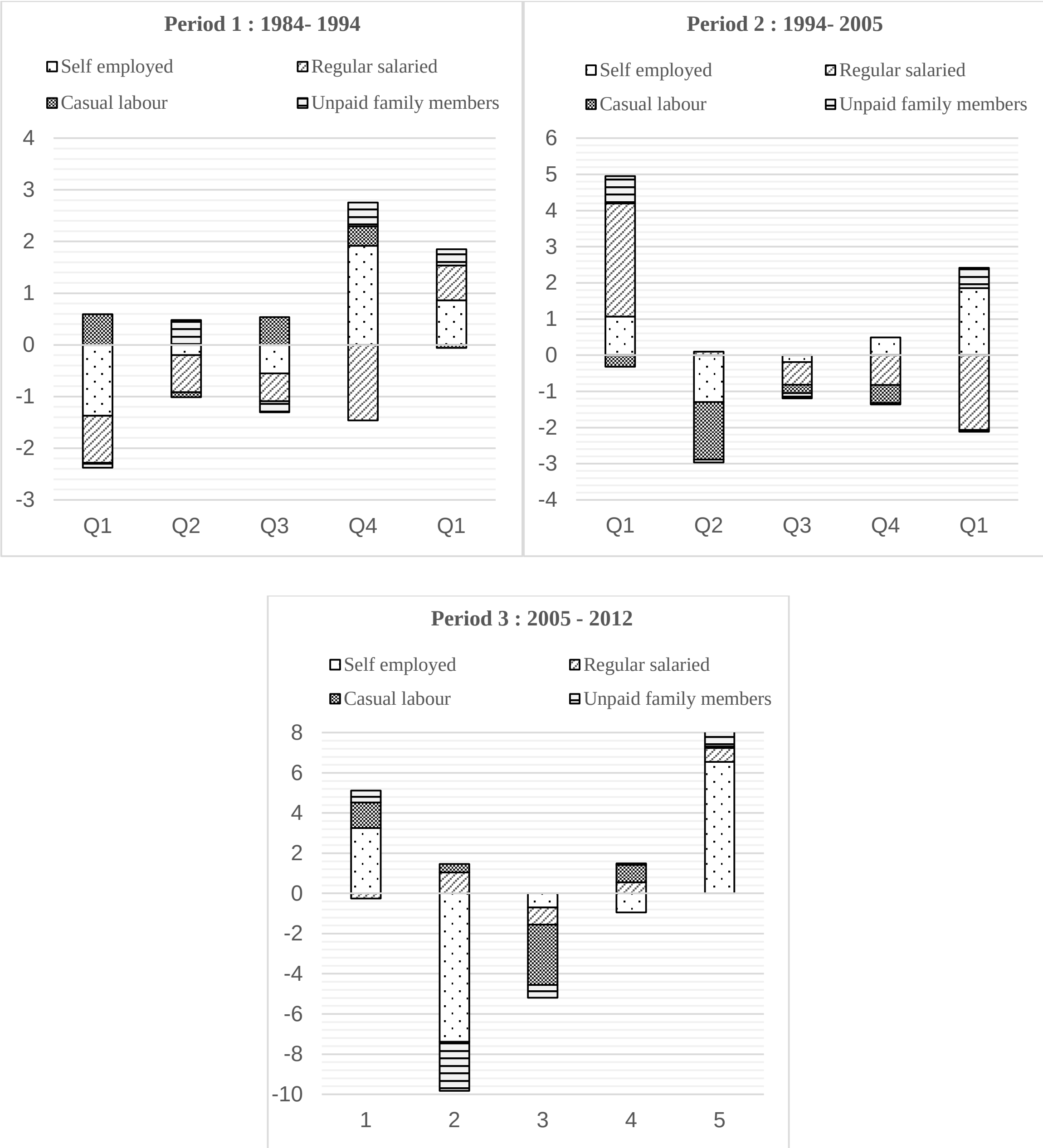
Note: Occupational skill quintile is created by dividing 281 occupations into approximately 20 equally weighted groups in 1984 based on the mean earnings of the same year for the period 1984 to 2005. For period 3 (2005 to 2012), NCO 2004 3 digit occupational codes are matched to NCO 1968 codes at to 2 digit level, and then the combination of occupation and broad industry has been grouped into quintiles using mean wage of the year 2005.

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

the year 2005 (using combination of 2 digit occupation and 1 digit industry). The figures show different pattern in three decades.

Both the figures show an upgrading employment change in the 80s and a polarized U-shaped employment growth during the 90s and 2000s. Strong growth is observed in the share of employment in the top quintile in each of the past three decades. Employment shares of the second lowest and middle quintiles decreased in all the three decades. For occupations in the lowest quintile the employment share fell in the 1980s, and rose considerably in the 1990s and 2000s.

Figure 3.3: Decomposition of the Changes in Employment Share by Employment Type



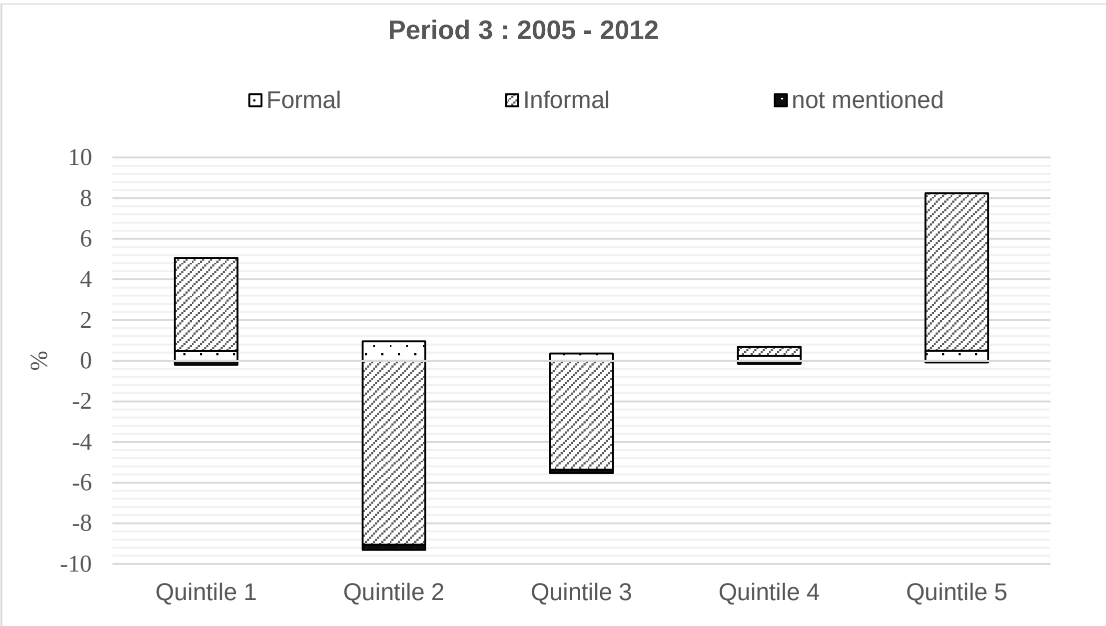
Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

However, a decomposition into self-employed, regular salaried and casual wage earners (Figure 3.3) reveal that most of the growth in the lowest and the highest quintiles during the

1990s and 2000s is due to the increase in self-employed in both the quintiles in the two extreme poles of the skill distribution.

These are the occupations of tailors, dress makers, low skilled sales and shop assistants in the bottom quintiles, and working proprietors and managers in the top quintiles (Table 3.A2). There is evidence in the literature which suggests that micro and small enterprises (MSE) have increased in 2011-12 which might have created managers in the top quintile (Mehrotra et al. 2014). A further decomposition of the changes in employment across the skill quintiles reveal that the sharp increase in employment share in the bottom and top most quintiles is due to the high growth in employment share in the informal sector (Figure 3.4).[44]

Figure 3.4: Decomposition of the Changes in Employment Share by Formal and Informal Sector (in %)



Note: NSSO has information on formal and informal sector in rounds 1999 onwards. So we are unable to present the results for period 1 and period 2.

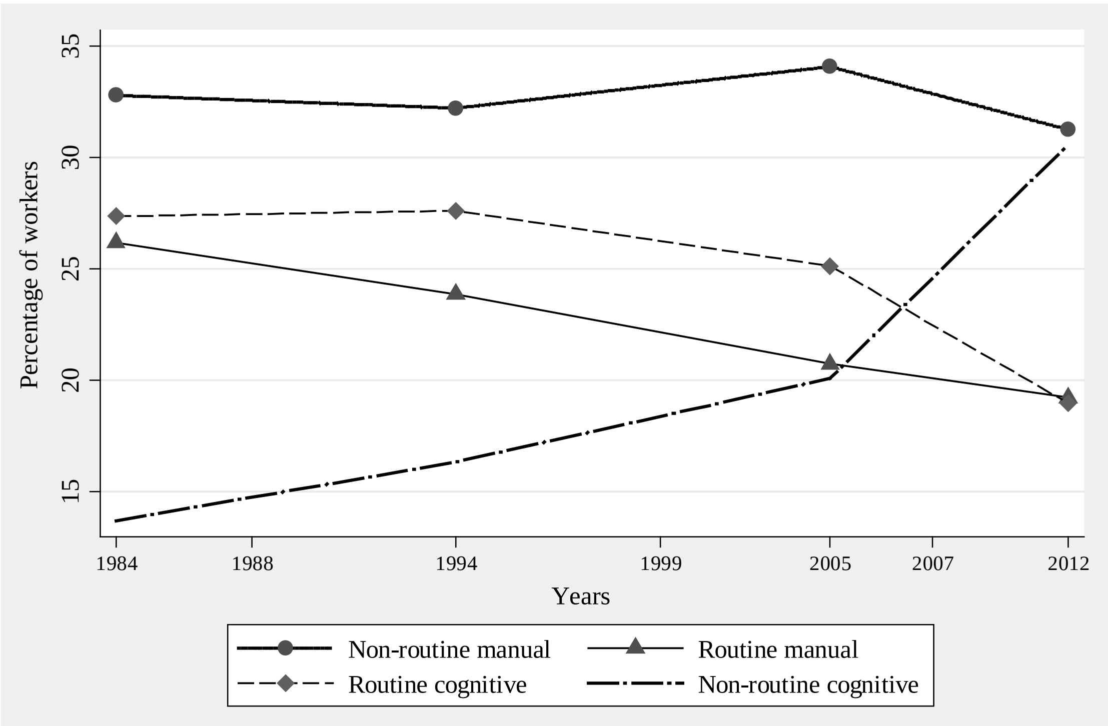
Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

[44] NSS has information on formal and informal sector in the rounds surveyed in 1999 and onwards. We, therefore, provide the decomposition analysis only for the recent decade, 2005 to 2012.

3.6.2. Employment change by task-based occupations

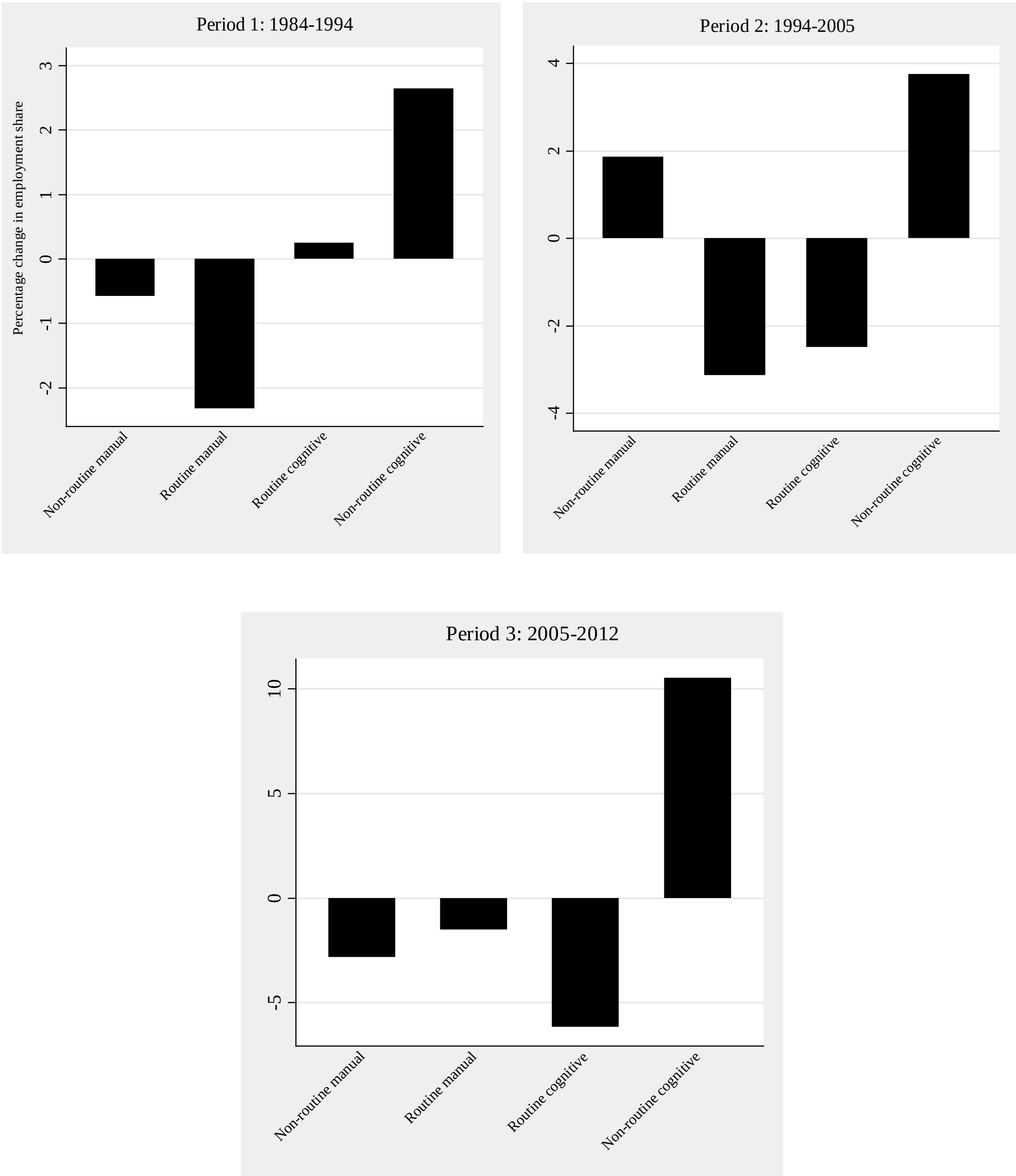
Earlier section provides evidence of employment upgrading in period 1 and employment polarization in period 2. In this section I analyse the changes in employment share in urban India across four task-based occupation categories. The classification of NCO one digit occupations into four non-routine and routine task-based categories is presented in the appendix (Table 3.A1). Figure 3.5 provides the employment share in each of the four categories across the years, 1984 to 2012. Clearly, both the routine categories have experienced decline in their employment share during this period – the employment share in routine manual and routine cognitive occupations has gone down from above 25% in 1983 to below 20% in 2012. On the other hand, the shares of non-routine occupations have shown continuous increasing trend during this period which is particularly strong for non-routine cognitive occupations.

Figure 3.5: Employment Share in Task-based Occupation Categories across Years



Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Figure 3.6: Change by Task-based Occupation Categories



Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

The changes can be easily seen in the next figure (Figure 3.6) where I present the estimated percentage change in employment share for three periods. It gives similar trends of somewhat employment upgrading and strong polarization for the period 1 and period 2 respectively. The recent period, on the other hand, have experienced reduction in employment share in non-routine manual occupations along with routine occupations. One possible reason why I don't find further increase in non-routine manual occupations is because the employment share in non-routine manual occupations has already been quite high at 33% in 2005. It started increasing in 1990s, in the period immediately after trade liberalisation. This can be a result of both economic liberalisation giving a push to demand for low-skilled labour as well as a rural-to-urban migration during this period.

The similarities in observed employment change among the three periods are decreasing share of routine manual jobs and increasing share of non-routine cognitive jobs. Routine manual jobs are mostly concentrated in manufacturing sector (Appendix Table 3.A4). Most of the industries in manufacturing sector have undergone mechanisation in India in the recent past. Mechanisation in manufacturing started in the early 70s particularly in textile manufacturing. The evidence in the existing literature suggests that there has been employment destruction in manufacturing sector during the 1980s and the 1990s (Jain, 1983; Nagaraj, 2004). While the employment loss in 1980s can be attributable partly to mechanisation (adaptation of power loom etc.), the 1990s employment loss is explained as a result of technological-upgradation and modernisation of industries. Whether the increase and decrease in employment are results of industrial shift or occupational shift is revealed in the next section.

3.6.3. Sources of employment change – within-industry or between-Industry change?

The results of shift-share analysis presented in Table 3.3 suggest that all the increase and decrease in these four task-based occupation categories are the results of occupational shift within-industry employment change in all the periods; the only exception is the decrease in routine manual occupation share in the first period which is largely attributed to the industrial change.

As discussed in earlier section, routine manual occupations are mainly concentrated in the manufacturing industry. Production and related workers in manufacturing sector has experienced a sharp decrease in employment share until 2005 while employment in operative occupation has remained almost stable over the years (Figure 3.7). This finding is consistent with the literature which suggests that there was huge employment destruction in manufacturing because of mechanisation particularly in textile and clothing in India during 1980s (Jain 1983).[45] Workers in weaving and knitting jobs lost their employment once the power loom took over in 1974. It is also worth noting that the reduction in routine cognitive category is mainly due to the reduction in clerical occupation which has experienced a sharp decline after 1993 and has reduced from around 11% to 7% in 2012.

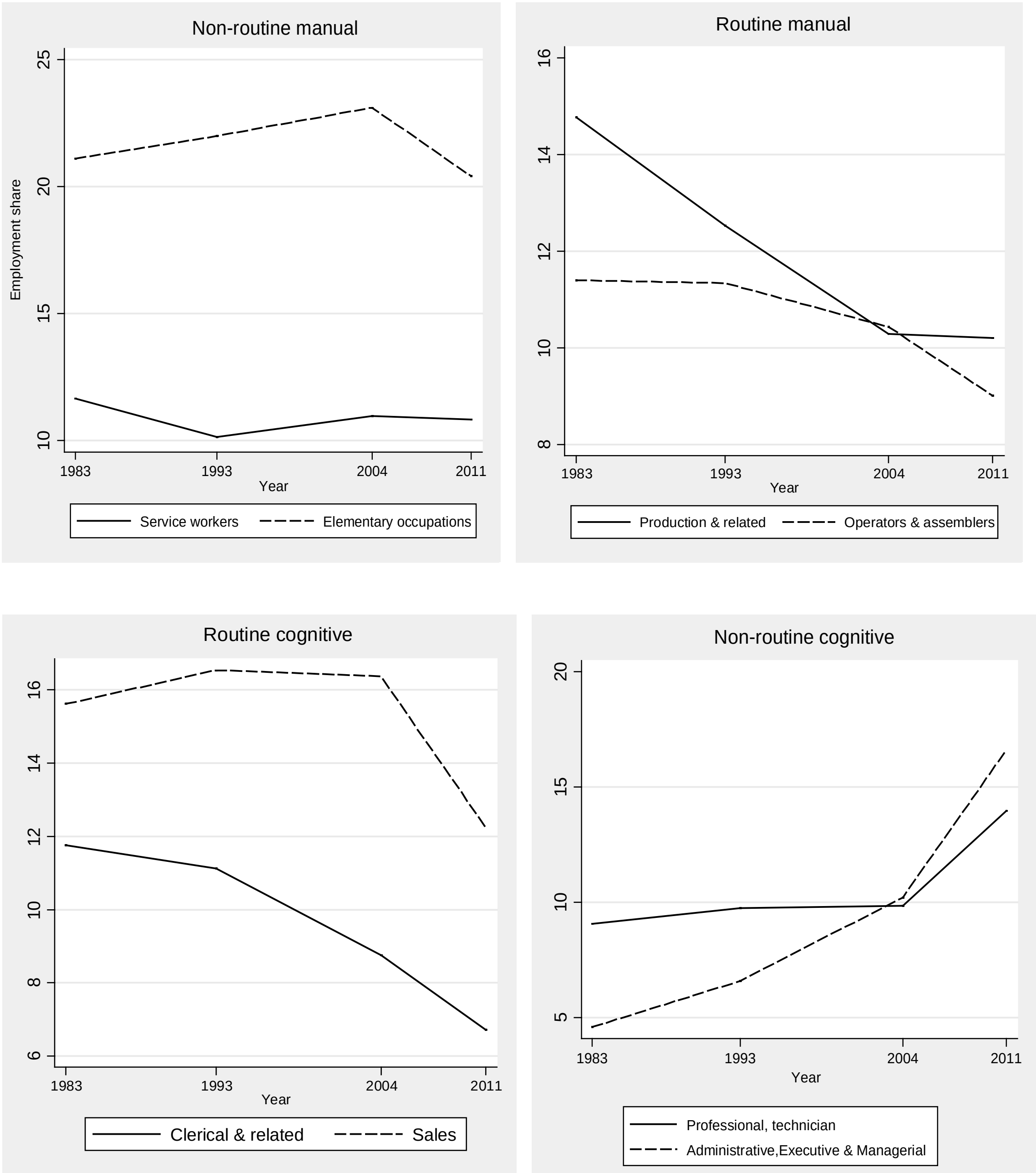
Table 3.3: Shift-share Analysis

Categories	Period 1 (1984-1994)	Period 2 (1994-2005)	Period 3 (2005-2012)
Non-routine manual			
Total change	-0.63	1.94	-2.82
Industry change	2.30	0.05	2.62
Occupational change	-2.93	1.89	-5.44
Routine manual			
Total change	-2.31	-3.14	-1.51
Industry change	-2.19	-0.75	-0.52
Occupational change	-0.12	-2.40	-0.99
Routine cognitive			
Total change	0.28	-2.53	-6.17
Industry change	0.29	2.24	-1.94
Occupational change	-0.01	-4.77	-4.22
Non-routine cognitive			
Total change	2.66	3.74	10.50
Industry change	-0.40	-1.54	-0.15
Occupational change	3.06	5.27	10.65

Source*:* Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

[45] A power loom is a mechanised loom powered by a line shaft, and was first introduced in the industrialization of weaving during the early 1970s. As written by Jain (1983), "the resultant loss of employment in weavers' household is unimaginable" and the real number of affected persons as estimated by him is 5.5 million men and women in 1980s.

Figure 3.7: Employment Share in 1 digit Occupations under Each Task-based Categories (in %)

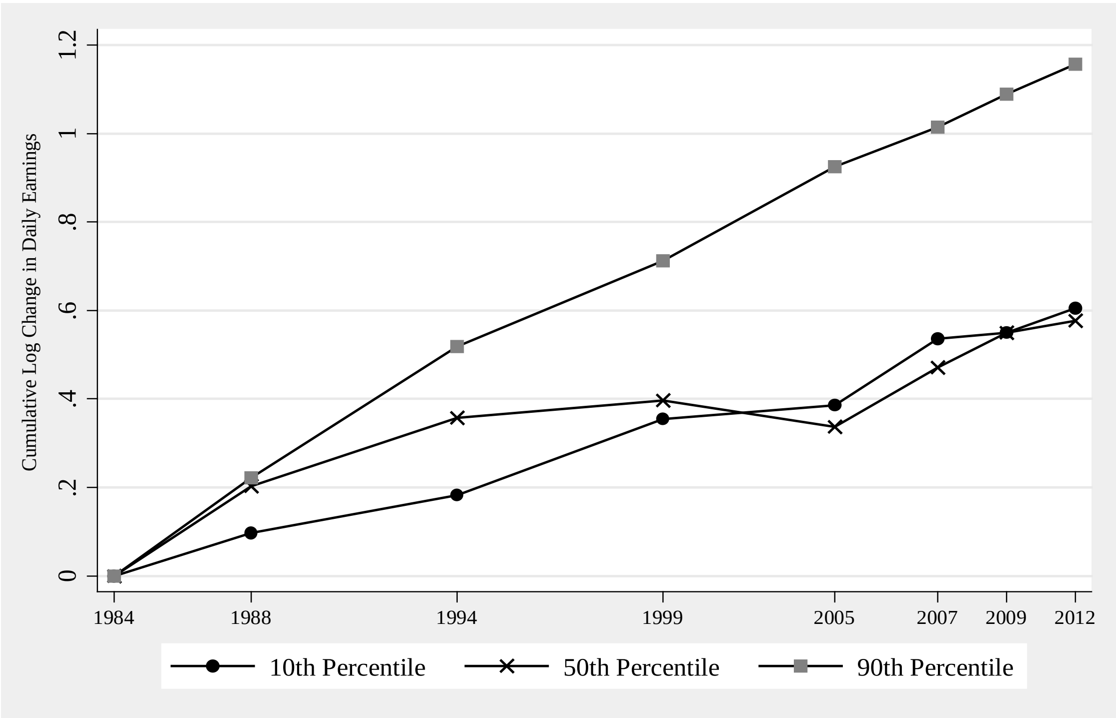


Source*:* Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

3.6.4. Wage Change

Employment and wage changes are the observable effects of labour market polarization. To understand overall wage inequality trends I begin by looking at the changes in daily wage of urban salaried and casual wage earners at 10th, 50th and 90th percentile. Figure 3.8 plots the log real daily wages of both male and female working for at least 5 days a week at these three percentiles of wage distribution during 1984 to 2012. The wages for these three groups are all normalised to 0 in 1984; it therefore gives the change in real daily wage in the respective percentile from the year 1984. The figure shows that the real daily wages for the highest (90th) and the lowest (10th) groups show sharp and monotonic rise during this period while the median (50th) wage group shows a decline in real daily wage after 1999. Moreover, the increase in median wage was lower than the 10th percentile in 2005 and it continues to be so until 2012. So the increase in the inequality between 1984 and 2005 has been mainly due to the increasing divergence between the wealthy and the middle class as shown in the figure. The findings are consistent with that of Azam (2012), Kijima (2005) and also consistent with the SS theorem which predicts increasing return to unskilled labour which is measured by the wage of 10th percentile in this figure.

Figure 3.8: Normalised Real Daily Wage for Urban Male and Female- 1984 to 2012

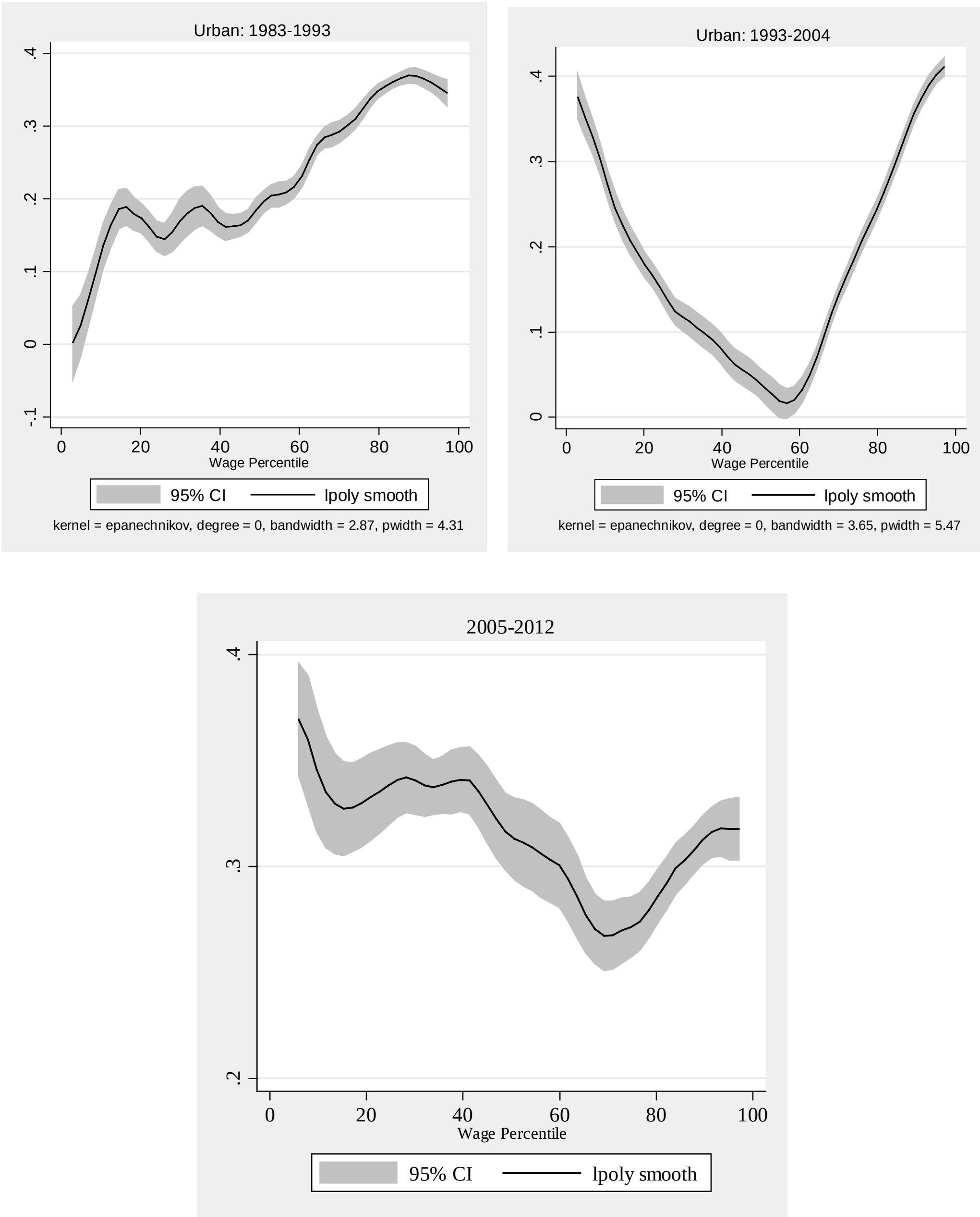


Note: This figure is obtained by computing the real daily wage for each year at the 10th, median and 90th percentiles of the wage distribution. The sample includes male and female working for at least 5 days a week. The real daily wages are computed using CPI for industrial workers at base year 1982.

Source: Authors' own calculation using NSS Employment and Unemployment Survey.

In order to know if the wage gap is limited only to comparisons of the highest, medium and least skilled workers, in Figure 3.9 I also plot the log real wage changes between the three periods (1984- 1994, 1994- 2005 and 2005-2012) across the wage percentile. The figure shows that real daily wage increased monotonically from lowest to highest percentile of wage during the first decade. As noted in earlier figure, the monotonic growth in real daily wage in the 1980s is notably non-monotonic during the subsequent two decades. Consistent with the employment change, the real daily wage increased more in the bottom as well as top compared to the middle of the wage distribution creating a perfect U-shaped polarized growth in the second decade. The recent period, on the other hand, has experienced an asymmetric polarized wage growth – highest growth in the bottom tail, somewhat less growth in the top tail and lowest growth in the middle of the wage distribution.

Figure 3.9 Changes in Log Real Daily Wages by Wage Percentile for Urban Workers- 1984 to 2012



Source: Authors' own calculation using NSS Employment and Unemployment Survey.

If the wage change is induced by changes in the demand for workers by occupation, there may be a positive co-variation. For instance, it might be the case that increased demand for high skill workers may raise wages in high skill occupations. I explore this in Table 3.4 by providing the changes in average earnings across the task-based occupational groups as well as the skill quintiles. The figures in both the upper and lower panels reveal that earnings growth has been highest in the high-skill and non-routine cognitive occupations over the three periods. This should lead to overall earnings inequality. The increase in average earnings in the top quintile as well as in the non-routine cognitive occupations has been doubled in period 2 (the 90s) while comparing with the earlier decade. However, earnings growth is quite similar (lower) in the top quintile (non-routine cognitive jobs) during the 2000s and in the 90s. Not only that, the lowest quintile has also experienced relatively higher earnings growth compared to the middle quintiles during the 90s and the 2000s.

Table 3.4: Changes in Real Daily Wages across Occupational Categories

Categories	Change in mean real daily wage		
	Period 1	Period 2	Period 3
By task-based occupational groups			
Non-routine manual	3.1	2.9	8.6
Routine manual	4.7	2.2	6.2
Routine cognitive	8.3	7.7	8.8
Non-routine cognitive	13.4	25.5	17.1
By occupational quintiles			
Quintile 1	2.3	3.6	6.5
Quintile 2	2.6	1.8	7.1
Quintile 3	4.1	1.9	6.3
Quintile 4	5.7	7.2	13.4
Quintile 5	12.5	23.5	29.0

Source*:* Authors' own calculation using NSS Employment and Unemployment Survey.

3.7. CONCLUSION

There has been considerable interest globally in how technological change has affected employment in different occupations. This article analyses employment change and wage change trends in urban India for the last three decades covering 1984 to 2011-12. This period also allows us to see the changes for the decade before and after economic liberalisation in India. Many industrialised countries have exhibited employment change pattern consistent with job polarisation (the UK, USA, Australia and some European countries). The focus now has shifted to the developing countries. Recent research on some developing and transition countries has provided evidence of job polarizing pattern in countries such as

Colombia, Mexico, and Ukraine (Medina and Posso, 2010; Kupets, 2016). This manuscript adds to this evidence to show that urban India has also experienced job polarisation.

During the 90s and the 2000s employment as well as wage has increased more in the lower and upper tails compared to the middle of the skill and wage distribution. Both routine manual and routine cognitive jobs have reduced their employment share which seems to be consistent with the task biased technological change hypothesis. However, our results suggest that routine manual jobs started shrinking its employment share during the 1980s. This might be the consequence of mechanisation in the manufacturing industry which replaced huge amount of manual labour during this period as evident in the literature. However, the large decline in employment shares in both clerical and sales occupations may be an indication that computerisation has started replacing some routine tasks in urban India, particularly in last few years.

Finally, high-paid occupations corresponding to the abstract reasoning, creative, and problem-solving tasks performed by professionals, managers, administrative officers and some technical occupations have been expanding during all the three periods; the increase is much higher during the 2000s. However, this does not necessarily imply an increase in quality employment in India during this period. Our analysis reveals that the high increase in low- and high-skill jobs has mainly been in the informal sector and very little growth has occurred in the formal sector. Self-employment in wholesale and retail trade industry has increased employment in low-skill sales jobs and high-skill managerial jobs in micro and small enterprises.

We further find that earnings change during this period is consistent with the employment change pattern. Employment expansion in both low-skill and high-skill jobs appears to be one of the contributing factors in increasing earnings inequality in urban India. Therefore, the structural employment change across occupational skill distribution remains an important factor for understanding earnings inequality in India.

3.8. APPENDIX

Table 3.A1: Classification of Task-based Occupation Categories

Task-based categories	**Broad NCO 1968**	**Specific tasks**
Non-routine manual	5-Service Workers 9-Elementary Occupations	Non-methodical, flexible use of brain, eyes, hands and legs
Routine manual	7-Production and related workers, transport workers 8-Plant and Machine Operators and Assemblers	Repetitive works which involve systematic physical movement, use of fingers and hands
Routine cognitive	3- Clerical and related 4-Sales workers	Calculating, bookkeeping, correcting texts/data, and measuring following a well-defined method
Non-routine cognitive	0-1- Professional, technical and related 2-Administrative, executive and managerial	Analysing, interpreting, thinking creatively, guiding, directing, establishing relationship

Note: For a more detailed understanding of job-tasks refer to Acemoglu and Autor (2011) and Fernandez-Macias and Hurley (2016)

Table 3.A2: Largest Decrease and Increase in Employment Share in Jobs (in %)

Industry	Occupation	Quintile	Change in % share
Loss in employment share			
Period 1 (1984- 1994)			
Textile manufacturing	Tailors and dress makers	1	-1.7
Other service	Sweepers, cleaners and related workers	2	-0.5
Manufacture of tobacco product	Bidi makers	1	-0.4
Period 2 (1994-2005)			
Manufacturing	Labourers	2	-1.1
Wholesale & Retail Trade	Merchants and shop keepers	2	-1.0
Other service	Labourers	2	-1.0
Period 3 (2005-2012)			
Transport	Transport Equipment Operators	4	-2.2
Manufacturing	Production and Related Workers	3	-1.3
Manufacturing	Spinners, Weavers, Knitting, and Related Workers	2	-1.3
Increase in employment share			
Period 1 (1984- 1994)			
Construction	Labourers	1	1.4
Manufacturing	Working Proprietors, Directors and Managers	5	0.5
Service	Working Proprietors, Directors and Managers	5	0.4
Period 2 (1994-2005)			
Textile manufacturing	Tailors and dress makers	1	1.8
Wholesale & Retail Trade	Salesmen, Shop Assistants and Demonstrators	2	1.1
Service	Working Proprietors, Directors and Managers	5	1.0
Period 3 (2005-2012)			
Wholesale & Retail Trade	Working Proprietors, Director & managers	5	5.1
Wholesale & Retail Trade	Salesmen, Shop assistants, & Related Workers	1	4.1
Manufacturing	Material Handling & Related Equipment Operators	2	2.9

Source*:* Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Table 3.A3: Employment share in each of the skill quintiles by gender, caste, employment type, industry sector and level of education

Components	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	1984	2012	1984	2012	1984	2012	1984	2012	1984	2012
Gender										
Male	72.3	77.6	85.8	76.5	93.8	92.2	95.3	79.8	85.0	87.3
Female	27.7	22.4	14.2	23.5	6.3	7.8	4.7	20.2	15.1	12.7
Average age (in year)	33.3	36.4	33.9	34.8	33.9	36.5	34.8	37.7	36.7	40.0
Caste										
Sc/St	17.2	21.7	20.8	16.3	18.2	22.3	13.5	20.3	7.9	11.4
Others	82.8	78.3	79.2	83.8	81.8	77.7	86.5	79.7	92.1	88.6
Employment type										
Self-employed	41.6	34.2	41.6	22.0	27.2	29.6	17.5	21.0	14.9	47.1
Regular salaried	25.4	32.6	32.0	51.4	45.8	37.8	71.9	67.7	81.3	43.1
Casual labour	22.7	23.1	15.9	17.6	19.9	27.7	8.0	8.5	0.9	0.7
Unpaid family worker	10.3	10.2	10.5	9.0	7.1	4.9	2.7	2.9	3.0	9.0
Industry sector										
Manufacturing and Mining Quarrying	33.3	7.1	30.7	85.5	44.6	35.6	34.7	15.1	18.4	21.9
Construction	10.2	22.1	0.3	0.0	12.9	23.1	2.0	8.3	2.8	0.9
Service	56.5	70.8	69.0	14.5	42.5	41.3	63.3	76.6	78.8	77.2
Level of education										
Below primary	54.5	31.5	48.6	29.3	44.3	29.2	24.4	13.1	5.1	8.4
Primary completed	34.4	34.7	35.4	42.5	39.8	34.6	40.5	24.2	14.9	16.8
Secondary completed	9.7	15.9	12.4	16.9	13.4	20.3	28.2	20.4	41.2	18.3
Tertiary or above completed	1.5	17.9	3.7	11.2	2.4	15.8	6.9	42.3	38.9	56.6
Number of obs.	11,105	12,386	13,276	12,102	6,386	10,480	10,354	11,673	11,263	11,249

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Table 3.A4: Employment share in each of the task-based occupation categories by gender, caste, employment type, industry sector and level of education

Components	Non-routine manual		Routine manual		Routine cognitive		Non-routine cognitive	
	1984	2012	1984	2012	1984	2012	1984	2012
Gender								
Male	82.2	82.9	85.1	82.5	91.3	87.6	80.2	79.8
Female	17.9	17.1	14.9	17.5	8.7	12.4	19.8	20.2
Average age (in year)	34.0	37.4	34.4	38.2	34.6	38.3	35.7	38.4
Caste								
Sc/St	26.2	27.5	15.1	16.3	8.2	13.9	8.0	10.8
Others	73.8	72.5	84.9	83.7	91.8	86.1	92.0	89.3
Employment type								
Self-employed	25.0	18.7	27.4	28.7	37.3	32.1	30.9	48.1
Regular salaried	43.6	51.2	44.4	43.6	50.6	55.2	62.3	42.5
Casual labour	26.7	27.7	20.2	18.2	2.7	2.8	1.0	0.4
Unpaid family worker	4.8	2.5	8.1	9.6	9.4	9.9	5.8	8.9
Industry sector								
Manufacturing and Mining Quarrying	18.0	17.9	80.8	68.6	8.1	6.9	19.0	18.2
Construction	14.1	20.5	1.3	12.9	0.5	0.8	4.0	3.8
Service	67.5	61.3	17.8	18.4	91.0	92.2	76.7	77.5
Level of education								
Below primary	55.9	33.4	44.2	27.8	20.0	9.7	9.3	7.5
Primary completed	33.4	37.6	39.2	39.4	32.6	20.0	17.0	15.2
Secondary completed	9.4	23.6	15.1	19.9	31.0	37.4	35.7	29.4
Tertiary or above completed	1.4	5.4	1.6	12.9	16.5	32.9	38.1	47.9
Number of obs.	16,716	16,130	13,283	8,739	15,956	10,839	7,847	16,394

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Chapter 4

Employment Transition of Women in India: A Panel Analysis

4.1 INTRODUCTION

In spite of having significant economic growth in the last two decades, India has not witnessed commensurate rise in the female labour force participation rate. High economic growth has been accompanied by increased educational level of the population and decreased gender gap in educational participation. Moreover, fertility rate has also declined from 4.2 in 1988 to 2.6 in 2012 (World Bank Report, 2012). While this environment seems conducive for women's participation in economic activities, various studies document rather low, stagnant, and declining female labour force participation in India during this period (Himanshu, 2011; Klasen and Pieters, 2015; Siddiqui et al., 2017). This apparently puzzling issue has been recently paid attention both in the academic discourse and policy circles.

The decision for a woman to work is a complex issue that depends on social norms, educational attainment, fertility rate, household care, access to other services, and availability of opportunity. There is a growing literature which seeks to explain the drivers of women's labour force participation by analysing various supply and demand side factors in the economy (Klasen and Pieters, 2015; Lahoti and Swaminathan, 2016). Most of the studies in this literature analyse repeated cross-section data to examine the trend in women's employment over time, and how that is associated with the changes in potentially explanatory factors. In absence of individual level panel data, the analysis in the existing literature has been done at an aggregate level (state or district) without observing how individual employment decision changes along with the explanatory factors over time.

We use a nationally representative individual level panel dataset to investigate women's employment transitions in India. The contribution of our study is twofold. First, we show that there is substantial dynamics in female employment over time. In particular, we estimate the rate of entry into and exit from employment at the individual level. Second, we exploit cross-sectional and temporal variations to attribute the employment dynamics of women to various explanatory factors. Specifically we estimate how the entry and exit probabilities are impacted by factors such as household and spousal income, asset, childcare needs, education, caste, religion and other policy relevant variables including a large rural workfare program.

Using individual level panel data for 2005 and 2012 from the India Human Development Survey (IHDS), we show that women in India are not only participating less, they are also dropping out of the labour force at an alarming rate. We consider the sample selection problems of endogenous initial employment and panel attrition in our analysis of employment entry and exit probabilities. We estimate a switching regression model that rectifies this issue of double selectivity. Our results indicate that an increase in income of other members of the household leads to lower entry and higher exit probabilities of women. This income effect persists even after controlling for the dynamics of asset holding of the household. While the effect of household income is consistent with other studies in the literature, our identification strategy relies on temporal variation and hence it offers more credibility on the direction of the effect. We argue that the estimated negative (positive) effect of household income on women's entry into (exit from) employment is a lower bound of the true effect. Further, we find that presence of an adult male with higher levels of education significantly discourages women to enter the labour market. Along with the effects of caste and religion, these results reveal the interplay between cultural and economic factors that are important in explaining the declining workforce participation of women in India. With an improvement in socio-economic status, households discourage its women to step out and engage in employment. This finding offers a plausible explanation why economic growth may not necessarily promote women's labour force participation.

Also, having a new-born child has an adverse effect on women's employment, indicating that provision of childcare facilities can be an important policy instrument in this context.

We also explore the effects of education, marital status, household composition and regional characteristics. We find that the National Rural Employment Guarantee Scheme (NREGS), a large public workfare program, has significant effect on women's employment transition. NREGS targets one third of the beneficiaries to be women, and it also offers equal wage rate to men and women. Thus it is favourable for women's labour force participation. We find that women are significantly less likely to exit from the labour force in districts with higher incidence of NREGS implementation measured by the average level of administrative funds allocated to the district.

Our study highlights the importance of designing policies that create a favourable condition for women to retain their employment status. Such policies need to be multipronged given the role women have to play in the household economy. On one hand, female employment has direct positive effect on women's empowerment and indirect effect on her children's welfare (Afridi et al. 2016). On the other hand, employment may pose a double burden for women as the prevailing social norms make them responsible for the care economy and household chores as well. Our study shows that many of these factors are intertwined in determining the dynamics of women's labour force participation. From a macroeconomic perspective, India has a 'demographic dividend' with 65 percent of its population in the working age population (National Sample Survey, 2011-2). But the demographic dividend will be under-utilised if women, who constitute almost half the population, mostly stay out of the labour force.

4.2 LITERATURE REVIEW

A number of studies have tried to explain declining female labour force participation rate in India. Female labour force participation is said to be related to the economic growth of a country and the relationship is argued to be U-shaped. This suggests as the economy grows, moving from an agrarian society to an industrial and service sector-based economy, female labour force participation rates fall; it increases again at a later stage of economic development. However, recent studies have found little empirical evidence which supports the feminization U-hypothesis in India (Gaddis and Klasen, 2014; Lahoti and Swaminathan, 2016). On the one hand, although economic development in India has not been led by labour-intensive manufacturing sector, thus producing jobless growth which disadvantages women more than men (Lahoti and Swaminathan, 2016), the sectors that hire female workers such as Agriculture, Education and Health sector, and Public Administration have expanded the least during the last decades (Klasen and Pieters, 2015; Chatterjee, Murgai and Rama, 2015). Therefore, the type of economic growth that has taken place in India is less relevant to women.

On the other hand, the supply side factors which play important role in explaining low labour force participation of women are mainly household's income, particularly husband's income for married women, husband's education along with women's own education (Chand and Srivastava, 2014; Klasen and Pieters, 2015; Sorsa et al., 2015). There has been a substantial increase in the pursuit of education by rural females in India between the year 1993 and 2009-10. Sorsa et al. (2015) find that in contrast to other BRIC countries or OECD countries, education and incomes are negatively correlated with female labour for participation in India.

While household incomes and husband's education have emerged as the main supply side factors, the demand side factor has been mainly insufficient job opportunities for female (Klasen and Pieters, 2015). Apart from lack of jobs, social and cultural factors also keep women outside the labour force. Other determinants relate to infrastructure, access to finance, labour laws and rural employment programmes (Sorsa et al., 2015).

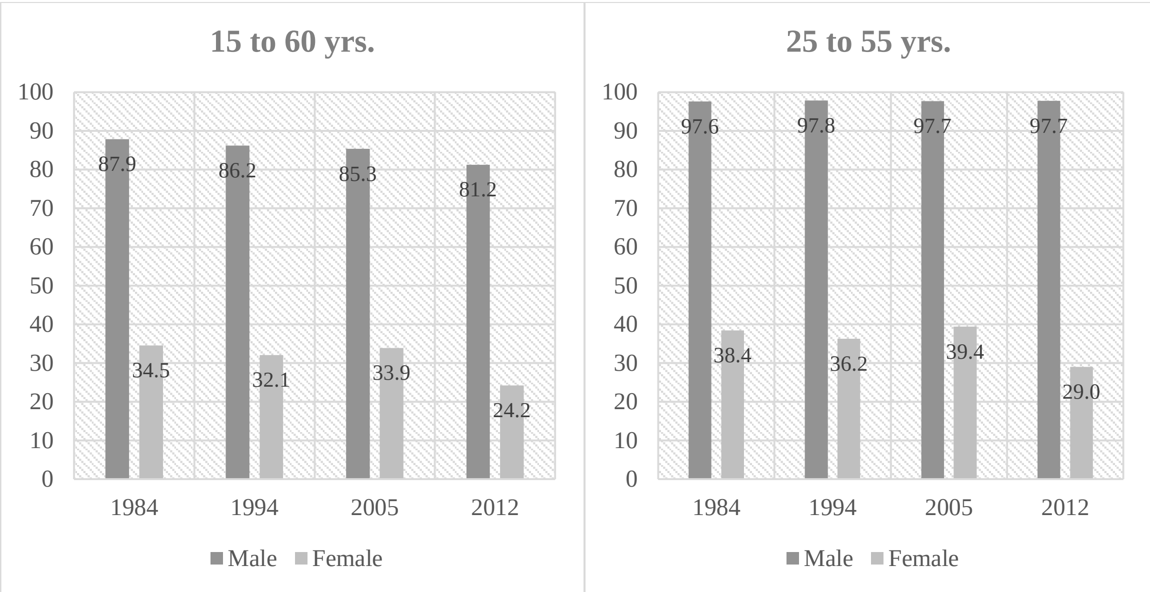
Our paper contributes to this literature by studying women's employment transitions in India. This phenomena has been paid attention in other countries such as USA (Long and Jines, 1980), Canada (Jeon, 2008) and some countries of Europe (Gustafsson et al., 1996). In the context of India, our study is the first to explicitly model employment entry and exit probabilities of females. The determinants of women's labour force participation has been studied and documented extensively. Our study goes one step further to analyse the factors that explain women's entry into and withdrawal from employment.

4.3 BACKGROUND

In this section, we foreground our later analysis of women's employment transitions by first looking at (a) the labour force participation rate of male and female over the years starting from the 80s, to understand the gender gap in labour force participation in India and (b) then analysing how female labour force participation rate is changing over time across age groups and education level.

Figure 4.1 presents the LFPR of male and female computed from nationally representative data from National Sample Survey Organisation (NSSO).[46] The figure shows huge difference in LFPR between male and female in India. While more than 80% male of age group 15 to 60 year participate in the labour force, only 34% of women are seen to be working in 1984 which has further declined to 24% in 2012 (Figure 4.1). The LFPR for male does not show any decline for the age group 25 to 55 year (96% across the years). This difference in LFPR is due to the increasing educational enrolment for the age group 15 to 24 year (Figure 4.2). Almost half of the population in 15 to 24 year age group are currently enrolled in 2012. Though very similar trend is observed for female in the same age group (almost 40% are currently enrolled in 2012), the LFPR of 25 to 55 year old women does not show much improvement; it shows the same declining pattern over time from 38% in 1984 to 28% in 2012. We, therefore, restrict our sample to the age group 25 to 55 year old female for the main analysis.

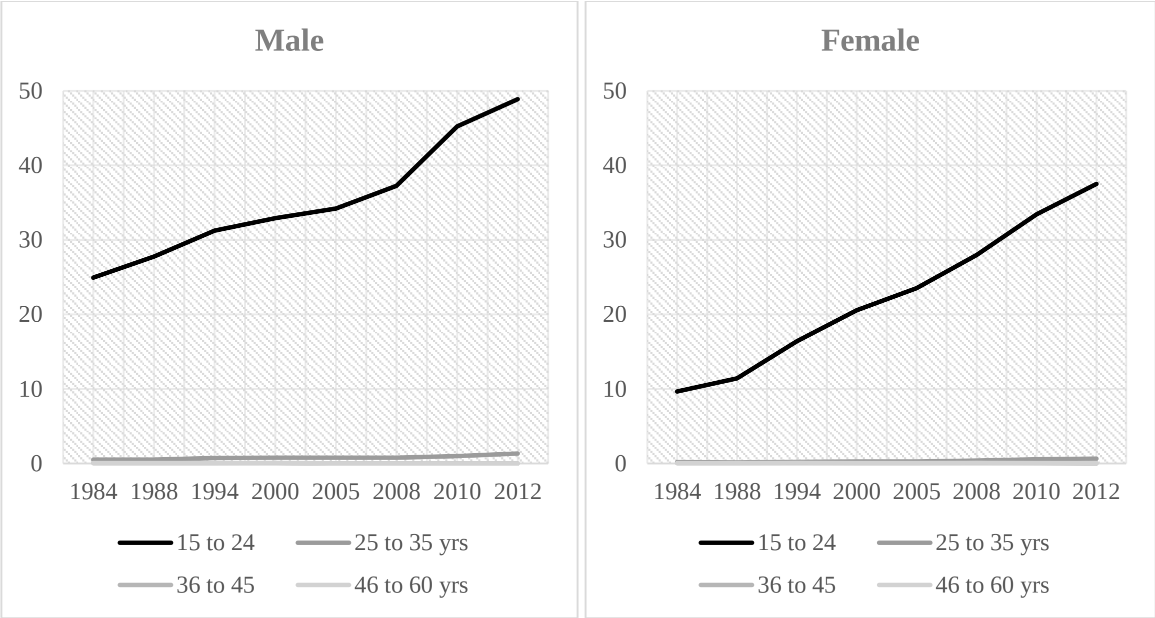
Figure 4.1: Labour force participation rate by gender (%)



Source: Authors' own computation using National Sample Survey Data.

[46] Labour force participation includes both employed and those who are seeking for employment.

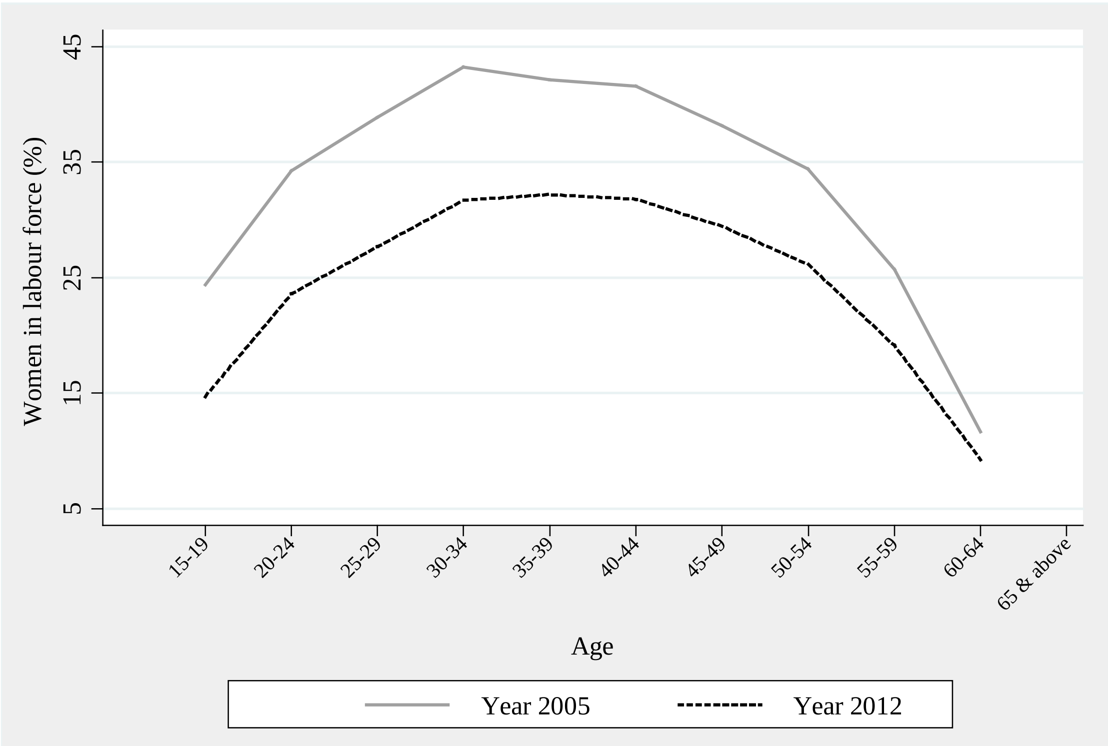
Figure 4.2: Currently enrolled male and female by age group (%)



Source: Author's own computation using National Sample Survey Data.

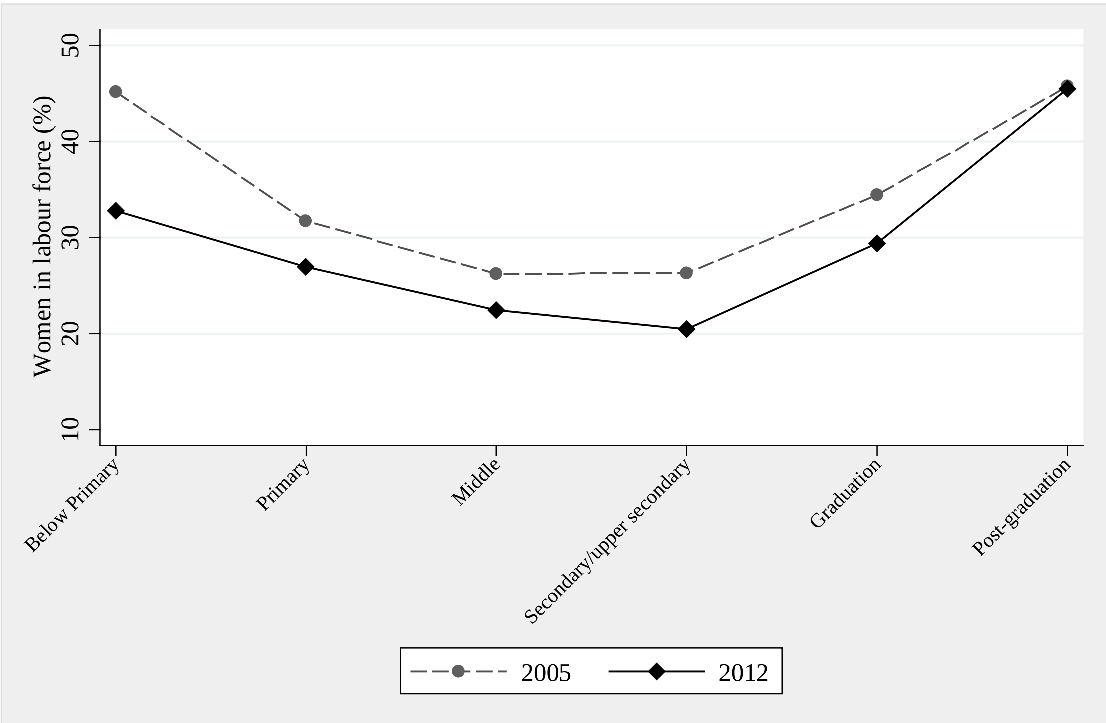
As it is clear in the figure, female labour force participation rate was stable until the year 2005 at around 33% but then decreased by almost 10 percentage point between the year 2005 and 2012. This decline has been observed for every age group and across the educational levels as shown in Figure 4.3 and 4.4. The gap is clear across the age groups and the education levels; though there is no difference for the women with highest level of education, post-graduate and above. In this study we focus on this two time points, 2005 and 2012 to investigate the employment transition of women.

Figure 4.3: Female Labour Force Participation Rate- by age groups



Source: Authors' own computation using National Sample Survey Data.

Figure 4.4: Female Labour Force Participation Rate- by education



Source: Authors' own computation using National Sample Survey Data.

4.4 DATA AND DESCRIPTIVES

The data we use for this study come from the Indian Human Development Survey (IHDS). It is a nationally representative, multi-topic survey of 41,554 households and 215,754 individuals in 1503 villages and 971 urban neighbourhoods across the 33 states and union territories of India. IHDS is a household level panel survey which was first conducted in 2004-05 and the second round of re-interview has been conducted in the year 2011-12 (for simplicity we will refer to the first survey round as 2005 and second round as 2012). Most of the households surveyed in the first round were re-surveyed in the second round including some (around 1000) additional households. These are the households which have been split up from a sample household in between two survey rounds and living in the same locality.[47] The sample for our analysis includes 41,665 women aged 25–55 years from the first IHDS panel (2005), of which 33,013 are re-interviewed in the second IHDS panel (2012). The sample is treated as panel data at the individual level to define the entry into and exit from the labour force.

Use of longitudinal data allows us to explicitly look into the change in employment status of women between the two years when the data were collected. We follow the literature on labour force transition and define labour market "entry" and "exit" for every woman in the sample (Long and Jones, 1980; Gould and Saupe, 1989). The outcome of entry is defined for the sub-sample of women who were not employed in 2004. For this set of women, one can either enter the labour market (Entry = 1) or remain not working (or without work) (Entry = 0) in 2012.[48] Similarly, the outcome of exit is defined based on the sub-sample of women who were employed in 2004. Among them, one can either leave the employment (Exit = 1) or remain to be employed (Exit = 0) in 2012.

A woman is considered to be employed if she has reported working as a salaried, casual wage earner, in business or in the family farm for more than 240 hours in the survey year.

[47] The sample households in this case are joint family households where more than one generation or the families of siblings (specially the male siblings) live in one house. These joint families are considered as one household as they live under the same roof and have one kitchen.

[48] IHDS do not provide information on whether a person has been seeking work or not. We, therefore, consider 'working' and 'not working' as employed and unemployed.

$$Entry = \begin{cases} 1 & if\ unemployed\ in\ 2005\ but\ employed\ in\ 2012 \\ 0 & if\ unemployed\ in\ both\ 2005\ and\ 2012 \end{cases} \quad (1)$$

The sample in this case is the 8.29% (3, 454) of women not working in 2005 who entered labour market in 2012 and those who were never working (10,619 women) (refer to Table 4.1).

$$Exit = \begin{cases} 1 & if\ employed\ in\ 2005\ but\ unemployed\ in\ 2012 \\ 0 & if\ employed\ in\ both\ 2005\ and\ 2012 \end{cases} \quad (2)$$

Table 4.1: Sample

	Number	Percent
Attrition	8,652	20.77
Working in both rounds	11,559	27.74
Working in round 1, not in round 2 (Exit)	7,381	17.72
Not working in round 1, working in round 2 (Entry)	3,454	8.29
Not working in both rounds	10,619	25.49
Total	41,665	100

Source: Author's own calculation from IHDS data.

Almost 17.7% (7,381) of the sample women have reported as not working in the second round in 2012 while 27.7% (11,559) of women have reported working in both the years (Table 4.1). The exit sample consists of these women working in the first round.

Table 4.2: Employment status in both the rounds

	Work status in 2005		Status in 2012 (distribution)		
	A. Percentage	B. Number	C. Working (%)	D. Not working or exit (%)	E. Attrition (%)
Working	55.5	22,171	52.1	33.3	14.6
Salaried	*9.9*	*2187*	*48.2*	*22.6*	*29.2*
Casual wage in agriculture	*25.5*	*5,644*	*67.3*	*19.4*	*13.3*
Casual wage in non-agriculture	*6.9*	*1,527*	*55.4*	*25.1*	*19.5*
Family business	*5.8*	*1286*	*43.7*	*36.2*	*20.1*
Family farm and animal work	*52.0*	*11527*	*46.0*	*42.9*	*11.1*
Not working	44.5	19,494	18.7	55.4	25.9
Total	100	41,665	36.82	43.93	19.25

Source: Author's own calculation from IHDS data.

Table 4.3: Distribution of entry and exit across type of employment

	Exit from	Entry into
Salaried	6.69	23.48
Casual wage in agriculture	14.85	19.02
Casual wage in non-agriculture	5.19	17.72
Family business	6.30	16.21
Family farm and animal work	66.97	23.57
Obs.	7,381	3,454

Source: Author's own calculation from IHDS data.

While 33% of women who were working in the first round have quit the work in the second round, only 18% of those who were not working in the first round have entered into employment (Table 4.2). It is, therefore, clear that women are not only participating less, the rate of withdrawal is almost double of the rate of entry. Most of these women who have dropped out of employment in 2012 were working in family farm (Table 4.3). However, the women who have entered into employment in 2012 are almost uniformly distributed in all types of employment. This may be due to the fact that Agriculture has become stagnant in India. Employment in Agriculture has been declining continuously as shown in chapter 3. Both men and women in rural India are mostly dependent on agriculture for work. Women who have reported working in family farm are largely agricultural workers and are withdrawing from work as working in agriculture has become less remunerative.

One of the problems of using panel data is attrition. The sample in this study has 19% (8,652 women) attrition. The following section describes how we deal with the sample selection problem which arises due to the attrition.

4.5 EMPIRICAL METHODOLOGY

The objective of this study is to identify the employment transition probabilities and their determinants. In particular, we are interested in estimating how the probabilities of entry into and exit from employment are affected by various individual, household, and other factors. Towards this objective, we estimate two separate linear probability models for entry and exit given as follows.

$$Prob(Entry_{ihds} = 1) = \boldsymbol{X}_{ihds}\,\boldsymbol{\beta} + u_{ihds} \qquad (3)$$

The subscripts i, h, d, and s respectively denote individual, household, district and state. The dependent variable is a binary indicator of whether a woman has entered the labour force between 2005 and 2012. Similarly, we have the equation for exit:

$$Prob(Exit_{ihds} = 1) = \boldsymbol{X}_{ihds}\,\boldsymbol{\gamma} + \varepsilon_{ihds} \qquad (4)$$

Here the dependent variable indicates whether a woman has exited from employment between 2005 and 2012. The vector $\boldsymbol{X}_{ihds}$ includes various individual, household, and regional characteristics that affect the employment transition probabilities. While we include the same explanatory factors in the two equations, we allow their effects to differ for entry and exit.

The definition of entry and exit depends on the initial status of employment. The sample of women considered in the regression for entry consists of those who were unemployed in 2005. On the other hand, the exit decisions are observed only for those who were employed in 2005. Since the initial employment status is potentially endogenous, we have a sample selection problem if we estimate the entry and exit probabilities based on these sub-samples and ignore the endogeneity of the initial status of employment (Heckman, 1981). The empirical literature on poverty dynamics and employment transitions deals with the issue of endogenous initial condition using a switching regression model (Stewart and Swaffield, 1999; Bruce, 2000; Cappellari and Jenkins, 2004; Jeon, 2008). We adopt a similar framework and specify the initial employment decision in the following equation:

$$Emp^{*}_{0,ihds} = \boldsymbol{Z}_{ihds}\boldsymbol{\phi} + v_{ihds} \tag{5}$$

$$Employed_{0,ihds} = 1\left[Emp^{*}_{0,ihds} > 0\right];$$

$$Unemployed_{0,ihds} = 1\left[Emp^{*}_{0,ihds} \leq 0\right]$$

$Emp^{*}_{0,ihds}$ is a latent continuous variable which measures the gains from employment and whose observable counterpart is the binary indicator of whether a woman was employed in 2005 ($Employed_{o,ihds} = 1$) or not ($Unemployed_{o,ihds} = 1$). $\boldsymbol{Z}_{ihds}$ is the vector of baseline characteristics that determine the probability of employment in 2005. Similar to the Heckman's two step estimator, this method involves estimating a first stage probit equation of initial employment status, and calculating the inverse Mills ratio (IMR_{emp}) which is then included in the entry and exit equations to correct for sample selection bias (Orme, 1997; Bruce, 2000; Jeon, 2008).[49]

In addition to initial employment status, we also need to take into account the problem of panel attrition in our model. Almost 20 percent of the women from 2005 sample are not included in the 2012 sample; therefore, we do not observe their employment status in 2012 and hence we cannot define entry or exit variables for these women. If attrition is non-random, excluding these women can result in biased estimates in the entry and exit equations. From Table 4.2 we find that women who were unemployed in 2005 are more likely to be absent from the 2012 sample. It is possible that these women managed to get employment by migrating to some other place, although they are not considered in our estimation of the entry equation. Existing literature suggests that sample drop-outs are often

[49] For identification, the initial employment equation should include some explanatory variable which is validly excluded from the main entry and exit equations. Women's employment is found to be affected by rainfall in the Indian context. We include district level rainfall of 2004 that correspond to the baseline employment status as the identifying variable. To ensure that the exclusion restriction is met, we include the average rainfall between 2005 and 2011 in the main entry and exit equations. It is plausible to assume that the rainfall of 2004 will affect employment in 2005; however, it will not have any direct effect on employment decisions made between 2005 and 2012 especially after the rainfall during this time span has been included as control variable. We include a linear and a quadratic term of rainfall to account for any non-linearity in its effect. The effect of 2004 rainfall on initial employment is significant and u-shaped, suggesting that female employment is higher when there is either very low or very high rainfall.

endogenous for estimating transition probabilities and hence should not be ignored (Cappellari and Jenkins, 2004; Cappellari, 2007). Therefore we specify another equation to express the retention probability of women:

$$Retention_{ihds}^{*} = \boldsymbol{W}_{ihds}\boldsymbol{\psi} + e_{ihds} \qquad (6)$$
$$Retention_{ihds} = 1[Retention_{ihds}^{*} > 0]$$

The latent continuous variable $Retention_{ihds}^{*}$ captures the propensity of remaining in the sample; we can observe the binary indicator of whether the individual remained in the sample ($Retention_{ihds} = 1$) or dropped out ($Retention_{ihds} = 0$). We estimate both Equation (5) and (6) using probit models and calculate the inverse Mills ratios which are then included as additional explanatory variables in the main entry and exit equations. These inverse Mills ratios would correct for endogeneity arising from sample selection due to initial employment and attrition (Tunali, 1986; Kimmel, 1998; Cutillo and Centra, 2017). If the coefficients of these selection correction terms are found to be statistically significant, then it would indicate that such endogeneity problem should not be ignored in the estimation procedure.[50]

The final entry and exit equations are estimated following linear probability models as it is straightforward to estimate the marginal effects of the explanatory factors from a linear model. The standard errors, which are clustered at the village/town level, are bootstrapped because of the additional inverse Mills ratios included as regressors. The initial employment and retention equations include only characteristics from 2005 data. In the entry and exit equations, we also include the changes in the main variables such as income and asset between 2005 and 2012 to investigate how employment transitions are affected by the

[50] The retention equation should also contain an identifying explanatory variable that is validly excluded from the main equations. Existing literature dealing with non-random attrition issues in developing country panel data indicates that the survey interview procedure often captures variables that are able to predict panel attrition. For example, Maluccio (2004) uses quality of first round interview variables as instruments for such selection at the household level. Mahringer and Zulehner (2015) use whether the individual was the respondent for the family specific questions in the interview to predict individual level attrition. Following the same line of thought, we use a linear function of the person identifier in the 2005 sample as our identifying variable. Person identifiers are numbers that are assigned to each member of the household by the survey enumerator. We posit that persons who are recorded first are those with higher attachment to the household and hence less likely to subsequently drop out of the sample. To ensure that the person identifier is not picking up the effect of intra-household relationship which may be an important determinant of labour supply decisions, we include relationship to household head as a control variable in all the equations. After controlling for relationship patterns, the person identifier should predict attrition but not have any direct effect on labour supply decisions. The results from the retention regression support our hypothesis: we find a significant negative effect of individual identifier variable on the probability of retention. Thus, individuals recorded lower in the list in 2005 have higher probability of attrition from the 2012 survey.

dynamics of these explanatory factors. We carry out the analysis for the overall sample, and also for rural and urban areas separately.

4.6 RESULTS

In this discussion we focus on the estimates from the selectivity corrected entry and exit regressions presented in Tables 4.4 and 4.5. The selection equations for the initial employment and sample retention are presented in Appendix Table 4.A2 and 4.A3 respectively. We discuss the effect of various individual, household, and region level variables as follows.

Table 4.4: Entry probability

VARIABLES	(1) All	(2) Rural	(3) Urban
Age (years)	-0.002	0.026	-0.003
	(0.007)	(0.019)	(0.008)
Square of age	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Marital status: Single	-0.036	-0.148	0.074
	(0.054)	(0.103)	(0.067)
Marital status: Widowed	-0.034	-0.057	0.001
	(0.022)	(0.037)	(0.035)
Marital status: Separated/Divorced	-0.023	-0.025	-0.012
	(0.026)	(0.036)	(0.042)
Wife of head	0.032	-0.049	0.036
	(0.027)	(0.041)	(0.044)
Daughter of head	0.093**	0.023	0.114**
	(0.043)	(0.079)	(0.056)
Daughter-in-law of head	0.037	-0.108*	0.063
	(0.033)	(0.065)	(0.047)
Other relationship to head	0.087**	-0.096	0.096**
	(0.036)	(0.084)	(0.047)
Primary educated	-0.001	-0.056**	0.007
	(0.013)	(0.025)	(0.016)
Secondary educated	0.004	-0.053	-0.005
	(0.016)	(0.038)	(0.017)
Tertiary educated	0.051**	0.092	0.062*
	(0.024)	(0.066)	(0.036)
Number of children below 5	0.037***	0.028**	0.019*
	(0.007)	(0.012)	(0.010)
Mother/Father-in-law cohabitates	-0.014	0.006	-0.031
	(0.015)	(0.023)	(0.024)

Caste: OBC	0.008	0.039*	-0.004
	(0.012)	(0.021)	(0.015)
Caste: SC	0.063***	0.082***	0.027
	(0.013)	(0.020)	(0.021)
Caste: ST	0.050*	0.132***	0.058*
	(0.028)	(0.048)	(0.035)
Religion: Muslim	-0.065***	-0.107***	-0.060***
	(0.016)	(0.035)	(0.021)
Religion: Others	0.003	0.052	0.034
	(0.017)	(0.033)	(0.022)
Household size	0.002	0.004	-0.006
	(0.002)	(0.003)	(0.006)
Highest education level of male	-0.002	-0.005**	-0.001
	(0.001)	(0.002)	(0.002)
Household asset	-0.011***	-0.021***	-0.011***
	(0.002)	(0.004)	(0.003)
Household income excluding own income (100 thousands)	0.0027	-0.0004	-0.005
	(0.000)	(0.000)	(0.000)
Number of elderly (above 65)	0.008	0.005	0.024
	(0.011)	(0.016)	(0.016)
Change in household asset	-0.010***	-0.012***	-0.009***
	(0.001)	(0.002)	(0.002)
Change in household income excluding own income (100 thousands)	-0.0056**	-0.009**	-0.005
	(0.000)	(0.000)	(0.000)
Change number of elderly	0.007	0.010	0.003
	(0.008)	(0.011)	(0.010)
Number of new children born	-0.017**	-0.022*	-0.017
	(0.009)	(0.012)	(0.013)
Average annual rainfall 2005-2011	-0.039*	-0.042	-0.041
	(0.022)	(0.033)	(0.027)
Square of average annual rainfall 2005-2011	0.011***	0.011*	0.010*
	(0.004)	(0.006)	(0.006)
Log of average NREGS funds in district	-0.008	-0.000	0.001
	(0.006)	(0.011)	(0.007)
Urban area	0.035		
	(0.036)		
Inverse mills ratio_employed	0.260***	-0.085	0.129
	(0.059)	(0.164)	(0.090)
Inverse mills ratio_retention	0.191	-0.178	-0.416
	(0.341)	(0.681)	(0.652)
Constant	0.307	0.637*	0.705*
	(0.199)	(0.356)	(0.406)
Observations	12,860	6,361	6,499
R-squared	0.151	0.163	0.084

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. State fixed effects are included in the regressions.

Table 4.5: Exit probability

VARIABLES	(1) All	(2) Rural	(3) Urban
Age (years)	-0.044***	-0.032***	-0.018
	(0.007)	(0.009)	(0.022)
Square of age	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)
Marital status: Single	0.108*	0.088	0.155
	(0.057)	(0.090)	(0.110)
Marital status: Widowed	-0.014	-0.008	0.012
	(0.022)	(0.026)	(0.069)
Marital status: Separated/Divorced	0.031	0.028	0.058
	(0.026)	(0.031)	(0.080)
Wife of head	0.079***	0.041	0.008
	(0.024)	(0.026)	(0.096)
Daughter of head	0.082**	0.039	0.055
	(0.037)	(0.048)	(0.083)
Daughter-in-law of head	0.146***	0.095***	0.013
	(0.030)	(0.035)	(0.130)
Other relationship to head	0.212***	0.142***	0.000
	(0.038)	(0.047)	(0.153)
Primary educated	0.065***	0.049***	0.027
	(0.013)	(0.015)	(0.041)
Secondary educated	0.060***	0.048**	-0.045
	(0.018)	(0.023)	(0.043)
Tertiary educated	-0.226***	-0.186***	-0.091
	(0.039)	(0.053)	(0.123)
Number of children below 5	-0.011*	-0.014*	-0.026
	(0.006)	(0.008)	(0.025)
Mother/Father-in-law cohabitates	-0.061***	-0.044***	-0.061
	(0.012)	(0.012)	(0.047)
Caste: OBC	-0.029**	-0.023	0.011
	(0.014)	(0.015)	(0.034)
Caste: SC	-0.044***	-0.045***	-0.046
	(0.014)	(0.016)	(0.041)
Caste: ST	-0.087***	-0.078***	0.002
	(0.020)	(0.025)	(0.070)
Religion: Muslim	0.177***	0.140***	0.125**
	(0.023)	(0.027)	(0.058)
Religion: Others	-0.034	-0.019	-0.047
	(0.022)	(0.025)	(0.053)
Household size	-0.000	0.002	0.006
	(0.002)	(0.002)	(0.011)
Highest education level of male	0.006***	0.004***	0.003
	(0.001)	(0.001)	(0.005)

Household asset	0.014***	0.012***	0.004
	(0.002)	(0.003)	(0.008)
Household income excluding own income (100 thousands)	0.047***	0.028*	0.007
	(0.000)	(0.000)	(0.000)
Number of elderly (above 65)	0.014	0.015	0.023
	(0.010)	(0.012)	(0.034)
Change in household asset	0.006***	0.006***	0.008**
	(0.001)	(0.001)	(0.004)
Change in household income excluding own income (100 thousands)	0.013**	0.019**	0.002
	(0.000)	(0.000)	(0.000)
Change number of elderly	0.019***	0.021***	-0.010
	(0.007)	(0.008)	(0.023)
Number of new children born	0.035***	0.032***	0.064**
	(0.008)	(0.008)	(0.029)
Average annual rainfall 2005-2011	0.056**	0.053	0.001
	(0.028)	(0.036)	(0.062)
Square of average annual rainfall 2005-2011	-0.014***	-0.017**	-0.001
	(0.005)	(0.008)	(0.011)
Log of average NREGS funds in district	-0.026***	-0.035***	-0.008
	(0.009)	(0.012)	(0.014)
Urban area	0.205***		
	(0.046)		
Inverse mills ratio_unemployed	-0.167**	-0.042	0.270
	(0.082)	(0.121)	(0.249)
Inverse mills ratio_retention	-1.279***	-0.569	-2.065**
	(0.418)	(0.617)	(1.053)
Constant	1.245***	0.802**	1.099
	(0.234)	(0.320)	(0.759)
Observations	18,559	16,019	2,540
R-squared	0.165	0.174	0.139

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. State fixed effects are included in the regressions.

Individual characteristics: We do not find any strong effect of age on the probability of entry, although a negative linear and positive nonlinear effect of age is found on the exit probability in the overall and rural sample. This implies that probability of exit increases with women's age until a certain point and then it decreases with further increase in age. Women who were unmarried in 2005 are more likely to quit work. This is plausible because given the patriarchal social norms, many women drop out of the labour force after marriage. Working women may also get lower value in the marriage market due to such norms. The relationship variables reveal that daughter in laws of the household heads are less likely to enter and more likely to exit the labour force.

The education level of women seems to have a U-shaped relationship pattern with women's labour force participation: women who have education level below primary and above tertiary are more likely to be employed than those with mid-levels of education. This relationship becomes weaker in the case of entry, but significantly shows up for exit in the overall and rural sample.

Social category and religion: Women from socially disadvantaged or backward caste such as Scheduled Tribes (ST), Schedule Caste (SC) and other backward caste (OBC) categories are significantly more likely to enter into employment and less likely to exit as compared to the high caste category.[51] This finding is consistent with the literature which suggests that women from upper castes have less freedom to be economically active compared to their counterpart belonging to socially disadvantaged categories. Even if they participate in work, they are not able to continue it unlike the women from the lower caste categories. Apart from caste, religion also plays an important role in determining women's employment transition. Muslim women are less likely to take employment and more likely to quit as compared to the Hindu women; the coefficients are highly significant across overall, rural and urban sample.

Household's education: We have included highest adult-male education in the household. We find that higher adult-male education increases women's withdrawal from work significantly in the rural area and overall sample but not in the urban area. It is also associated negatively with women's entry into the employment; the coefficient is significant for rural sample.

Household income and asset: We investigate the hypothesis that women participate in the labour market when there is a need for augmenting household income, and they withdraw from employment when the household becomes affluent. In the initial employment regression, we do find a significant negative effect of both household wealth (captured by asset holding) and income on women's employment in 2005. But this cross-sectional

[51] Caste system in India is a form of social stratification based on castes. Officially Dalits, a group of people considered as 'untouchable' are identified as Scheduled Castes (SCs). Adivasis, a tribal group as Schedule Tribes (STs), and Shudras as Other Backward Caste (OBCs). Together, these three groups are identified to be placed lower in the caste hierarchy while all other belong to the Upper Castes are placed higher.

relationship may be capturing other household specific unobserved effects such as household's preference towards female employment and other gender norms. Therefore we are interested in investigating the relationship from the entry and exit equations where for the same individual belonging to the same household, we look at the changes in employment over time. First we examine how the probability of entry and exit varies with initial level of household asset and income. We find that females from wealthier households are less likely to enter and more likely to exit from employment. While initial income does not significantly affect entry probability, it affects the exit probability in the same direction as wealth. For the urban sample we do not find any significant effect of initial wealth and income on exit probability.

Further, we measure the changes in household wealth and income between 2005 and 2012 and include them as additional explanatory variables in the regression. An increase in income of other members of the household significantly reduces the probability of woman's entry into employment, and it increases the probability that she will exit from employment. This relationship is present in the overall and the rural sample. An increase in rupees 100, 000 yearly income is associated with 1.3 percentage point increase in the probability of woman's withdrawal from employment in the overall sample, which is even higher (1.9 percentage points) in the rural sample. The effect of household wealth is also in the same line: when a household becomes wealthier, women from that household have greater chance of becoming unemployed and lower chance of becoming employed. This effect is found to be significant in the overall, rural, and urban samples.

One potential concern in identifying the effect of household income on women's employment transition is the fact that we do not have an exogenous change in income. Income may itself be affected by individual's labour supply decisions, resulting in reverse causality. We try to mitigate this endogeneity problem by excluding an individual's own income from the measure of household income. Therefore, our income measure essentially consists of other household members' income. Furthermore, we argue that our estimated effect is potentially a lower bound of the true effect due to the following reason. If a woman enters employment, then total income of household increases because of the additional contribution from the woman. However, we find a negative effect of rising income on women's entry probability. Therefore, it must be the case that the true negative effect is even larger in magnitude, which off-sets the positive effect of woman's own contribution to household income, and yields a negative coefficient. Similar argument can be made for the exit probability. The use of temporal variation in our analysis is particularly useful in this case; it provides a more credible estimation strategy than other studies in the literature which use cross-sectional variation.

Number of children in the household: Number of new children born between the two rounds has a significant negative (positive) effect on women's entry into (exit from) the labour market. While expressed as a partial derivative, the coefficients indicate that an additional child raises (decreases) the probability of exit (entry) by 3.5 (1.7) percentage points. The size of the coefficint is even higher for urban women's withdrawal from work.

Number of elderly in the house: Increase in the number of elderly between two rounds increases women's exit from the employment significantly; the coefficient is not significant for urban sample.

Presence of in-laws in the same house: Presence of in-laws in the same house has a negative effect on women's exit from employment. While increase in number of other elderly members of the households play as a hindrance in continuing work, in-laws might be helping women by providing in-house child care or by helping in the household chores. The insignificant coefficients in entry equation implies that presence of in-laws in the house only helps those who are already in the employment but does not help the unemployed women in taking employment.

Among other, National Rural Employment Guarantee Scheme (NREGS) which is a large active labour market policy to provide employment to rural people has an important role to play in women's withdrawal from employment. Given that this program provides equal employment opportunities to men and women within the locality, women may find it easier to continue the work.

4.7 CONCLUSION

This chapter contributes to the debate of female labour force participation in developing countries by analysing employment entry and exit of women in India. Our study highlights the fact that women in India are not only participating less in the labour force, their withdrawal from work is also very high. We estimate the determinants of the transition probabilities of women in a regression framework by tackling for two sample selection issues in the econometric estimation. We find that an increase in income of other members of the household leads to lower entry and higher exit probabilities of women. We also control for the asset dynamics of the household and the income effect holds true even after controlling for the asset. The significant effect of household income and wealth is an important finding that potentially provides an explanation why despite economic growth female labour force participation may not increase over time. It clearly shows that when other members have better earnings, then women are discouraged from participating in the labour market. This finding is consistent with the literature which highlights the possibility that women may be disinclined to be employed because of family status concerns and societal norms that stigmatize women's market work (Eswaran et al. 2013).

Household with higher educated adult male have less women entering into employment and more women withdrawing from employment. However, this seems to be the case only in the rural households. Along with the effects of caste and religion, these results reveal the interplay between cultural and economic factors that are important in explaining the declining workforce participation of women in India. With an improvement in socio-economic status, households discourage its women to step out and engage in employment. This finding offers a plausible explanation why economic growth may not necessarily promote women's labour force participation.

Also, having a new-born child has a detrimental effect on women's employment, indicating that provision of childcare facilities can be an important policy instrument in this context. The significant effect of the National Rural Employment Guarantee Scheme suggests that availability of opportunities play an important role in the employment transition. Our analysis sheds light on the important issue of low and declining female labour force participation in the context of a large and growing emerging economy. However, most of these factors are not significant for urban sample. It is possible that there is less variation in urban sample due to the smaller sample size. Rural and urban labour markets are also structurally different. Factors related to demand for labour may be more important determinants than those related to supply of labour in the urban labour market. Our data and empirical analysis focus mostly on supply side determinants, therefore, the urban scenario may not be adequately captured in the current analysis.

Economic participation of a woman not only has bearing on her own empowerment, but also leads to better intra-household resource allocation resulting in improvements in the human capital of the next generation. Besides, to reap the demographic dividend, it is imperative that policies are made conducive for greater participation of women in the workforce. However, a neglected issue in the literature is the fact that employment status is often dynamic, rather than static, in nature. In the context of India, our study is the first to explicitly model employment entry and exit probabilities of females. It shows the importance of designing policies that not only promote female employment, but also ensures that those who are already in the workforce can retain their employment status in the face of changing socio-economics within and outside the household.

4.8 APPENDIX

Table 4.A1: Summary statistics

VARIABLES	(1) N	(2) mean	(3) sd
Entry	14,073	0.25	0.43
Exit	18,940	0.39	0.49
Age (years)	41,665	37.93	8.92
Square of age	41,665	1,518.37	704.56
Marital status: Married	41,665	0.87	0.34
Marital status: Single	41,665	0.03	0.17
Marital status: Widowed	41,665	0.07	0.26
Marital status: Separated/Divorced	41,665	0.03	0.17
Household head	41,665	0.06	0.24
Wife of head	41,665	0.69	0.46
Daughter of head	41,665	0.04	0.19
Daughter-in-law of head	41,665	0.15	0.36
Other relationship to head	41,665	0.06	0.24
edu==No formal education	41,535	0.56	0.50
Primary educated	41,535	0.15	0.35
Secondary educated	41,535	0.23	0.42
Tertiary educated	41,535	0.06	0.23
Number of children below 5	41,665	0.38	0.72
Mother/Father-in-law cohabitates	41,665	0.25	0.43
Caste: Others	41,665	0.34	0.47
Caste: OBC	41,665	0.39	0.49
Caste: SC	41,665	0.19	0.39
Caste: ST	41,665	0.08	0.27
Religion: Hindu	41,665	0.81	0.40
Religion: Muslim	41,665	0.12	0.32
Religion: Others	41,665	0.08	0.27
Household size	41,665	5.99	3.02
Number of elderly (above 65)	41,665	0.20	0.47
Highest education level of male	41,665	7.40	5.16
Household asset	41,665	12.86	6.28
Household income excluding own income (thousands)	41,665	55.47	85.99
Change number of elderly	33,013	0.06	0.56
Number of new children born	41,665	0.11	0.41
Change in household asset	32,996	3.05	3.67
Change in household income excluding own income (thousands)	41,662	4.84	134.48
Average annual rainfall 2005-2011	41,665	1.24	0.82
Square of average annual rainfall 2005-2011	41,665	2.22	3.81
Log of average NREGS funds in district	39,243	1.38	1.17
Urban area	41,665	0.36	0.48

Table 4.A2: Selection equation for the initial employment

VARIABLES	(1) All	(2) Rural	(3) Urban
Age (years)	0.126***	0.142***	0.090***
	(0.008)	(0.010)	(0.014)
Square of age	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)
Marital status: Single	-0.054	-0.325***	0.175*
	(0.059)	(0.079)	(0.092)
Marital status: Widowed	0.072*	-0.056	0.244***
	(0.043)	(0.052)	(0.076)
Marital status: Separated/Divorced	0.020	-0.066	0.226**
	(0.049)	(0.058)	(0.094)
Wife of head	-0.344***	-0.212***	-0.496***
	(0.045)	(0.055)	(0.078)
Daughter of head	-0.303***	-0.320***	-0.263***
	(0.057)	(0.074)	(0.088)
Daughter-in-law of head	-0.539***	-0.421***	-0.665***
	(0.048)	(0.058)	(0.087)
Other relationship to head	-0.764***	-0.668***	-0.811***
	(0.044)	(0.054)	(0.073)
Primary educated	-0.169***	-0.181***	-0.166***
	(0.021)	(0.027)	(0.037)
Secondary educated	-0.244***	-0.288***	-0.146***
	(0.022)	(0.028)	(0.036)
Tertiary educated	0.287***	-0.232***	0.604***
	(0.037)	(0.068)	(0.051)
Number of children below 5	-0.077***	-0.071***	-0.097***
	(0.012)	(0.014)	(0.023)
Mother/Father-in-law cohabitates	0.114***	0.093***	0.102**
	(0.024)	(0.029)	(0.045)
Caste: OBC	0.090***	0.084***	0.081***
	(0.018)	(0.023)	(0.030)
Caste: SC	-0.024	-0.077***	0.096**
	(0.022)	(0.027)	(0.038)
Caste: ST	0.266***	0.256***	0.297***
	(0.033)	(0.039)	(0.071)
Religion: Muslim	-0.251***	-0.257***	-0.261***
	(0.024)	(0.032)	(0.038)
Religion: Others	0.169***	0.215***	0.126**
	(0.031)	(0.040)	(0.051)
Household size	0.010***	-0.001	0.038***
	(0.003)	(0.003)	(0.006)

Number of elderly (above 65)	0.031*	0.042**	-0.009
	(0.018)	(0.021)	(0.034)
Highest education level of male	-0.012***	-0.007***	-0.023***
	(0.002)	(0.002)	(0.003)
Household asset	-0.038***	-0.035***	-0.040***
	(0.002)	(0.002)	(0.003)
Household income excluding own income (100 thousands)	-0. 145***	-0.131***	-0.183***
	(0.000)	(0.000)	(0.000)
Rainfall in 2004	-0.130***	-0.050*	-0.131***
	(0.020)	(0.026)	(0.037)
Square of rainfall in 2004	0.011***	-0.006	0.018***
	(0.002)	(0.004)	(0.004)
Urban area	-0.863***		
	(0.017)		
Constant	-0.583***	-0.888***	-0.913***
	(0.175)	(0.216)	(0.307)
Observations	41,531	26,639	14,892

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. State fixed effects are included but not reported in the table.

Table 4.A3: Selection equation for the sample retention

LABELS	(1) All	(2) Rural	(3) Urban
Age (years)	0.075***	0.084***	0.060***
	(0.009)	(0.011)	(0.013)
Square of age	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Marital status: Single	-0.457***	-0.621***	-0.310***
	(0.057)	(0.080)	(0.084)
Marital status: Widowed	-0.080*	-0.151***	0.050
	(0.044)	(0.057)	(0.072)
Marital status: Separated/Divorced	-0.090*	-0.144**	0.017
	(0.051)	(0.063)	(0.089)
Wife of head	0.026	0.018	0.085
	(0.047)	(0.060)	(0.076)
Daughter of head	-0.231***	-0.296***	-0.174*
	(0.058)	(0.077)	(0.089)
Daughter-in-law of head	-0.085	-0.176***	0.076
	(0.052)	(0.065)	(0.089)
Other relationship to head	-0.047	-0.058	-0.047
	(0.051)	(0.065)	(0.083)
Primary educated	-0.046**	-0.033	-0.056
	(0.023)	(0.031)	(0.035)
Secondary educated	-0.124***	-0.120***	-0.090***
	(0.023)	(0.032)	(0.033)
Tertiary educated	-0.251***	-0.410***	-0.150***
	(0.037)	(0.071)	(0.048)
Number of children below 5	0.026*	0.060***	-0.028
	(0.013)	(0.017)	(0.021)
Mother/Father-in-law cohabitates	0.148***	0.096***	0.180***
	(0.027)	(0.034)	(0.044)
Caste: OBC	0.108***	0.083***	0.101***
	(0.019)	(0.026)	(0.027)
Caste: SC	0.054**	0.002	0.108***
	(0.023)	(0.031)	(0.036)
Caste: ST	-0.017	-0.022	0.022
	(0.034)	(0.041)	(0.070)
Religion: Muslim	-0.090***	-0.064*	-0.110***
	(0.025)	(0.037)	(0.035)
Religion: Others	-0.040	-0.026	-0.066
	(0.031)	(0.044)	(0.046)
Household size	0.041***	0.028***	0.062***
	(0.004)	(0.005)	(0.007)
Number of elderly (above 65)	0.037*	0.031	0.050

	(0.019)	(0.024)	(0.033)
Highest education level of male	-0.007***	-0.005*	-0.010***
	(0.002)	(0.003)	(0.003)
Household asset	-0.003	0.004	-0.011***
	(0.002)	(0.003)	(0.003)
Household income excluding own income (100 thousands)	-0.044***	-0.043***	-0.040***
	(0.000)	(0.000)	(0.000)
Person ID within household	-0.042***	-0.039***	-0.038***
	(0.007)	(0.008)	(0.012)
Urban area	-0.388***		
	(0.018)		
Constant	-0.318*	-0.391	-0.544*
	(0.185)	(0.248)	(0.284)
Observations	41,531	26,639	14,892

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. State fixed effects are included but not reported in the table.

Chapter 5

Conclusion

The thesis explores important issues in labour economics such as job-education mismatch, employment polarization, and employment transition of women. The thesis also contributes to the literature of comparative economics by analysing and comparing different countries – Germany, India, Spain, Sweden and United Kingdom.

The first essay fills the gap in the literature by linking structural change in employment and over-education. Results from both descriptive and job fixed effects regression suggest that over-education is higher and prevalent in low-skill jobs in countries with a polarizing employment change pattern (employment growth in low- and high-skill jobs, and reduction in the middle). In UK and Spain where low-skill interpersonal service jobs are growing more than the intermediary routine jobs, over-education is high and shows an increasing trend in these jobs. Interpersonal service jobs are mostly performed manually by low skilled workers. Increasing supply of educated workers along with the increasing unemployment may be forcing some medium or high skilled workers to take low-skill jobs. The policy measure should focus on providing and promoting right skill and education which are compatible with the changing nature of jobs and production process. Moreover, the job fixed effects results also suggest that increase in women employees does not increase over-education within a job but it does increase the share of over-educated workers across jobs in some countries. This may imply the job segregation of labour market in terms of gender across countries. Future research can focus on sex segregation of occupation and how it is associated with skills mismatch.

The thesis also sheds light on the fact that developing country like India is on the verge of experiencing structural change in occupation due to technological progress. However, developing countries have very different and serious problems to address, such as its informal sector and decreasing women's participation in the labour force. The last two chapters of the thesis focus on the employment related issues in India and reveal that employment change has also been polarised in urban India during the 1990s and the 2000s. However, it does not seem to be the consequence of only technological change. Increasing self-employment in the informal sector has contributed in the expansion of two extreme poles of the occupational hierarchy. At the same time, reduction in jobs such as clerical and office assistant gives an indication that technology has started replacing some routine jobs in urban India. As India is achieving higher economic growth the use of machines and technology is slowly taking over its labour intensive production process. This process in some way can affect the growth of the occupations or sectors that hire women.

India's female labour force participation rate has been low and declining for the last few decades. The final chapter of the thesis contributes to the literature on female labour force participation in India by investigating women's entry into and exit from the employment. It adds significantly to the existing literature as most of the studies have focused on female labour force participation rate using cross sectional data. Employment transition of women using a panel data has been under researched. The results provide evidence on the fact that women are dropping out of employment at a significant rate. So policy should not only focus on bringing more women into the labour force but also to keep them in the employment.

The main findings suggest that along with the effects of social status and religion, household's economic status plays an important role in women's employment transition. An increase in income of other members of the household leads to lower entry and higher exit probabilities of women. While this problem is difficult to address, availability of quality jobs in the local labour market can be an effective measure in bringing more women and keeping them in the employment. As seen in the analysis women who work in agricultural farm are dropping out more than the salaried and casual wage earner. Availability of quality jobs is particularly important in this context. The significant effect of the National Rural Employment Guarantee Scheme (NREGS) suggests that availability of opportunities play an important role in the employment transition. Provision of child care seems to be another important policy measure in this context as having a new-born child has a detrimental effect on women's employment. Thus, the last two chapters of the thesis identify some important policy relevant issues in the context of a transitioning labour market in an emerging economy.

Capítulo 5

Conclusiones

Esta tesis explora algunos asuntos importantes de la economía laboral, como puedan ser la falta de correspondencia entre las necesidades educativas del sistema productivo y la educación de los trabajadores, esto es, el desajuste educativo, la polarización del empleo y la transición al empleo de las mujeres. La tesis también tiene una perspectiva de análisis comparado, al analizar y comparar distintos países – Alemania, India, España, Suecia y Reino Unido.

El primero de los ensayos pretende reducir la brecha existente en la literatura del desajuste educativo al vincular el cambio estructural del empleo y la sobre-educación. Los resultados alcanzados tanto del análisis descriptivo como de las regresiones con efectos fijos sugieren que la sobre-educación es mayor y prevalente en los trabajos de baja cualificación, en los países con un cambio del patrón de empleo del tipo polarizador (crecimiento del empleo en los trabajos de baja y alta cualificación, y reducción en el medio). En el Reino Unido y España, donde el empleo los servicios personales de baja cualificación crece más que los empleos intermedios rutinarios, la sobre-educación es alta y muestra una tendencia creciente. Los servicios personales, en su mayoría, son muy intensivos en mano de obra de baja cualificación. El aumento de la oferta de trabajadores con creciente nivel educativo junto con el aumento del desempleo puede obligar a algunos trabajadores con cualificación media o alta a aceptar puestos de trabajo de baja cualificación. La política económica más adecuada en este caso debería ser aquélla dirigida a promover y proveer la educación y cualificación apropiada compatible con la naturaleza cambiante de los empleos y los procesos productivos. Más aún, los resultados de análisis de efectos fijos sugieren que el aumento del empleo femenino no aumenta la sobre-educación dentro de cada tipo de empleo, aunque si contribuye al aumento del peso de los trabajadores sobre-educados en el conjunto del empleo. En lo que a esto respecta, futuras investigaciones deberían centrarse en la segregación ocupacional y cómo se asocia con el desajuste educativo.

La tesis también pretende mejorar nuestro conocimiento en lo que se refiere a la posición actual de un país en desarrollo de la importancia de la India en lo relativo al cambio estructural del empleo. En lo que a esto respecta, India se encuentra en el umbral de un cambio estructural en ocupaciones debido al cambio técnico. En todo caso, los países en vías de desarrollo, como India, se enfrentan también a problemas específicos como la informalidad y la participación decreciente de la mujer en el mercado de trabajo.

Los dos últimos capítulos de la tesis se centran en el análisis temas vinculados con el cambio estructural en la India y muestran que el cambio en la estructura del empleo ha adoptado un patrón polarizador en las dos últimas décadas (1990 y 2000). Sin embargo, no parece que tal patrón responda tan solo al cambio técnico. El aumento del autoempleo en el sector informal ha contribuido a la expansión de los dos extremos de la jerarquía ocupacional. Al mismo tiempo, la reducción del empleo administrativo parece indicar que la tecnología ha empezado a sustituir empleos rutinarios en India. Según India vaya alcanzando mayores niveles de crecimiento económico, el uso de maquinaria y tecnología irá lentamente sustituyendo actividades antes realizadas utilizando de forma intensiva mano de obra. Este proceso puede afectar el crecimiento de las ocupaciones o sectores que contratan mano de obra femenina.

La tasa de actividad femenina en India ha sido baja y decreciente durante las últimas décadas. El último capítulo de la tesis contribuye a la literatura de participación de la mujer en el mercado de trabajo en India, investigando desde una perspectiva dinámica la entrada y salida de la mujer en el mercado de trabajo. En nuestra opinión, los resultados alcanzados suponen un avance de nuestro conocimiento en este campo en la medida en que la mayoría de los trabajos que lo han investigado en el pasado lo hicieron con una metodología de análisis de corte trasversal, menos adecuada para el estudio de fenómenos dinámicos. Por el contrario el uso de datos de panel en este campo ha sido muy minoritario. Los resultados alcanzados en el capítulo 4 ofrecen evidencia sólida de que las mujeres están abandonando el mercado de trabajo a una tasa significativa. De esta forma, la política laboral no se debería centrar solo en atraer a más mujeres a la actividad laboral, si no también en cómo retenerlas en el mercado de trabajo.

Los resultados principales obtenidos sugieren que junto con los efectos de status social y religión, el estatus socioeconómico del hogar tiene un papel importante a la hora de explicar las transiciones de estatus laboral. El aumento de los ingresos de otros miembros del hogar tiene un efecto depresor sobre la probabilidad de entrada, al tiempo que aumenta la probabilidad de salida. Aunque este problema es difícil de resolver, la disponibilidad de puestos de trabajo de calidad en el mercado local parece ser una medida efectiva para atraer a más mujeres al mercado laboral y mantenerlas en éste. Como se ha visto en el análisis desarrollado, las mujeres que trabajan en la agricultura abandonan la actividad a tasas mayores que las asalariadas urbanas y aquéllas empleadas de forma esporádicas. La disponibilidad de empleo de calidad es especialmente importante en este contexto. El efecto significativo, y positivo, del *National Rural Employment Guarantee Scheme* (NREGS) sugiere que la disponibilidad de oportunidades de empleo tiene un papel importante a la hora de explicar las transiciones del mercado de trabajo en el mundo rural. La existencia de servicios de cuidados infantiles es también un aspecto a considerar, ya que en este contexto, el dar a luz un hijo tiene un efecto negativo sobre el empleo femenino. De esta forma los últimos dos capítulos de la tesis identifican algunos temas con importantes implicaciones de política económica y social en el contexto de mercados laborales en transición en economías emergentes.

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