UNIVERSITY OF SOUTHAMPTON

Essays in Labour Economics

by

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Declaration of Authorship

I, Elif Kara, declare that this thesis titled, 'Essays in Labour Economics' and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Abstract

Faculty of Social and Human Sciences

by Elif Kara

This thesis combines three essays in applied labour economics. The first essay in Chapter 2 mainly investigates three questions: (i) How has wage dispersion within male university graduates changed from 1997 to 2012 in the UK? (ii) What type of tasks and skills do university graduates apply on the job? (iii) To what extent can increased wage dispersion within university graduates be attributed to changes in job tasks and skills used in the workplace? The results suggest that male university graduates who are on the 90th percentile of the wage distribution have become better off, whereas the status of the workers in this group who are on the 10th percentile has not shown significant increase from 1997 to 2012. In addition, they show that this dispersion can be partly attributed to job skills such as numeracy and problem search and solving skills.

The second essay in Chapter 3 examines one important education policy-related question: How large are the efficiency gains from early tracking for the students who are streamed? In order to answer this question, a policy change which created an exogenous variation in the early tracking status of the students in Turkey was evaluated. The results show there was an additional 13% decrease in the mathematics test scores during the post-intervention periods for the students who were exposed to the policy change, compared to the students who were not subjected to it.

The third essay in Chapter 4 assesses to what extent returns to cognitive and motor skills vary across occupations in the UK by employing the heterogeneous human capital framework of Yamaguchi (2014), who defines occupations as a bundle of cognitive and motor task indices. Using self-reported cognitive and motor task information from the Skills Survey of Britain, the cognitive and motor task complexity vectors of occupations are calculated. Further, the varying returns to skills across occupations are quantified exploiting data from the British Household Panel Survey between 1991 and 2008. The results imply that there are heterogeneous rewards to cognitive skills depending on the workers' performed level of cognitive task complexity in their jobs.

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Contents

List of Figures

List of Tables

This thesis is dedicated to the memory of my beloved grandmother Fehime Kara (1929-2013) who never had a chance to go to school but managed to raise her children by herself.

Chapter 1

Introduction

This thesis consists of three distinct essays and attempts to shed more light on the important economic issues of wage inequality, the efficiency of selective education policies, human capital accumulation and wage growth in the labour market respectively.

There is a series of studies which documented that wage inequality had been rising from the late 1960s in the US and from the late 1970s in the UK until the early 1990s (e.g. Juhn et al. (1993), Machin (1996)). Several lines of recent evidence, however, suggest that ever since the 2000s, wage dispersion has been increasing mainly for workers at the highest end of the wage distribution and, hence, within the group of highest skilled workers (e.g. university graduates) in the US and the UK (see Autor et al. (2008) and Lemieux (2006b) for the US and see Lindley and Machin (2011) and Green and Zhu (2010) for the UK). In addition, the relevant literature, which has expanded with recent increase in the data availability of task measures, suggests that job-related activities (job tasks), occupations and skills used in the workplace are becoming more important for determining wage structure and other related inequalities (e.g. Autor et al. (2006), Goos and Manning (2007), Goldin and Katz (2007), Bacalod and Blum (2010), Ingram and Neumann (2006)).

In studies with a task approach to labour market, (job) task is defined as a unit of work related activity and skill is defined as a worker's endowment to perform tasks. Therefore, task data provides valuable information on what type of specific skills workers need to perform tasks on the job, why these skills are required and how these skill requirements have shifted over time. Moreover, the intensity and type of tasks that workers perform on the job are largely tied to specific firms, occupations and industries. Hence, the degree and type of skills that workers need to perform job tasks may reflect firm/occupation heterogeneity. The firm/occupation heterogeneity, in turn, would result in workers' self-selecting themselves into occupations where they get higher returns to their skills. On the other hand, unlike firm specific (e.g. Altonji and Shakotko (1987)), occupation specific (e.g. Kambourov and Manovskii (2009), Sullivan (2010)) and industry specific (e.g.Parent (1995)) labour market skill measures, recent studies have shown that task specific skills are not completely lost when workers switch occupations and can be attributed to workers' wage growth (see e.g.Gathmann and Schonberg (2010). It can be concluded that wage rewards to task-based labour market skills would reflect both firm/occupation and worker heterogeneity.

The first essay in Chapter 2 contributes to the literature by investigating the link between wage dispersion within university graduates and job skills they apply in the workplace using data from the Skills Survey in Britain between 1997 and 2012. The descriptives show that there has been some changes in the level of tasks performed by graduates over time in the workplace which can be rationalised by the demand and supply influences. In particular, the statistics show that intensity of some tasks increased over time. In addition, the Mincerian wage regression results suggest not only that problem search and solving and the numeracy skills are highly significant for which wage level of a male worker with a university degree will find himself but also that the value of these skills has increased over time. Finally, the residual wage gap analysis demonstrates that job skills alone account for around 3.2% of wage dispersion in 1997 and that this ratio increased to 6.6% in 2012.

Education policies play a crucial role in determining cognitive development and achievement and which would, in turn, affect the labour market outcomes of individuals. In particular, selective (i.e. academic tracking) versus comprehensive schooling policies have important economic consequences on levels of educational equality and efficiency since each avenue results in different peer group and teaching qualities, and significantly affects the academic curriculum which will be executed across schools/classes. Due to their importance, their various outcomes have been widely debated in the literature (e.g. Betts (2011), Duflo et al. (2011), Hanushek and Wobmann (2006), Ding and Lehrer (2007)). In an attempt to contribute to the literature, the second essay in Chapter 3 evaluates the effects of a policy change which took place in Turkey on students' test performance by providing new evidence about the efficiency gains from early tracking. The education regulation passed in 1997 increased the years of compulsory schooling and caused the removal of early tracking. This regulation also resulted in the exogenous variation of the early tracking statuses of students. Using mathematics test scores from the Third International Mathematics and Science Study (TIMMS) and the Program for International Student Assessment (PISA), we measured the effect of the removal of early tracking on students' mathematics achievement using the difference-in-difference-in-differences (DDD) method. The results suggest that there was an additional 13% decrease in the mathematics test score of those students exposed to the policy change, thereby making them lose the opportunity to go to high-ranked schools. This result can be rationalised with arguments stating that high-ranked schools provide better environments in terms of the quality in peer-groups, teachers, and the academic curriculum as a whole.

Over time, the human capital literature has evolved from models with homogeneous human capital to partially transferable heterogeneous human capital (labour market skills) models (see Sanders and Taber (2012) for a review). The last essay in Chapter 4 examines to what extent there are varying returns to cognitive and motor skills across occupations using a task-based approach, in the hopes of aspiring to shed more light on the task-based channels of wage growth and human capital accumulation in the labour market. In particular, we conduct an exploratory empirical analysis using data from the Skills Survey of Britain (SS) and the British Household Panel Survey (BHPS) and test one of the implications of the heterogeneous human capital model developed by Yamaguchi (2012) and Yamaguchi (2014) where occupations are characterised by cognitive and motor task complexity (intensity) vectors. The key prediction of the model is that, when a worker is employed in an occupation characterised by complex cognitive (motor) tasks, the worker will use more of his cognitive (motor) skills which, in turn, leads, both to the acquisition of task-specific cognitive (motor) skills and the increase in productivity becoming larger. This process results in heterogeneous cognitive (motor) skills and wage profiles (across workers) over time. Nevertheless, this work extends, in a way, the empirical implementation of the model by quantifying heterogeneous rewards to education categories, general labour market experience and accumulated cognitive and motor skills across occupations. The results suggest that the returns to education, general labour market experience and accumulated cognitive labour market skills vary across occupations in the UK depending on the workers' performed level of cognitive task complexity in their jobs. In addition, and in line with Yamaguchi (2014), we found that a high cognitive skilled worker, i.e. a highly educated worker who is employed in an occupation characterised by more complex cognitive tasks earns more when all other characteristics are held constant at their means. A low cognitive skilled worker, on the other hand, is better off being employed in an occupation which is characterised by simple cognitive tasks.

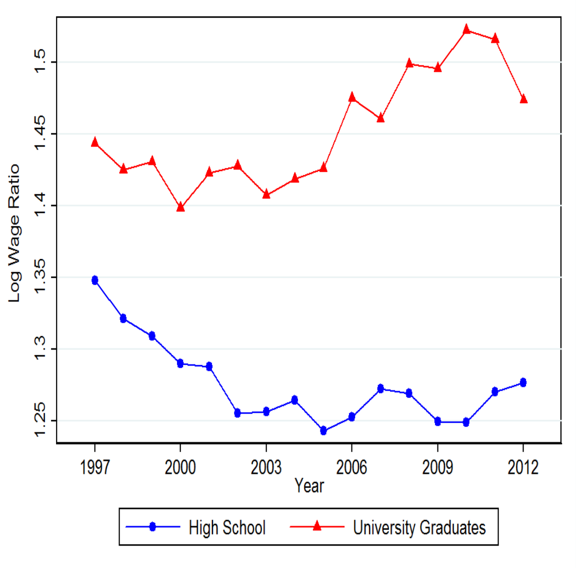
Chapter 2

An Empirical Analysis of the Link Between Wage Dispersion Within University Graduates and Job Skills in the UK

2.1 Introduction

It is well documented that returns to all skills and educational wage differentials have risen between the late 1960s and the early 1990s in the US and the UK. Nevertheless, recent studies have shown that wage dispersion has been increasing mainly within the highest skilled workers in the US (Autor et al. (2008), Lemieux (2006a)) and within university graduates in the UK (Lindley and Machin (2011), Green and Zhu (2010)). Figure 2.1 illustrates the evolution of the 90-10 wage ratio for male high school and university graduates in the UK from the Labour Force Survey sample. In line with the recent studies, wage dispersion within university and high school graduates display diverging trends between 1997 and 2012. Despite the fluctuations, the figure shows an increase in the university graduate wage dispersion and a substantial fall in the high school dispersion over the period.

FIGURE 2.1: Trend in 90-10 Log Wage Ratio of University and High School Graduates



Notes: LFS data sample, log hourly wage ratio for male full-time workers (excluding self-employed) aged between 16-65. The survey weights are used.

Empirical works in wage inequality literature typically attribute wage dispersion within the skilled groups to so-called 'unobserved skills' (Juhn et al. (1993), Katz and Autor (1999),Prasad (2002), Lemieux (2006a)), because this sort of inequality cannot be explained by worker characteristics (e.g., education levels, experience, gender, etc.), which are readily available in the standard data sets. However, recent studies which use more detailed data sets on occupations and job tasks suggest that the tasks and the skills which workers apply in the workplace[1] play an important role in explaining wage and employment trends (see Autor et al. (2003), Spitz-Oener (2006), Ingram and Neumann (2006), Bacalod and Blum (2010)). For instance, Lindley and Machin (2011) found that the skills possessed (in terms of job tasks performed) by workers within same qualification groups i.e. within a university degree show substantial differences in the UK. They consider that this heterogeneity gives rise to higher demand for some workers relative to the others and increases relative returns.

This study contributes to the literature by providing new empirical evidence on increasing wage dispersion within university graduates in the UK in light of the task-based approach to labour market outcomes. In particular, the following questions were examined: (i) How has wage dispersion within male university graduates changed from 1997 to 2012 in the UK? (ii) What type of tasks and skills do university graduates apply on

[1]Herein, the skills which workers apply in the workplace are defined as job skills, job related skills or task-based labour market skills unless stated otherwise. These skills are possessed by workers and applied in the workplace. A job task or a job activity is, in turn, a unit of work related activity.

the job? (iii) How did those task and skill requirements change over time? (vi) How are the generated job related skills of male university graduates valued in the UK labour market? (v) To what extent can increased wage dispersion within university graduates be attributed to changes in job tasks and skills used in the workplace?

In order to answer these questions and further illustrate the increased wage dispersion within male workers with a university degree, a quantile regression model was fitted, using cross-section data from the UK Labour Force Survey (LFS) between 1997 and 2012. Secondly, a sample of cross-section data from the Skills Survey of Britain (SS) between 1997-2012 was used, which provides self-reported job activities (tasks) information and five job related skills were identified by means of factor analysis. Further, using a similar reasoning to Ingram and Neumann (2006) and Dickerson and Green (2004), Mincerian wage regression models were used to estimate the contribution of the observed individual skill measures, particularly job skills to expected wage levels of university graduates in 1997 and 2012. Finally, by examining the residual wage gap from 1997 to 2012, the extent to which wage dispersion within university graduates can be attributed to changes in these skill measures was quantitatively assessed, in particular the job tasks and skills used in the workplace.

The descriptive quantile regression results show that the variation in wages of the university graduates has risen more than high school graduates. Moreover, male university graduates who are on the 90th percentile of the wage distribution have become better off, whereas the status of the workers in this group who are on the 10th percentile has not shown significant increase from 1997 to 2012. This has resulted in an increase in the wage dispersion between these workers over time. Moreover, the Mincerian wage regression results indicate that among the five job skill measures, problem search and solving and numeracy skills are highly significant factors in the wages of the male university graduates in 1997 and 2012. Furthermore, these skills are associated with higher pay; this effect has increased between the period of interest. In addition, the estimates suggest that, when other variables are held constant, workers who perform any degree of routine work substantially earn lower than the workers who never undertook routine work in 1997 and 2012. These findings can be rationalised by recognising the rising demand for skills related to non-routine cognitive job tasks. Finally, the residual wage gap analysis demonstrates that job skills alone account for around 3.2% of the wage dispersion in 1997; this ratio increased to 6.6% in 2012.

The outline of this chapter as follows: Section 2.2 reviews the related literature. Section 2.3 describes the first data set (the LFS) and additionally presents some descriptive findings including quantile regression results. Section 2.4 introduces the second data set used (the Skills Survey), presents the job related variables and the method of identification of the job related skills. This section then provides some descriptive statistics. Section 2.5 presents the econometric examination. Section 2.6 provides some sensitivity analyses. The final section concludes.

2.2 Background

The theory of human capital introduced by Becker (1964) proposes the hypothesis that education is an investment which produces income in the future. Further, it implies that wage differentials arise due to differences in productivity between individuals. Here, the differences in productivity mainly stem from investments in education or training undertaken by individuals, because education is the major source for acquiring those skills which lead to higher income.

In line with the theory, the early empirical findings on wage dispersion show that the return to skills, for instance as measured by relative wages of college graduates to high school graduates, has tended to rise over the decades, in spite of the significant increase in the relative supply of college graduates. However, a number of studies have found that the return to 'unobserved skills' has also showed an upward trend. They also suggested that increased residual wage inequality[2] was one of the most important factors of wage inequality throughout the second half of the twentieth century (Juhn et al. (1993), Prasad (2002), Lemieux (2006a)). Moreover, recent findings suggest that there has been increasing variation in the wages of those workers with the highest skills (education) (see Autor et al. (2008)and Lemieux (2006b), for the US and see Lindley and Machin (2011); and Green and Zhu (2010) for the UK).

The explanations of this phenomenon are varied. Martins and Pereira (2004) provide evidence from 16 countries and argue that there might be some elements which cooperate with education and these are heterogeneously distributed across workers within education groups. If these elements (e.g. school quality, class of degree, subject of degree) have a greater effect upon the earnings of workers with higher education, then this would explain why the wage dispersion is higher for those workers with a higher education. On the other hand, Green and Zhu (2010) suggest that the occupational destination of the graduates has become increasingly important in terms of returns after the growth of the participation in the graduate labour market. They also imply that there is a link between the rising dispersion of graduate wages and increasing over-qualification in the

[2] Juhn et al. (1993) suggested that wage inequality can be decomposed into two parts as between and within group (residual) wage inequality. The former refers to the wage differentials by education, occupation, age and experience groups and the latter implies the wage differentials within demographic and skill groups.

graduate labour market from 1994 to 2007 in Britain. Here, over-qualification is defined as mismatch between graduates and their occupations. Very recently, Lindley and Machin (2011) attempted to assess the wage dispersion within the group of workers who hold a university degree by employing a task-based view of technological change, using data from the UK and the US. They suggest that the skills possessed (in terms of job tasks performed) by workers within the same qualification groups, in particular within a university degree, show substantial differences. They consider that this heterogeneity gives rise to higher demand for some workers relative others, further increasing the relative returns. There is a consensus in the recent literature which study the trend in wage and employment structure that job related activities (job tasks), occupations and skills used in the workplace have had increasing influence on determining the wage structure and inequalities in various countries (Autor et al. (2006), Goos and Manning (2007), Goldin and Katz (2007), Goos et al. (2009), Michaels et al. (2010)). Moreover, Autor and Handel (2013) argue that Mincerian empirical analysis of the return to education based on the human capital theory does not provide information on what type of skills workers apply on the job, why these skills are required and how these skill requirements have shifted over time. Further, they find that the job tasks which workers perform are effective predictors of their hourly wages. In addition, Spitz-Oener (2006) finds that some skills like numeracy are associated with technological change and the requirement for these skills has increased. Lindley (2012) also finds that different job tasks and the skills of male and female workers has an impact on gender wage differentials.

Similarly, Ingram and Neumann (2006) provide evidence that variations of direct measure of skill could explain the trends of the US labour market better than education. They argue that since wages have not increased in a similar pattern within education groups, education can not be an isolated component of skill. In addition, they suggest that another measurement related to jobs could be more informative, reflecting advances in technological change and computerisation.

The contribution of this study to the literature is three-fold: firstly, it attempts to quantitatively assess the contribution of the job tasks and skills used in the workplace to wage dispersion among university graduates, thus improving upon Lindley and Machin (2011). Secondly, a (job) task-based approach was employed, to improve upon the previous works in the UK (e.g. Green and Zhu (2010)), which emphasise the importance of the occupational destinations of the graduates in terms of their wages. Sanders and Taber (2012) suggest that occupational factors capture the underlying job task structure, hence using job task information in the analysis provides more insight into modelling labour market outcomes. Finally, this chapter follows the work of Ingram and Neumann (2006), though with greater attention paid to available data. To identify the skills used in the workplace, Britain's Skills Survey was used to provide detailed self-reported job activities information. However, job skills information is extracted from occupational level data using the Dictionary of Occupational Titles in the US, which creates various complications for a task-based analysis, because it has not been tailored to provide job task (measure) information for research purposes (see Autor (2013)).

2.3 Data Set I: Labour Force Survey

2.3.1 Labour Force Survey

The (Quarterly) Labour Force Survey, which is a closer representative of the workforce, is the largest regular household survey in the UK. The survey provides valuable information on experience, qualification and levels of earning, as well as other demographic and work related characteristics. The LFS data sample was exploited for the descriptive statistics and descriptive quantile regression analysis.

In the analyses, hourly wage series of male university graduates[3] (excluding self-employed) working full-time and aged between 16-65 was used, from 1997 to 2012. Firstly, the dataset has been processed to obtain a consistent and comparable wage series over the period of interest. The gross hourly wage series of individuals are then deflated by quarterly CPI (Consumer Price Index).[4]

Figure 2.2 provides information on the trends in employment among male university graduates in the UK. The figure shows that the share of male workers with a university degree (15 and more years of education) has increased about 13 percentage points from 1997 to 2012 in the UK. These workers, consequently, form about 31% of the male full-time, graduate workforce by 2012.

2.3.2 Increased Wage Dispersion Within University Graduates

In this subsection, following the literature (see Lemieux (2006b),Green and Zhu (2010)) a quantile wage regression equation was fitted, using cross-section data from the Labour Force Survey, between 1997 and 2012. The quantile regression method models the relationship between a set of explanatory variables and specific quantiles of the dependent variable. The purpose of this analysis is two fold: First, we evaluate composition

[3]The sample of workers with a university degree is constructed from the variable reports the age workers left full-time education instead of highest academic qualification held to be in line with the literature (e.g.Manacorda et al. (2012))

[4]See Appendix A.1 and A.2 for the detailed information on the sample and data processing.

adjusted wages in the 90th and the 10th percentile of the university and high school graduate wage distributions. Second, we can examine how the trend in composition adjusted wage dispersion within male university graduates has changed in the UK in comparison to the wage dispersion among those workers with lower levels of formal education (i.e. high school) over the period of interest. The quantile wage models are fitted separately for university and high school graduates both in 1997 and 2012. In the fitted models, the 10th and 90th percentile of log hourly wages of male full-time workers are regressed on a quartic function of experience, years of formal education, native-born worker dummy,[5] which is set at one if a worker was born in the UK and zero otherwise.[6]

Figure 2.3 plots the fitted values. Fitted values are calculated for 20 years of experience and 15 years of education for university graduates where as 20 years of experience and 10 years of education for high school graduates. They are then standardised such that zero represents the 10th percentile wage of high school graduates in 1997. The wage dispersion within each education group is given by the distance between the 90th percentile and the 10th percentile of the predicted log hourly wages.

The figure reveals that on average, relative wages increase by education level in both periods. In addition, the relative wages of the university graduates who are on the 90th percentile have risen more than the workers' wages on the 10th percentile from 1997 to 2012. In this group, the workers who are on the 90th percentile have become better off over time. This implies that the variation of wages within the group of workers with a university degree (15 and more years of schooling) has increased over time. The predicted wages of workers with a high school diploma, in turn, has almost equally increased on the 10th and the 90th percentile from 1997 to 2012. This indicates that the composition adjusted wage dispersion within high school graduates has not shown a substantial change over time. The results also indicate that the wage dispersion within educational groups polarises at the highest education level. This is in line with what Lemieux (2006a) found using the US data. These results are also in line with the literature discussed in Section 2.2 and the findings on convexification in returns to education (e.g. Binelli (2014)).

[5]Manacorda et al. (2012) found that immigrant and native-born university graduates are not perfect substitutes in production in the UK.

[6]The regression estimates are presented in Table 2.1 and Table 2.2. The *qreg2* Stata command was used, introduced by Machado and Silva (2011), to run quantile regressions. Machado and Silva (2011) argue that it provides standard errors and t-statistics which are asymptotically valid under heteroskedasticity and misspecification of the quantile regression equation.

2.4 Data Set II: Britain's Skills Survey and Method

2.4.1 Skills Survey of Britain 1997-2012

Britain's Skills Survey (SS)[7] was carried out in 1997, 2001, 2006 and 2012, and aimed to be a representative of the working individuals in Britain.[8] The common objectives of the surveys are to provide information on the distribution of the skills (broad and generic), valuation of skills, work preferences and work motivation of respondents.[9]

In the analyses, we employ all four subsequent cross-section survey samples, including 1997, 2001, 2006 and 2012 which have 2190, 4000, 4228 and 2374 number of working individuals respectively.[10] Since we are only interested in hourly wage series[11] of male university graduates (excluding self-employed workers), the number of observations becomes considerably low for each single year. Therefore, the data sample is divided into two periods by appending the first two (1997 and 2001) and the last two (2006 and 2012) survey waves. The analyses henceforth are based on two (pooled) periods, where 1997 implies the first and 2012 represents the second (pooled) period.

Table 2.3 presents some summary statistics for the male workers with a university degree[12] in 1997 and 2012. The number of male workers with a university degree in the sample is 527 and 783, respectively. The average general labour market experience is 15.1 and 16.6 years. The trend in 90-10 log wage gap within the university graduates is in line with those in the LFS and has increased from 1.2 log points to 1.5 log points from 1997 to 2012 (see also Figure 2.4 for the trend in 90-10 log wage gap in each four individual waves). More than 90% of male workers with a university degree work full-time in both periods. In addition, the majority of male workers with a university degree are employed in professional and managerial occupations; these workers comprise 70.9% and 61.9% of the workers in 1997 and 2012. Moreover, the proportion of university graduates who work in associate professional occupations are 16.5% and 21.2% in 1997 and 2012 respectively.

[7] The surveys were funded by various institutions namely ESRC (The Economic and Social Research Council), the Department for Education and Skills and other various government agencies. An extensively detailed report of the skills surveys were prepared by Felstead et al. (2007).

[8] The surveys were sought to be consistent with the earlier studies namely the Social Change and Economic Life Initiative of 1986 and Employment in Britain in 1992 on this area.

[9] The cross-section micro data from the surveys has been widely employed for research purposes in particular for the detailed information on the job related activities including computer use and broad and generic skills (see e.g. Green et al. (2003), Green and Zhu (2010), Lindley (2012), Dickerson and Green (2004), Borghans and ter Weel (2004), Borghans and ter Weel (2011)).

[10] Table A.2 in Appendix A presents some summary statistics for all four subsequent Skills Surveys.

[11] Appendix A.1 and A.2 provide detailed information on the sample and data processing.

[12] The sample of workers with a university degree is constructed from the survey variable reports whether the respondent holds a degree.

2.4.2 Job Tasks and Identified Job Skills in the Survey

This study employs 20[13] job task measures which are generated from the 'Detailed Job Analysis Section' of the questionnaires.[14] In each job task question, respondents were asked '*How important is ...[each job task] in your job?*' For example, 'how important is writing long documents with correct spelling/grammar in your job?' Possible responses are '*Essential*', '*Very important*', '*Fairly important*', '*Not very important*' and '*Not at all important/Does not apply*'. In addition to the tasks above, the questionnaire provide information on routineness of performed activities on the job. The question relating to the repetitive task is '*How often does your work involve carrying out short repetitive tasks?*' and the options are '*Never*', '*Rarely*', '*Sometimes*', '*Often*', and '*Always*'.

In order to generate a set of job skill measures out of the job activities, we use a data reduction tool, namely factor analysis (see Ingram and Neumann (2006), Poletaev and Robinson (2008), Bacalod and Blum (2010) for other factor analysis examples). Factor analysis provides a means to find fundamental patterns in data to identify a measurement model for the principal drivers within the variables of interest. In the skills survey, the multiple individual task items embody common worker skill characteristics. Table 2.5 and Table 2.8 present the correlations between individual task measures in 1997 and 2012. Some tasks are highly correlated with each other. For instance, there is a high correlation among reading and writing based tasks. Therefore, factor analysis initially combines similar job characteristics into broader categories. It then generates a number of factors by decomposing the variance of each item into a unique part and a shared part which represent the common variations in different job tasks.

To run a factor analysis, 20 chosen job task variables are given numerical values between 0-4. In order not to loose any information that may emerge across years, instead of pooling the two periods, factor analysis is run separately in 1997 and 2012 using only task inputs of male graduate workers. I use principal component factor analysis to extract five factors. Table 2.6 and Table 2.9 present the loading coefficients of 20 job activities and the five generated factors in 1997 and 2012 .[15] In the tables, the first column presents the job task items included in the analysis. The values in the columns with Factor1-Factor5 represent the loading coefficients. The value of loading coefficients shows the correlation between a given job task and each factor. The sign of loading coefficients represents the way the item relates to the factor. The last column namely uniqueness, in turn, represents the variance of task items not shared with other variables.

[13]Tasks related to manual dexterity are not included in the analysis, since they are the least intensely performed tasks by graduates on the job. In addition, the tasks related to checking are not included because they are not reported in 2012.

[14]The list of the tasks measures used is displayed in Table 2.4.

[15]It is generated by employing an oblique rotation.

The smaller values of uniqueness indicate higher relevance of the variable in the factor model. For example, Maths1, Maths2 and Maths3 all have low uniqueness values hence it can be inferred that they jointly produce the best fitted factor model in both years. The factor loadings in bold indicate the factors with the highest explanatory power on the corresponding job activity variable. For instance, Factor 1 is largely responsible for the common variation in 'Reading Short Document', 'Reading Long Document', 'Writing Form', 'Writing Short Document' and 'Writing Long Document' variables. In order to identify skills from the factors generated we follow Green (2009) and Lindley (2012) who employ the Skills Surveys and utilise factor analysis to generate skills that workers apply on the job as well. This implies that comparing the results to their factor-task inputs, the factors are identified as the job skills that explain the common variation within each group of related job activities. Finally, the regression technique is employed to derive individual scores. Table 2.7 and Table 2.10 present the scoring coefficients which represents the regression coefficients used to estimate the standardised individual factor scores namely individual measure of five job skills.

The skills surveys provide wide range of detailed questions to cover different job related activities that workers perform at the workplace. For the purpose of the analyses, it is of interest to examine what type of detailed job activities performed by university graduates in 1997 and 2012 and any changes over time. Moreover, it is also of interest to analyse the set of specific skills possessed and applied by graduates which would be needed to perform those specific tasks on the job. Factor analysis provides a useful means to generate and quantify the set of specific skills we are interested in. It is also commonly employed by researchers who use the Skills Survey data samples. However, this method has also some shortcomings. First of all, identified factor labels can be arbitrary. Secondly, identified factors may not always be robust to the inputs. For instance, inclusion or exclusion of some variables may affect how the factors are formed. In this analysis, in particular in 2012, only Factor 5 and Factor 2 seem to be robust to variable changes whereas in 1997, except Factor 4, they are not sensitive to task input changes. This also implies that predicted individual scores may be sensitive to the inputs in the analysis.

2.4.3 Trends in the distribution of job tasks and related skills

Table 2.11 shows what type of tasks and skills university graduates apply on the job and how those task and skill requirements have changed from 1997 to 2012. The descriptive statistics suggest that the job task distribution of the workers has not been constant over the period. The distribution is in line with findings showing that some jobs involve more complexity than before (e.g. Spitz-Oener (2006)).

The table displays the percentage of the workers who report that the corresponding job task is essential and always performed on the job in 1997 and 2012. The main findings are: (i) The most commonly always performed tasks are including thinking of solutions to problems (54% on average), organising own time (54% on average) and dealing with people (66% on average) in both years. (ii) The importance of six out of the twenty job tasks associated with the job related skills of the university graduates, which are non-routine cognitive tasks, has increased from 1997 to 2012. (iii) Among all of the job tasks, the importance of analysing complex problems in depth, persuading and influencing others and dealing with people has increased the most by 8%, 6.1% and 6.4%, respectively. (iv) The degree of any task requirements has not decreased over time. (vi) The ratio of university graduates who never perform any repetitive (routine) tasks is about 13% on average and it has decreased by 5.4% from 1997 to 2012.[16]

The descriptives show that there has been some changes in the level of tasks performed by graduates over time in the workplace which can be rationalised by the demand and supply influences. In particular, the statistics show that performed intensity of some tasks increased over time. If how intensely a task is performed on the job is defined as an indicator of a direct measure of skill demand which is needed to perform a particular job activity (Autor et al. (2003)), the statistics may imply that the demand for skills associated with those tasks has increased over time. On the other hand, as it is displayed in Figure 2.2, the supply of graduates has substantially increased from 1997 to 2012 in the UK. There is also evidence that over-qualified workers has increased as well (see Green and Zhu (2010)). This indicates that graduates might be employed in non-graduate jobs where they may perform less task intensive jobs than traditional graduate jobs i.e. managerial and professional occupations. Consequently, the statistics presented here would be resulted from the increased skill demands and decreased performed-task-intensity of over-qualified university graduates.

2.5 Econometric Examination

The main goal of this section is to estimate the value of the identified job skills the male workers with a university degree applied at work, in 1997 and 2012. To achieve this, the

[16]This might be due to the mismatch between the university graduates and the occupations in which they are employed (Green and Zhu (2010)).

econometric specifications were focussed on using wage regression models[17] presented in Ingram and Neumann (2006).[18]

Log hourly wages ($log(W_i)$)[19] of the university graduates are regressed on the set of observable worker traits $X \equiv [S, J, T]$ including standard skill measures, S, job related skills, J, routineness of job tasks, T, using Ordinary Least Squares (OLS) estimation. The set of standard skill measures, S, covers experience (EXP) and experience-squared (EXPSQ).[20] The five job related skills, J, are as follows: Literacy (LITERCY), self-planning (SELF-PL), problem search and solving (PROB-SLV), communication-influencing (COMM-INF) and numeracy (NUMERCY).The routineness of job related activity dummy, T, is namely repetition in work (REPEAT).

I employ a Mincerian earnings equation, with all sets of variables, of the following form:

$$log(W_i) = \beta_0 + EXP_i\beta_1 + EXPSQ_i\beta_2 + LITERACY_i\beta_3 + SELF - PLAN_i\beta_4$$

$$+PROB - SOLV_i\beta_5 + COMMUN - INF_i\beta_6 + NUMERACY_i\beta_7$$

$$+ REPEAT_i\beta_8 + \epsilon_i \qquad (2.1)$$

Where β_1 andβ_2 measures the return to general labour market experience and experience-squared, β_3-β_7 capture the returns to job related skills, β_8 captures any influence of routine work on pay and ϵ_i is the error term.

Table 2.12 and Table 2.13 present the results for different log wage regression specifications in three columns for 1997 and 2012 respectively.

Specification (1) only controls for the standard skills measures. Holding other variables constant, the estimated coefficient of linear experience term implies that an additional year of experience at work is associated with an increase in log wages in both periods.

Specification (2) adds the job skill measures to the Mincerian type log wage regression. The inclusion of work related skill controls slightly lowers the effect of work experience in both periods. The estimated coefficient of literacy skills is positive in both periods

[17]Dickerson and Green (2004) calls the wage regression models with job skills hedonic wage equations. In the hedonic wage equations, the right hand side variables are the job characteristics and the estimated coefficients are in turn the shadow prices of these job characteristics.

[18]The job skills which Ingram and Neumann (2006) identify are intelligence, fine motor skill, coordination and strength. However, the Skills Survey allow the identification of job skills that are more specific than the job skills they identify.

[19] i denotes the observations, N is the sample size, $i = 1, ..., N$

[20]The regression equation also includes year dummies and full-time work dummy.

but not different than zero in 1997 and 2012. The self-planning skills are negatively correlated with pay in 1997 and positively correlated with wages in 2012 but the estimates are only significant in the latter. In fact, a university graduate using self-planning skills at work one standard deviation above the mean level earns 6.4% higher in 2012 than a worker using mean level of problem search and solving skills in 2012. [21] A university graduate using problem search and solving skills at work one standard deviation above the mean level in 1997 earns 5.28% and 6.3% higher in 1997 and 2012, respectively, than a worker using mean level of problem search and solving skills when other characteristics are held constant. This indicates that problem search and solving skills are associated with higher pay; this effect has increased between 1997 and 2012.[22] This is in line with the findings that show that non-routine cognitive tasks, [23] such as analysing complex problems, characterise high-waged jobs; these are polarized on the upper part of the wage distribution (Goos and Manning (2007)).[24] Finally, a university graduate using numeracy skills at work one standard deviation above the mean level in turn earns 5.66% and 7.22% higher in 1997 and 2012, respectively, than a worker using mean level of numeracy skills in those years when other characteristics are held constant. This indicates that numeracy skills are associated with higher pay; this effect has increased between 1997 and 2012. [25] This would indicate that the demand for these skills has risen over time (Spitz-Oener (2006)).

Specification (3) introduces a repetitive task dummy, which is used as a proxy for routine task engagement. The repetitive task variable is zero if workers' job activities never involve any routine work and it is one if workers perform some degree of routine work. The estimated coefficients suggest that involvement of some form of routine work is associated with considerably lower wages in 1997 and 2012. If other variables are held constant, being engaged to routine activities in the workplace is associated with 15.5% reduction in the expected log wages of the university graduates in 1997, while it is associated with 27.7% decrease in wages in 2012. Several factors might influence this: (i) Routine job activities might be positively correlated with the job tasks which are associated with negatively valued tasks such as motor tasks. (ii) Those workers who involve routine activities might be punished with lower wages in line with the task based

[21]Standard deviation of all five job skills is equal to 1 in each year, hence the estimated coefficient of a job skill measure captures the value of a holding level of the skill that is one standard deviation above the mean level of the skill in the population (Ingram and Neumann (2006))

[22]The change is significantly different from zero. Two sample unpaired Z test is used following Clogg et al. (1995).

[23] Problem search and solving skills are associated with non-routine cognitive tasks.

[24]Goos and Manning (2007) examine the employment trends by occupations and show that there has been growing job polarisation in the labour market. Their results indicate that the non-routine cognitive task jobs are high waged, non-routine manual task jobs are low waged and the routine task jobs are middle waged jobs; thus a considerable proportion of the rising wage inequality in the UK over the period 1975-2002 can be explained.

[25]The change is significantly different from zero (Z test is used).

view of technological change hypothesis. The hypothesis suggests that there is decreasing demand for routine tasks with the advent of new technologies and computerization (Autor et al. (2003)). The results also suggest that controlling for the proxy for routine activities involvement results in only slight changes (less than 2%) in the estimated effects of the job skill measures on wages in comparison to the job skill estimates in specification (3).

2.5.1 Explained Part of the Wage Dispersion

In order to determine whether and what proportion of wage dispersion within the university graduates can be attributed to the job skill measures, following Ingram and Neumann (2006), we employed wage regression residuals. In the wage inequality literature, examining within-group wage inequality using different percentiles of log wage residual distribution has been commonly applied (see e.g. Juhn et al. (1993),Prasad (2002), Xing (2010)). In fact, the difference between the 90th percentile and the 10th percentile of the regression residuals provides a wage dispersion measurement which shows the part of the wage dispersion that can not be explained by the explanatory variables.

The bottom rows of Tables 2.12 and 2.13 present the 90-10 residual wage gaps in four wage regression models. In addition, it also shows parts of the wage gaps that can be explained by the job skill measures; the gaps were initially unexplained by the standard skill measures.

In Specification (1), the residual wage gap is calculated by taking difference of the wage regression residuals at the 90th and the 10th percentiles. The residual wage gap is found to be 1.134 in 1997 and 1.242 in 2012. This illustrates that part of the wage dispersion of male university graduates that cannot be explained by (only) their general labour market experience. The residual wage gap in the other two specifications, where we added job skill and task measures to the wage models, are calculated in a similar way. The results show that once the job skill measures are added to the wage model in specification (2) and (3), the residual wage gap decreases. This implies that once the job skill measures are added to the standard wage model, the explained part of the wage dispersion within the male workers with a university degree increases.

In order to quantify the part of the wage dispersion that remains unexplained by the standard skill measures but explained by the job skill measures, the ratio of the residual wage gaps in specifications (2) and (3) were taken, compared to the residual wage gap in specification (1).[26]. For instance, Figure 2.5 illustrates the explained part of the

[26]The job skills in specification (2) account for around 3.2% (1.134-1.098/1.134) of the wage dispersion in 1997 and this ratio increased to 6.6%(1.242-1.160/1.242) in 2012

wage dispersion within male university graduates by job skills, as well as routineness of work. The figure demonstrates that the job skills alone in specification (2) account for around 3.2% of the wage dispersion in 1997 and this ratio increased to 6.6% in 2012. This result implies that importance of the job skill measures in relation to explaining wage dispersion within the university graduates has increased over time. In addition, the routineness of job and the job skill measures together account for around 5.1% of the wage dispersion in 1997 and around 7.4% of the wage spread in 2012.

2.6 Sensitivity Analysis

2.6.1 Additional Controls

In order to examine the sensitivity of the OLS regression results with respect to the included controls, some robustness checks were performed. By changing the set of the covariates, simply by adding and removing some of the confounding variables, the effect of job skills on expected wages was analysed, with regard to differences in the other observable characteristics of the workers. The result of the sensitivity analysis suggests that overall, the estimated value of the job skills are robust to different model specifications.

Tables 2.14 and 2.15 display the results for the chosen specification and modified versions in 1997 and 2012, respectively. Column (1) presents the main wage regression results where only general labour market experience and the five job skill measures were controlled for (this is given by specification (2) in Table 2.12 and 2.13). In column (2), the main wage regression parameters are estimated excluding part-timers. Although, the number of observations becomes even smaller, the estimates are not significantly affected by it. In column (3), general labour market experience is excluded; wages were estimated conditional solely on the five job related skills. The influence of the job skills on the wages increases with the exclusion of experience, but there is no observed substantial change. In column (4), nine occupation dummies were added into the wage regression. By controlling for workers' occupations, one can examine if the job related skills are only a proxy for the occupation. Although the magnitude of the coefficients drops slightly, the inclusion of the occupation controls does not substantially change the estimates. Column (5) controls for region of work, since region of work is commonly used as a control in wage regressions. The results show that adding a London dummy only slightly changes the magnitude of most of the significant variables compared to column (1). The main difference is that numeracy and self-planning skills become not different than zero in 1997 and 2012 respectively. Column (6) adds both the occupation and region dummies together, along with the wage regression. The inclusion of both sets of the variables results in an average decrease of 2%, in terms of the effect of the job skills on the wages. Nevertheless, the estimates of the problem search solving and numeracy skills remain significant at the 10% level.

2.6.2 OLS Regressions with Job Tasks and Alternative Skill Measures

Tables 2.16 present results of three OLS wage regression models which control for individual task and alternative skill measures.

In column (a), log hourly wages of university graduates are regressed on experience, experience-squared and individual task measures. [27] Among the 20 job activities, seven of them are significant at least at the 10% level. The results suggest that reading long documents, writing long documents, calculation using more advanced mathematical and statistical techniques, making speeches/presentations, planning the activities of others and analysing complex problems in depth are positively correlated where as writing forms are negatively correlated with pay in the labour market. Moreover, it is shown that analysing complex problems in depth is the most significant task item.

In column (b), an alternative individual skill measure is presented. Following Lindley (2012), individual job skill measures are calculated by averaging the raw factor task items instead of predicting regression scores. In the second model, log hourly wages of university graduates are regressed on experience, experience-squared and the skill measures. The results suggest that three out of five skill measures are still significant for pay.

In the last column (c), squared function of skill measures in column (b) is added to the wage model in order to test any existing non-linearities of these skill measures. The results show that squared function of literacy and communication-influencing skills are significant at the 5% level. The exploratory results suggest that the wage reward to these skills might increase at a decreasing rate.

2.7 Summary and Concluding Remarks

This discussion builds on those studies which show that the wage dispersion within the university graduates has increased over the last decades, whereas the wage dispersion within lower education groups has been stagnant, in both the UK and the US. In order to examine the wage dispersion within the university graduates, recent examples of wage inequality literature are followed, which suggest that the job tasks and skills needed to

[27] In order to increase the precision of the estimates all periods are pooled.

perform those tasks on the job would be significant factors in explaining wage and employment structure. In particular, we quantitatively assess how job related skills of male workers with a university degree are valued in the UK labour market and the extent to which job tasks and job related skills contribute to the increasing wage dispersion within these workers in the UK. Therefore, this work improves upon Lindley and Machin (2011) who suggest skills possessed (in terms of job tasks performed) by workers within same qualification groups in particular within a university degree show substantial differences in the UK and this heterogeneity gives rise to higher demand for some workers relative to the others and increases the relative returns.

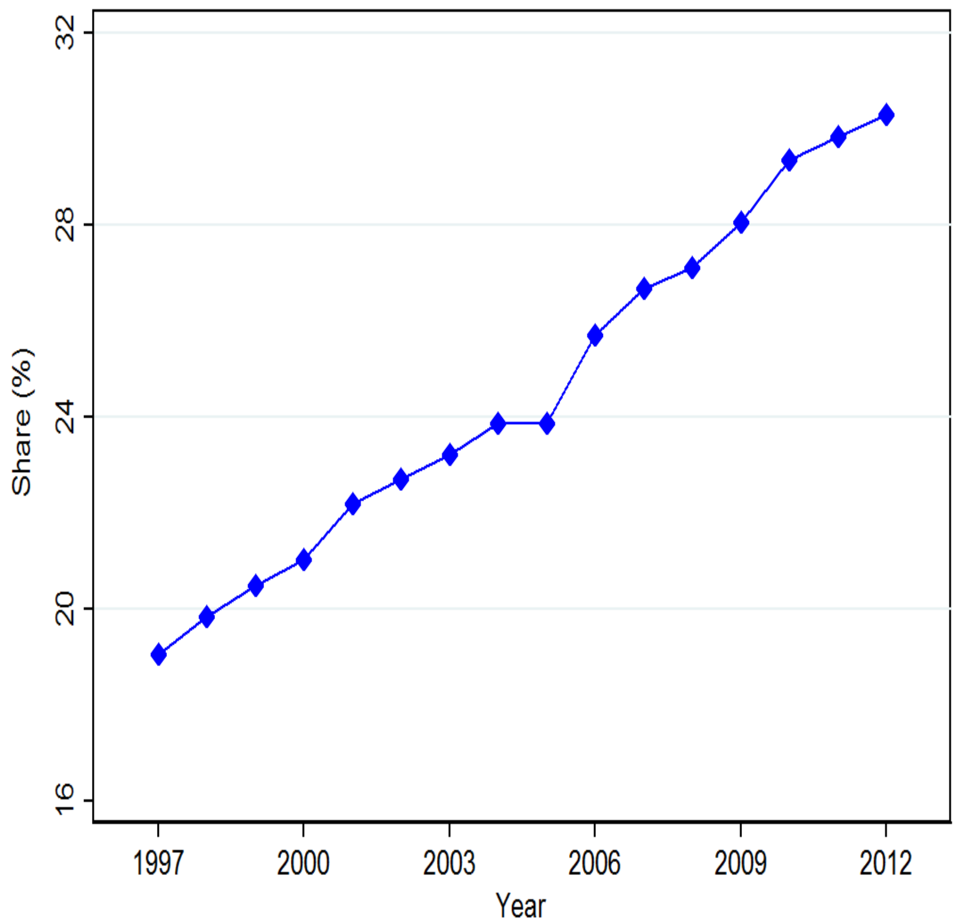
Descriptive findings from the wage regressions suggest that among all the job skill measures identified, the problem search and solving and numeracy skills are highly significant factors for the wage levels of male university graduates. Further, the value of these skills has increased over time. Furthermore, when other variables are held constant, workers who perform any form of routine work earn substantially less than the workers who never perform any form of routine work. In addition, the residual wage gap analysis suggests that the job skills alone account for around 3.2% of the wage dispersion in 1997; this ratio increased to 6.6% in 2012. Moreover, this result indicates the importance of the job skill measures in terms of explaining how wage dispersion among university graduates has increased over time.

The results provide insights into job related skills of male university graduates are valued in the UK labour market and to what extent can increased wage dispersion within university graduates be attributed to changes in job tasks and skills used in the workplace. However, the estimates would be subject to some biases. First, the intensity and type of tasks that workers perform on the job are largely tied to specific firms, occupations and industries. Hence, the degree and type of skills that workers need to perform job tasks may reflect firm/occupation heterogeneity. The firm/occupation heterogeneity, in turn, would result in workers' self-selecting themselves into occupations where they get higher returns to their skills. In order to, tackle the endogeneity bias a more detailed dataset with valid instrument measures is required. Second, although factor analysis provides a useful means to generate and quantify the set of specific skills we are interested in, it has also some shortcomings as previously discussed. Finally, despite the rise in the explained part of the wage dispersion within the university graduates, once the job related skills are added to the standard Mincerian form of wage regression model, the findings imply that a substantial part of the wage dispersion still remains unexplained.

2.8 Tables and Figures

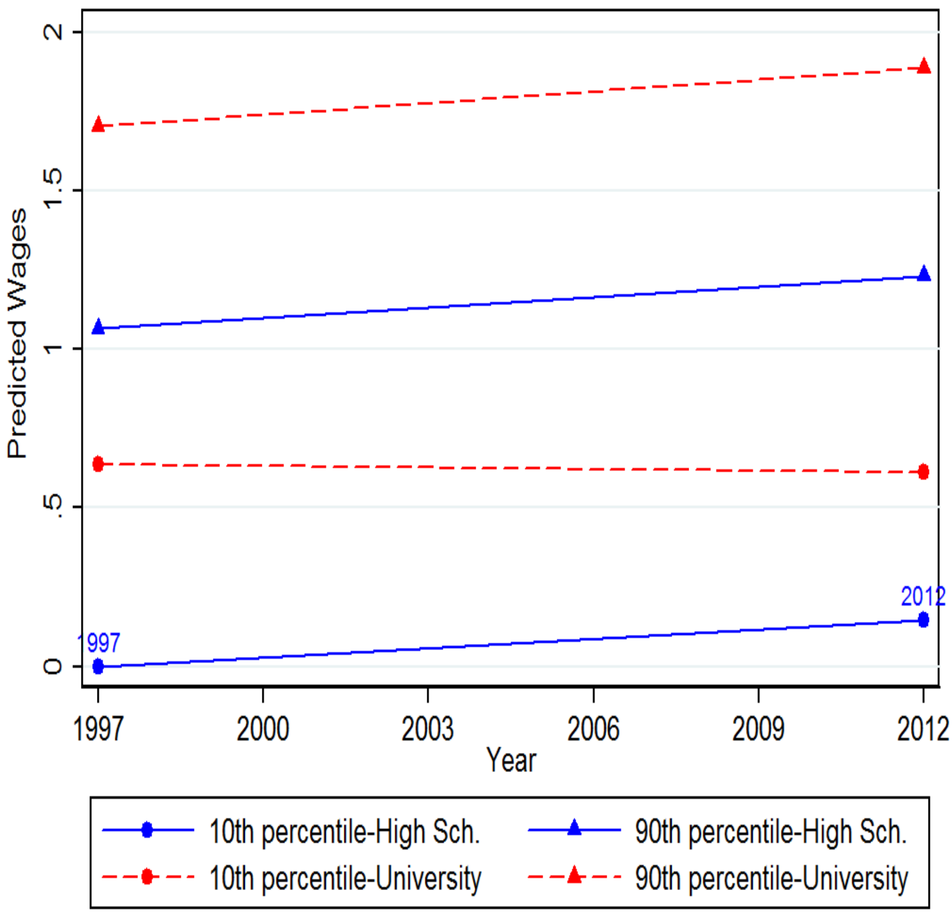
2.8.1 Figures

Figure 2.2: Share of Workers with a University Degree (%)



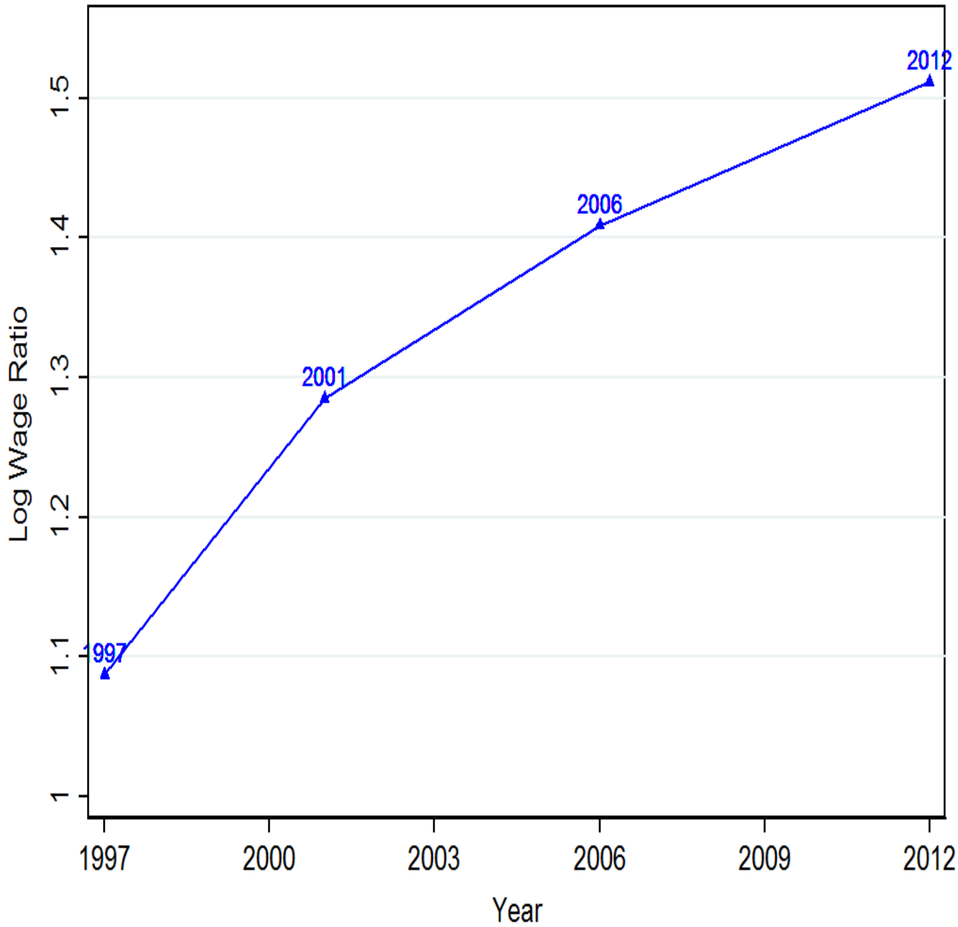
Notes: LFS data sample, the share of male full-time workers(excluding self-employed)aged between 16-65. The survey weights are used.

Figure 2.3: Relative Predicted Log Hourly Wages by Education in 1997 and 2012



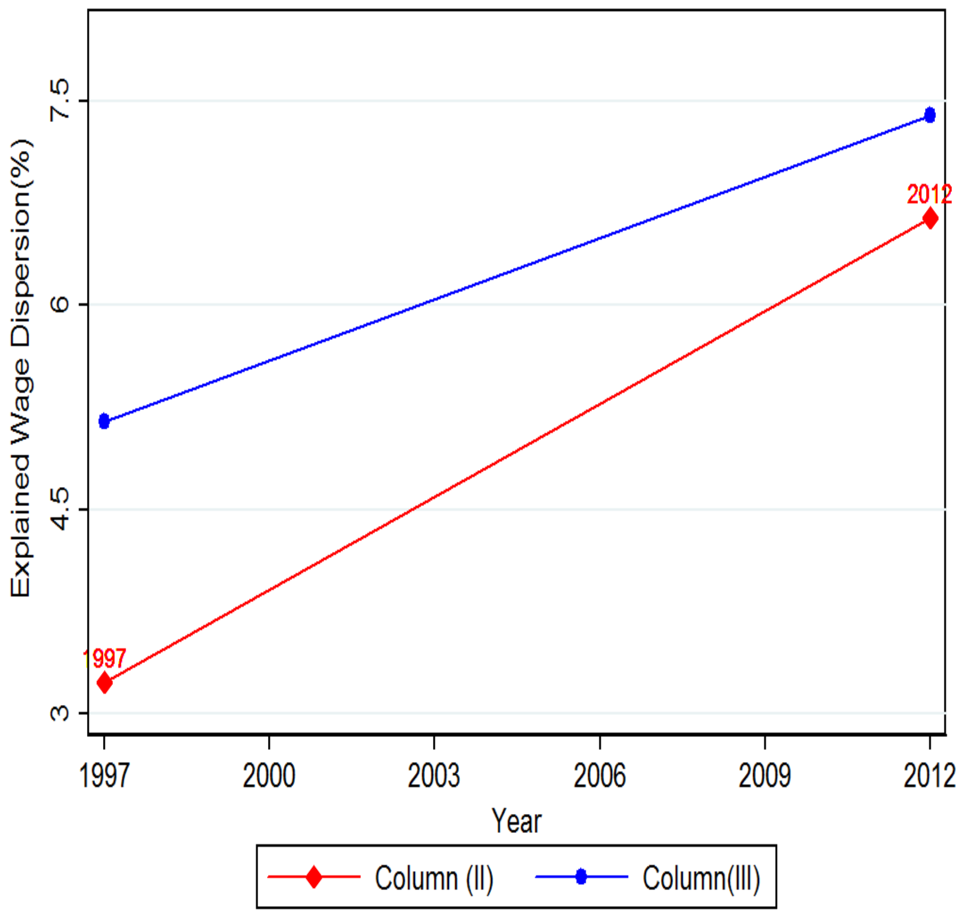
Notes: LFS data sample, hourly wage series of male full-time workers (excluding self-employed) aged between 16-65. The data pooled by three years centred on the years shown. The wages on the 10th and 90th percentiles are standardised such that zero represents the 10th percentile for high school graduates in 1997.

Figure 2.4: Trend in 90-10 Log Wage Ratio of University Graduates, Skills Survey



Notes: SS data sample, hourly wage series of male workers (excluding self-employed) aged between 20-65. The survey weights are used.

Figure 2.5: Explained Part of the Wage Dispersion(%)



Notes: SS data sample, male workers (excluding self-employed) aged between 20-65.

2.8.2 Tables

Table 2.1: Quantile Wage Regression Results for University Graduates

In 1997 Regressors	P10	P90
Experience	0.148***	0.157***
	(0.0230)	(0.0157)
Exp^2	-1.035***	-0.789***
	(0.329)	(0.179)
Exp^3	0.355**	0.165**
	(0.162)	(0.0722)
Exp^4	-0.0469*	-0.0117
	(0.0254)	(0.00942)
Years Educ.	0.0137	0.0156**
	(0.00902)	(0.00768)
Native	0.399***	-0.102**
	(0.0468)	(0.0417)
Constant	0.709***	2.035***
	(0.151)	(0.152)
Observations	4,827	4,827
R-squared	0.179	0.203

In 2012 Regressors	P10	P90
Experience	0.0652***	0.0747***
	(0.0162)	(0.0162)
Exp^2	-0.179	0.0296
	(0.183)	(0.160)
Exp^3	0.00205	-0.103*
	(0.0740)	(0.0572)
Exp^4	0.00231	0.0163**
	(0.00966)	(0.00667)
Years Educ.	0.0178***	0.0181***
	(0.00573)	(0.00519)
Native	0.319***	-0.0463
	(0.0303)	(0.0302)
Constant	0.970***	2.199***
	(0.106)	(0.105)
Observations	5,052	5,052
R-squared	0.133	0.147

Notes: The dependent variable is log hourly wages of male full-time workers (excluding self-employed) aged between 16-65. Robust Standard errors in parentheses. P10 refers to quantile regression on the 10th percentile and P90 on the 90th percentile of the wage distribution. *** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

TABLE 2.2: Quantile Wage Regression Results for High School Graduates

In 1997 Regressors	P10	P90
Experience	0.205***	0.169***
	(0.00747)	(0.00803)
Exp^2	-1.246***	-0.918***
	(0.0664)	(0.0778)
Exp^3	0.334***	0.246***
	(0.0225)	(0.0275)
Exp^4	-0.0324***	-0.0244***
	(0.00252)	(0.00318)
Years Educ.	0.108***	0.155***
	(0.00566)	(0.00567)
Native	0.201***	0.0451*
	(0.0339)	(0.0249)
Constant	-0.961***	-0.226***
	(0.0746)	(0.0755)
Observations	18,464	18,464
R-squared	0.320	0.325

In 2012 Regressors	P10	P90
Experience	0.178***	0.0838***
	(0.00954)	(0.0128)
Exp^2	-1.045***	-0.127
	(0.0807)	(0.107)
Exp^3	0.264***	-0.0189
	(0.0264)	(0.0340)
Exp^4	-0.0238***	0.00437
	(0.00289)	(0.00359)
Years Educ.	0.0581***	0.108***
	(0.00533)	(0.00752)
Native	0.196***	0.120***
	(0.0173)	(0.0330)
Constant	-0.160**	0.531***
	(0.0788)	(0.108)
Observations	11,802	11,802
R-squared	0.177	0.187

Notes: The dependent variable is log hourly wages of male full-time workers (excluding self-employed) aged between 16-65. Robust Standard errors in parentheses. P10 refers to quantile regression on the 10th percentile and P90 on the 90th percentile of the wage distribution. *** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Table 2.3: Summary Statistics for University Graduates in the SS Sample

	1997				2012			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Experience (Years)	15.150	(9.847)	0	41	16.598	(11.351)	0	50
Age	37.575	(9.542)	20	60	39.454	(10.817)	22	65
Log Hourly Wages	1.964	(0.494)	0.772	4.696	2.005	(0.594)	0.887	4.837
90-10 Wage Gap	1.196				1.533			
Literacy Skills	0	(1)	-3.491	1.380	0	(1)	-3.144	1.466
Communication-Influencing Skills	0	(1)	-3.333	1.611	0	(1)	-4.023	1.631
Self-Planning Skills	0	(1)	-4.816	1.259	0	(1)	-5.025	1.448
Problem Search and Solving Skills	0	(1)	-4.562	1.325	0	(1)	-4.222	1.178
Numeracy Skills	0.405	(1)	-2.172	1.370	0	(1)	-2.317	1.412
ReadShort	3.262	(0.872)	0	4	3.257	(0.963)	0	4
ReadLong	2.904	(1.080)	0	4	2.920	(1.159)	0	4
WriteForm	2.762	(1.168)	0	4	2.592	(1.240)	0	4
WriteShort	3.097	(1.018)	0	4	3.057	(1.078)	0	4
WriteLong	2.580	(1.343)	0	4	2.642	(1.331)	0	4
Maths1	2.779	(1.255)	0	4	2.891	(1.253)	0	4
Maths2	2.663	(1.312)	0	4	2.698	(1.373)	0	4
Maths3	1.938	(1.474)	0	4	2.141	(1.467)	0	4
Instruct	2.708	(1.096)	0	4	2.745	(1.165)	0	4
Speech	2.341	(1.315)	0	4	2.424	(1.303)	0	4
Persuade	2.868	(1.037)	0	4	2.966	(1.056)	0	4
Planoth	2.323	(1.270)	0	4	2.235	(1.248)	0	4
People	3.477	(0.798)	0	4	3.535	(0.831)	0	4
Ahead	3.360	(0.768)	0	4	3.306	(0.867)	0	4
OwnAct	3.286	(0.815)	0	4	3.255	(0.895)	0	4
OwnTime	3.388	(0.769)	0	4	3.374	(0.819)	0	4
Fault	3.268	(0.839)	0	4	3.175	(0.939)	0	4
ProbSolve	3.372	(0.832)	0	4	3.296	(0.954)	0	4
Cause	3.192	(0.876)	0	4	3.012	(1.077)	0	4
Analyse	3.052	(1.025)	0	4	3.118	(1.106)	0	4
Repeat	2.622	(1.047	0	4	2.882	(1.079)	0	4

	1997	2012
Employment(%)		
Part-Time	3.7	8.1
Full-Time	96.3	91.9
Total	100	100
One Digit Occupations/SOC2000 (%)		
Managers	26.6	28.7
Professionals	44.3	33.2
Associate Profes.	16.5	21.2
Administrative	5.1	7.3
Skilled Trades	3.1	2.8
Personal Serv.	0.9	1.1
Sales	1.3	1.2
Operatives	1	1.7
Elementary	1.1	2.9
Total	100	100
Number of Observations	527	783

Notes: SS data sample, male workers (excluding self-employed)aged between 20-65. The survey weights are used.

Table 2.4: Tasks in the Britain's Skill Survey

ReadShort: Reading short documents such as short reports, letters or memos
ReadLong: Reading long documents such as long reports, manuals, articles or books
WriteForm: Writing material such as forms, notices or signs
WriteShort: Writing short documents (for example, short reports, letters or memos)
WriteLong: Writing long documents with correct spelling and grammar

Maths1: Adding, subtracting, multiplying or dividing numbers
Maths2: Calculations using decimals, percentages or fractions
Maths3: Calculations using more advanced mathematical or statistical procedures

Instruct: Instructing, training or teaching people, individually or in groups
Speech: Making speeches or presentations
Persuade: Persuading or influencing others
Planoth: Planning the activities of others
People: Dealing with People

Ahead: Thinking ahead
OwnAct: Planning your own activities
OwnTime: Organising your own time

Fault: Spotting problems or faults
ProbSolve: Thinking of solutions to problems
Cause: Working out the cause of problems or faults
Analyse: Analysing complex problems in depth

Routine Work
Repeat: Carrying out short repetitive tasks

Notes: SS data sample 1997-2012.

TABLE 2.5: Correlation Coefficients in 1997

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1.ReadSh	1.000																			
2.ReadLg	0.644	1.000																		
3.WriteFrm	0.488	0.435	1.000																	
4.WriteSh	0.645	0.570	0.588	1.000																
5.WriteLg	0.471	0.677	0.428	0.634	1.000															
6.Maths1	0.157	0.153	0.138	0.150	0.097	1.000														
7.Maths2	0.162	0.179	0.110	0.150	0.106	0.916	1.000													
8.Maths3	0.106	0.206	0.052	0.135	0.192	0.620	0.687	1.000												
9.Instruct	0.292	0.226	0.206	0.244	0.264	0.001	0.033	0.065	1.000											
10.Speech	0.347	0.384	0.251	0.409	0.418	0.045	0.073	0.132	0.533	1.000										
11.Persuade	0.336	0.325	0.231	0.358	0.318	0.046	0.043	0.044	0.414	0.552	1.000									
12.Planoth	0.294	0.252	0.183	0.295	0.317	0.005	0.037	0.042	0.484	0.430	0.463	1.000								
13.Ownact	0.391	0.308	0.261	0.410	0.322	0.115	0.110	0.121	0.319	0.453	0.411	0.481	1.000							
14.Owntime	0.404	0.319	0.267	0.399	0.306	0.134	0.127	0.101	0.279	0.414	0.420	0.366	0.702	1.000						
15.Ahead	0.417	0.373	0.250	0.396	0.357	0.116	0.118	0.106	0.333	0.442	0.402	0.396	0.565	0.587	1.000					
16.Cause	0.224	0.256	0.126	0.160	0.186	0.108	0.133	0.127	0.163	0.007	0.107	0.128	0.114	0.172	0.188	1.000				
17.Fault	0.169	0.186	0.069	0.122	0.159	0.157	0.148	0.124	0.103	-0.029	0.080	0.076	0.091	0.104	0.135	0.687	1.000			
18.ProbSlv	0.251	0.298	0.149	0.266	0.248	0.121	0.154	0.218	0.086	0.129	0.190	0.189	0.237	0.259	0.298	0.636	0.453	1.000		
19.Analyse	0.316	0.436	0.197	0.336	0.407	0.175	0.211	0.283	0.137	0.237	0.244	0.145	0.231	0.265	0.286	0.409	0.298	0.552	1.000	
20.People	0.287	0.195	0.260	0.289	0.188	-0.041	-0.026	-0.084	0.414	0.472	0.461	0.406	0.328	0.308	0.369	0.010	-0.073	0.021	0.037	1.000

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 1997, aged between 20-65.

Table 2.6: Factor Loadings in 1997

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
ReadShort	**0.726**	0.1277	0.0023	0.0105	-0.0145	0.3648
ReadLong	**0.8253**	-0.0674	0.0149	0.0966	0.0255	0.2937
WriteForm	**0.8036**	-0.051	-0.0345	-0.1276	-0.027	0.4596
WriteShort	**0.8334**	0.1074	-0.0231	-0.0664	-0.0138	0.2624
WriteLong	**0.7987**	-0.0951	0.0934	0.0506	-0.0136	0.3431
Maths1	-0.0054	0.0424	-0.0389	-0.0586	**0.9404**	0.1283
Maths2	-0.0182	0.0052	0.0146	-0.0281	**0.9651**	0.0848
Maths3	0.0029	-0.0448	0.05	0.05	**0.8304**	0.2952
Instruct	-0.0425	-0.1901	**0.909**	0.1136	0.0292	0.3194
Speech	0.1693	0.0909	**0.6683**	-0.1126	0.0647	0.3532
Persuade	0.0491	0.1501	**0.6255**	0.0452	-0.0076	0.4408
Planothers	-0.0825	0.1939	**0.6464**	0.0833	-0.0211	0.4463
People	0.0384	0.0661	**0.6847**	-0.1495	-0.0775	0.226
OwnAct	-0.022	**0.8786**	0.0344	-0.0426	0.0153	0.2055
OwnTime	-0.0031	**0.93**	-0.0742	-0.005	0.0047	0.3601
Ahead	0.0503	**0.704**	0.0905	0.0657	-0.0029	0.1981
Cause	-0.0314	-0.0633	0.0596	**0.9217**	-0.0564	0.338
Fault	-0.0663	-0.0979	0.0388	**0.8439**	0.0018	0.3106
ProbSolve	0.0312	0.1953	-0.0768	**0.7676**	-0.0163	0.4966
Analyse	0.3026	0.0691	-0.0479	**0.504**	0.0917	0.4538
	Literacy	Self-plan.	Com-Inf.	Prob Solv.	Numeracy	
Standard Dev.	1	1	1	1	1	
Mean	0	0	0	0	0	

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 1997.

Table 2.7: Regression Scoring Coefficients in 1997

Variable	Factor1	Factor2	Factor3	Factor4	Factor5
ReadShort	0.21729	0.04813	-0.01026	0.00116	-0.0045
ReadLong	0.24855	-0.03686	-0.00263	0.03577	0.01272
WriteForm	0.24313	-0.02795	-0.02069	-0.05377	-0.00973
WriteShort	0.25037	0.03916	-0.02046	-0.02973	-0.00446
WriteLong	0.23999	-0.05001	0.02896	0.01691	-0.00321
Maths1	0.00061	0.01637	-0.01728	-0.01631	0.37123
Maths2	-0.00357	-0.00077	0.00423	-0.00406	0.38118
Maths3	0.00228	-0.02288	0.01865	0.02595	0.32867
Instruct	-0.02179	-0.10153	0.3561	0.04156	0.0113
Speech	0.04307	0.02252	0.25526	-0.04855	0.02368
Persuade	0.00614	0.0498	0.2381	0.0144	-0.0041
Planothers	-0.03428	0.06923	0.24654	0.02981	-0.00959
People	0.00357	0.01323	0.26411	-0.06391	-0.03304
OwnAct	-0.01471	0.37547	-0.00582	-0.01874	0.00301
OwnTime	-0.00842	0.39964	-0.0494	-0.00343	-0.00083
Ahead	0.00755	0.29868	0.01849	0.02417	-0.00282
Cause	-0.01304	-0.02979	0.02036	0.36738	-0.01546
Fault	-0.02259	-0.04383	0.01376	0.33704	0.00703
ProbSolve	0.00567	0.08354	-0.03821	0.3061	-0.00116
Analyse	0.08935	0.02664	-0.0262	0.20081	0.04048
	Literacy	Self-plan.	Com-Inf.	Prob Solv.	Numeracy

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 1997, aged between 20-65.

TABLE 2.8: Correlation Coefficients in 2012

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
—																				
1.ReadSh	1.000																			
2.ReadLg	0.687	1.000																		
3.WriteFrm	0.444	0.404	1.000																	
4.WriteSh	0.634	0.594	0.477	1.000																
5.WriteLg	0.497	0.666	0.413	0.627	1.000															
6.Maths1	0.197	0.200	0.080	0.205	0.196	1.000														
7.Maths2	0.190	0.220	0.062	0.234	0.220	0.842	1.000													
8.Maths3	0.166	0.270	0.088	0.226	0.302	0.632	0.727	1.000												
9.Instruct	0.177	0.181	0.220	0.281	0.213	0.061	0.075	0.102	1.000											
10.Speech	0.323	0.388	0.254	0.436	0.451	0.149	0.159	0.192	0.428	1.000										
11.Persuade	0.283	0.310	0.169	0.386	0.271	0.079	0.095	0.080	0.356	0.531	1.000									
12.Planoth	0.218	0.204	0.177	0.304	0.257	0.127	0.098	0.113	0.417	0.391	0.386	1.000								
13.Ownact	0.355	0.365	0.229	0.384	0.336	0.165	0.143	0.128	0.289	0.421	0.395	0.401	1.000							
14.Owntime	0.386	0.384	0.261	0.459	0.386	0.160	0.148	0.124	0.311	0.402	0.364	0.363	0.672	1.000						
15.Ahead	0.376	0.413	0.251	0.416	0.320	0.187	0.199	0.152	0.269	0.403	0.412	0.401	0.589	0.604	1.000					
16.Cause	0.139	0.174	0.071	0.144	0.146	0.206	0.239	0.241	0.136	0.073	0.121	0.191	0.173	0.141	0.165	1.000				
17.Fault	0.173	0.188	0.073	0.164	0.130	0.201	0.196	0.184	0.120	0.040	0.120	0.161	0.183	0.169	0.179	0.772	1.000			
18.ProbSlv	0.239	0.275	0.134	0.285	0.234	0.229	0.269	0.253	0.183	0.226	0.308	0.262	0.323	0.303	0.322	0.655	0.559	1.000		
19.Analyse	0.349	0.465	0.163	0.430	0.438	0.269	0.307	0.399	0.193	0.334	0.286	0.238	0.354	0.314	0.383	0.427	0.350	0.611	1.000	
20.People	0.251	0.254	0.254	0.342	0.216	-0.021	-0.013	-0.064	0.331	0.365	0.483	0.284	0.364	0.333	0.362	0.013	0.035	0.161	0.165	1.000

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 2012.

Table 2.9: Factor Loadings in 2012

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
ReadShort	**0.8202**	0.1247	-0.1305	0.001	-0.0419	0.324
ReadLong	**0.8433**	0.0845	-0.1025	0.0332	0.0163	0.2622
WriteForm	**0.7406**	-0.1643	0.1086	-0.0463	-0.1268	0.5193
WriteShort	**0.7454**	0.0529	0.1256	-0.013	0.0205	0.2967
WriteLong	**0.7931**	-0.0515	0.06	-0.0212	0.0803	0.3349
Maths1	-0.0453	0.0736	-0.0216	-0.051	**0.9168**	0.1842
Maths2	-0.0263	0.022	0.0016	-0.0247	**0.9486**	0.119
Maths3	0.0847	-0.1127	0.0459	0.0249	**0.8517**	0.2391
Instruct	-0.0602	-0.1907	**0.8771**	0.0555	0.0224	0.386
Speech	0.1861	0.0473	**0.6515**	-0.1184	0.1127	0.3917
Persuade	-0.0008	0.1423	**0.664**	0.0319	-0.0297	0.4311
Planothers	-0.1384	0.1923	**0.6024**	0.0925	0.0358	0.5093
People	0.0763	0.1858	**0.5483**	-0.0827	-0.1851	0.5259
Ownact	-0.0151	**0.8694**	0.0096	0.0026	-0.0077	0.2488
Owntime	0.0857	**0.8529**	-0.0416	-0.0421	-0.0147	0.2608
Ahead	0.0418	**0.8046**	0.0093	-0.0065	0.036	0.3001
Cause	-0.0402	-0.0933	0.0102	**0.9549**	-0.0175	0.1555
Fault	-0.0099	-0.0274	-0.0538	**0.9085**	-0.0672	0.2418
ProbSolve	0.0088	0.1195	0.0753	**0.7769**	0.0124	0.2731
Analyse	0.293	0.1115	0.0218	**0.4562**	0.157	0.4439
	Literacy	Self-plan.	Com-Inf.	Prob Solv.	Numeracy	
Standard Dev.	1	1	1	1	1	
Mean	0	0	0	0	0	

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 2012.

Table 2.10: Regression Scoring Coefficients in 2012

Variable	Factor1	Factor2	Factor3	Factor4	Factor5
ReadShort	0.24883	0.03745	-0.06346	-0.00075	-0.01771
ReadLong	0.25642	0.0193	-0.05122	0.01172	0.005
WriteForm	0.22958	-0.08864	0.04491	-0.02105	-0.05135
WriteShort	0.22571	0.00307	0.04682	-0.0069	0.00586
WriteLong	0.24296	-0.04099	0.0208	-0.00987	0.02929
Maths1	-0.01717	0.03174	-0.0132	-0.01442	0.35645
Maths2	-0.01048	0.00896	-0.00264	-0.00439	0.36888
Maths3	0.02623	-0.05142	0.01832	0.01344	0.33122
Instruct	-0.02041	-0.09817	0.37535	0.01748	0.00644
Speech	0.05131	0.00161	0.27352	-0.0481	0.04063
Persuade	-0.00804	0.04641	0.27796	0.00976	-0.01369
Planothers	-0.05105	0.07211	0.25131	0.0342	0.01258
People	0.01591	0.06543	0.22853	-0.03487	-0.07456
Ownact	-0.02409	0.36925	-0.01433	0.00332	-0.00379
OwnTime	0.00756	0.361	-0.03614	-0.01402	-0.00678
Ahead	-0.0053	0.34042	-0.01358	-0.00025	0.01311
Cause	-0.01232	-0.03629	0.00265	0.36824	-0.0016
Fault	-0.00389	-0.0077	-0.02573	0.35047	-0.02108
ProbSolve	-0.00224	0.05103	0.02597	0.29991	0.00858
Analyse	0.08558	0.04142	0.00239	0.17648	0.06269
	Literacy	Self-plan.	Com-Inf.	Prob Solv.	Numeracy

Notes: SS data sample, male workers (excluding self-employed) with a university degree in 2012.

Table 2.11: Distribution of (essential) job tasks performed by university graduates in 1997 and 2012 (%)

	1997(%)	**2012(%)**	**1997-2012(%)**
Literacy			
ReadShort	48.1 (2.15)	54.1 (1.53)	6**
ReadLong	36.7 (2.07)	42.7 (1.52)	6**
WriteForm	34.2 (2.04)	32.1 (1.44)	-2.1
WriteShort	43.7 (2.13)	45.2 (1.53)	1.5
WriteLong	34.1 (2.04)	37.1 (1.49)	3
Numeracy			
Maths1	41.9 (2.12)	46.3 (1.53)	4.4
Maths2	38.9 (2.10)	43 (1.52)	4.1
Maths3	24.1 (1.84)	26.9 (1.36)	2.8
Communication-Influencing			
Instruct	29.6 (1.96)	34 (1.46)	4.4*
Speech	24.5 (1.85)	26.3 (1.35)	1.8
Persuade	32.3 (2.01)	38.4 (1.50)	6.1**
Planoth	20.1 (1.72)	18.3 (1.19)	-1.8
People	63.4 (2.07)	69.8 (1.41)	6.4**
Self-Planning			
OwnAct	48.3 (2.15)	47.7 (1.54)	0.6
OwnTime	53.9 (2.14)	55 (1.53)	1.1
Ahead	51.4 (2.15)	50.3 (1.54)	-1.1
Problem Search and Solving			
Cause	43.6 (2.13)	40.6 (1.51)	-3
Fault	48.2 (2.15)	44 (1.53)	-4.2
ProbSolve	55.6 (2.14)	53.3 (1.53)	-2.3
Analyse	41.2 (2.12)	49.2 (1.54)	8**
Routineness of Work			
Not performing any routine work	16 (1.58)	10.6 (9.48)	-5.4**
Performing some routine work	84 (1.58)	89.4 (9.48)	5.4**

Notes: SS data samples, male workers (excluding self-employed) aged between 20-65. The survey weights are used. The standard errors are in parenthesis. Refer Table 2.4 for full definition of the job tasks.
* Indicates change is significantly different from zero. (** $p \prec 0.05$, * $p \prec 0.1$).

Table 2.12: OLS Regressions with the Job Skills in 1997

Explanatory Variables	**(1)**	**(2)**	**(3)**
Experience	0.0458***	0.0410***	0.0400***
	(0.00755)	(0.00735)	(0.00731)
Experience Squared	-0.000980***	-0.000872***	-0.000864***
	(0.000218)	(0.000214)	(0.000210)
Literacy		0.0424	0.0393
		(0.0263)	(0.0263)
Self-Planning		-0.0125	-0.0132
		(0.0300)	(0.0301)
Problem Search and Solving		0.0528**	0.0495**
		(0.0228)	(0.0228)
Communication-Influencing		0.0308	0.0282
		(0.0266)	(0.0267)
Numeracy		0.0566**	0.0615**
		(0.0252)	(0.0246)
Routine work dummy			-0.155***
			(0.0593)
Constant	1.643***	1.688***	1.835***
	(0.0594)	(0.0561)	(0.0787)
Observations	492	492	492
R-squared	0.103	0.152	0.164
90-10 Residual Wage Gap	1.134	1.098	1.076
Explained Part of Wage Gap(%)		3.2	5.1

Notes: The dependent variable is log hourly wages of male workers with a university degree in the Skills Survey sample. Robust standard errors in parentheses.
*** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Table 2.13: OLS Regressions with the Job Skills in 2012

Explanatory Variables	**(1)**	**(2)**	**(3)**
Experience	0.0606***	0.0501***	0.0465***
	(0.00649)	(0.00659)	(0.00681)
Experience Squared	-0.00116***	-0.000940***	-0.000871***
	(0.000170)	(0.000170)	(0.000173)
Literacy		0.0254	0.0247
		(0.0221)	(0.0221)
Self-Planning		0.0644***	0.0636***
		(0.0245)	(0.0241)
Problem Search and Solving		0.0634***	0.0591***
		(0.0214)	(0.0215)
Communication-Influencing		0.0159	0.0148
		(0.0252)	(0.0251)
Numeracy		0.0722***	0.0773***
		(0.0204)	(0.0201)
Routine work dummy			-0.277***
			(0.0898)
Constant	1.392***	1.496***	1.782***
	(0.0545)	(0.0566)	(0.117)
Observations	638	614	614
R-squared	0.157	0.242	0.262
90-10 Residual Wage Gap	1.242	1.160	1.15
Explained Part of Wage Gap(%)		6.6	7.4

Notes: The dependent variable is log hourly wages of the male workers with a university degree in the Skills Survey sample. Robust standard errors in parentheses.
*** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Table 2.14: OLS Regressions with the Job Skills in 1997: Additional Controls

Explanatory Var.	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0410***	0.0438***		0.0427***	0.0332***	0.0350***
	(0.00735)	(0.00747)		(0.00732)	(0.00716)	(0.00718)
Experience-Squar.	-0.000872***	-0.000972***		-0.000892***	-0.000666***	-0.000690***
	(0.000214)	(0.000212)		(0.000211)	(0.000203)	(0.000201)
Literacy	0.0424	0.0316	0.0518*	0.0407	0.0298	0.0286
	(0.0263)	(0.0269)	(0.0273)	(0.0261)	(0.0251)	(0.0249)
Self-Planning	-0.0125	-0.0191	0.00273	-0.00721	-0.0411	-0.0354
	(0.0300)	(0.0310)	(0.0317)	(0.0297)	(0.0306)	(0.0304)
Problem S. and Solv.	0.0528**	0.0412*	0.0507**	0.0541**	0.0603***	0.0601**
	(0.0228)	(0.0219)	(0.0238)	(0.0230)	(0.0231)	(0.0235)
Comm.-Influenc.	0.0308	0.0171	0.0385	0.0314	0.0173	0.0160
	(0.0266)	(0.0268)	(0.0279)	(0.0257)	(0.0258)	(0.0253)
Numeracy	0.0566**	0.0676***	0.0622**	0.0616**	0.0394	0.0440*
	(0.0252)	(0.0241)	(0.0252)	(0.0250)	(0.0242)	(0.0241)
Controls						
Occupation	No	No	No	Yes	No	Yes
Region	No	No	No	No	Yes	Yes
Constant	1.688***	1.682***	2.043***	1.630***	1.133***	1.127***
	(0.0561)	(0.0574)	(0.0269)	(0.0595)	(0.119)	(0.118)
Observations	492	472	492	492	492	492
R-squared	0.152	0.145	0.084	0.175	0.229	0.247

Notes: The dependent variable is log hourly wages of male workers with a university degree in the Skills Survey sample. Robust Standard errors in parentheses. year dummy is used. *** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Table 2.15: OLS Regressions with the Job Skills in 2012: Additional Controls

Explanatory Var.	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0501***	0.0494***		0.0518***	0.0403***	0.0420***
	(0.00659)	(0.00728)		(0.00640)	(0.00616)	(0.00595)
Experience-Squar.	-0.000940***	-0.000945***		-0.000953***	-0.000698***	-0.000717***
	(0.000170)	(0.000191)		(0.000165)	(0.000158)	(0.000153)
Literacy	0.0254	0.0218	0.0252	0.0203	0.0374*	0.0326
	(0.0221)	(0.0226)	(0.0240)	(0.0221)	(0.0218)	(0.0218)
Self-Planning	0.0644***	0.0722***	0.0725***	0.0673***	0.0293	0.0322
	(0.0245)	(0.0271)	(0.0259)	(0.0244)	(0.0232)	(0.0231)
Problem S. and Solv.	0.0634***	0.0602***	0.0820***	0.0648***	0.0463**	0.0475**
	(0.0214)	(0.0231)	(0.0231)	(0.0211)	(0.0205)	(0.0202)
Comm.-Influenc.	0.0159	0.00470	0.0479*	0.0168	-0.00314	-0.00164
	(0.0252)	(0.0264)	(0.0263)	(0.0249)	(0.0244)	(0.0243)
Numeracy	0.0722***	0.0761***	0.0767***	0.0679***	0.0559***	0.0531***
	(0.0204)	(0.0214)	(0.0217)	(0.0200)	(0.0197)	(0.0195)
Controls						
Occupation	No	No	No	Yes	No	Yes
Region	No	No	No	No	Yes	Yes
Constant	1.496***	1.524***	1.982***	1.432***	1.113***	1.047***
	(0.0566)	(0.0605)	(0.0350)	(0.0554)	(0.108)	(0.117)
Observations	614	572	616	614	614	614
R-squared	0.242	0.210	0.143	0.260	0.342	0.353

Notes: The dependent variable is log hourly wages of male workers with a university degree in the Skills Survey sample. Robust Standard errors in parentheses. year dummy is used. *** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Table 2.16: OLS Regressions with Tasks and Alternative Skill Measures

Explanatory Var.	(a)	(b)	(c)
Experience	0.0441*** (0.00435)	0.0440***(0.00433)	0.0437 (0.00427)***
Experience-Squar.	-0.000833***(0.000113)	-0.000851***(0.000114)	-0.000841***(0.000113)
ReadShort	-0.0522 (0.117)		
ReadLong	0.176**(0.0864)		
WriteForm	-0.325*** (0.0787)		
WriteShort	0.144 (0.0931)		
WriteLong	0.120* (0.0654)		
Maths1	-0.0222(0.0801)		
Maths2	0.0248(0.0626)		
Maths3	0.131*** (0.0362)		
Instruct	-0.0559 (0.0592)		
Speech	0.153*** (0.0568)		
Persuade	0.0221(0.0889)		
Planoth	0.134*** (0.0491)		
OwnAct	0.0414(0.173)		
OwnTime	0.0797(0.262)		
Ahead	0.0359 (0.197)		
Cause	0.0209 (0.147)		
Fault	0.132(0.175)		
ProbSolve	0.000561(0.115)		
Analyse	0.271*** (0.0756)		
People	0.0868 (0.162)		
Literacy		0.0234 (0.0175)	0.267***(0.0867)
Numeracy		0.0381***(0.0112)	0.0376(0.0471)
Comm.-Influenc.		0.0749***(0.0208)	0.339***(0.0874)
Self-Planning		0.00974 (0.0252)	0.127 (0.0852)
Problem S. and Solv.		0.102***(0.0183)	0.0577(0.0805)
Literacy^2			-0.0465***(0.0156)
Numeracy^2			-0.00129 (0.00999)
Comm.-Influenc.^{2}			-0.0517***(0.0163)
Self-Planning^2			-0.0227(0.0149)
Problem S. and Solv.^{2}			0.00600 (0.0144)
Constant	0.470**	0.775***	0.157
	(0.220)	(0.0763)	(0.128)
Observations	1,385	1,385	1,385
R-squared	0.249	0.218	0.240

Notes: The dependent variable is log hourly wages of male university graduates in the pooled Skills Survey sample 1997-2012. Robust Standard errors in parentheses. Year dummies are used. *** $p \prec 0.01$, ** $p \prec 0.05$, * $p \prec 0.1$

Chapter 3

Does Early Tracking Affect Achievement? The case of Turkey

3.1 Introduction

Academic tracking (streaming) is separating students by academic ability. This sort of selective schooling policy is commonly implemented in two forms. One form is where students are sent to certain schools depending on ability as in some European countries such as Germany, Austria, etc. Another form is where they are divided into different classes by ability within schools as in some areas of the United States and Canada. Nevertheless, the extent as well as the timing of tracking students may vary across countries.

The economic consequences of tracking stem from the fact that tracking results in variations in peer group, teaching quality [1] and academic curriculum across schools/classes, which directly relates to the education production function of the students (see Betts (2011) for a survey on the economics of tracking).

The outcome of tracking, as an education policy, matters considerably in terms of efficiency and equality. The academic tracking debate in the literature is centred broadly around these two outcomes. There is a common argument that tracking increases the efficiency of students' learning because teaching lower variance classes helps teachers to pay particular attention to the needs of student groups with similar abilities, which can be said to help both high-achieving and low-achieving students (see e.g. Duflo et al.

[1] There might be teacher sorting such that better teachers prefer better schools and students.

(2011)). In addition, it is suggested that studying in lower variance classes (in terms of peer ability) increases the performance of high-ability students. Ding and Lehrer (2007) find that there exists a strong and positive peer effect for high-ability students from high-achieving school mates and from studying in environments with less peer quality variation. Galindo-Rueda and Vignoles (2004) also find that high-ability students who study in selective school systems perform better than their peers with similar ability who study in comprehensive school systems. On the other hand, other evidence show that tracking might deteriorate the achievement equality among students, because students who are not tracked in the high-ranked schools might suffer the loss of the possible positive effects from the most able peers. Zimmer (2003) provides evidence that tracking mitigates the positive effects from more able peers on low and average ability students. In addition, it is argued that if the students who are tracked in the high-ranked schools are mostly the socio-economically advantaged students then it also makes an impact on the intergenerational mobility of society. Brunello and Checchi (2007) find that academic tracking strengthens the effect of family background on educational attainment and future labour market outcomes of the students. They suggest that tracking precludes some students from studying further at university level. Waldinger (2006) also finds that family socio-economic background plays a bigger role for academic achievement in the countries where the early tracking system is implemented. Hanushek and Wobmann (2006) evaluate the consequences of tracking in terms of both outcomes. They find that early tracking increases achievement inequality but does not contribute to the achievement gains in Mathematics and Reading. They only find efficiency gains in Science from early tracking.

This chapter contributes to the literature by providing new evidence on the efficiency gains from early tracking. In particular, we evaluate a policy change and further measure the effect of the removal of early tracking (the treatment) on mathematics test scores of the students in Turkey using data from the Third International Mathematics and Science Study (TIMMS) and Program for International Student Assessment (PISA).[2] The education policy change which took place in 1997 provides the exogenous variation in the early tracking status of the students (who were eligible) to evaluate the causal impact of the early academic tracking on the achievement levels. During the early tracking period, the students who achieved the highest scores in the nationally held examination were streamed into the high-ranked schools (Anatolian High Schools)[3] after completing the 5th grade (see Figure 3.1). The education regulation passed in 1997, in particular,

[2]Early tracking in this chapter refers to the tracking of students aged around 11-12.

[3]High-ranked schools are used as an equivalent to tracking schools and the schools which admit students based on an examination throughout this chapter.

altered the years of compulsory schooling and increased them from five years to eight years. As a result, the alteration in the law caused the removal of early tracking.[4]

Turkey also provides an interesting and a relevant case for other developing countries simply because the selective schooling policies have been one of the key characteristics of national education system, below the tertiary schooling level. In addition, the schools that high-achieving student are tracked in Turkey traditionally are very similar to the German gymnasium schools, the French lycees and the British grammar schools in terms of their more academic oriented curricula, therefore Turkish case would also provide some insight into these cases as well.

The results show that when the possibility of the time varying covariates are not taken into account, the estimated effect of the removal of early tracking on the mathematics test scores is -106.4 points. This implies an additional 13% decrease on the mathematics test score of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods. Moreover, the magnitude of the treatment effect implies an additional 5% decrease on the mathematics test score of the treated students when student and family characteristics are both controlled for.

This chapter proceeds as follows. Section 3.2 provides the necessary information for the Turkish Education System and the change on the tracking policy. Section 3.3 explains the data sources. Section 3.4 explains the various aspects of the identification strategy. Section 3.5 describes the evaluation method. Section 3.6 provides the results with some robustness checks. Finally, Section 3.7 summarises and concludes.

3.2 The Education System and Early Tracking Process in Turkey

The Ministry of National Education (MONE) plans, advances, monitors and inspects all of the services related to education and training in Turkey. Formal education below tertiary education consists of three parts namely pre-primary, primary and secondary education. Pre-primary education is optional and covers the children between 36-72 months old who are aged under the age of compulsory primary education. Primary education is compulsory for all children, boys and girls. Moreover, until 1997, children were obliged to take at least five years of (primary) education. The education reforms in 1997 increased the years of compulsory education from five to eight years for children

[4] Academic tracking policy in Turkey however still implemented in the secondary school level. Students are now tracked after the completion of the 8th grade.

between 6-14 years old in Turkey. Eight years of primary education can be decomposed as primary level (for children aged between 6-11, between 1st and 5th grade) and lower-secondary level (for children aged between 12-14, between 6th and 8th grade).

The education regulation which resulted in the removal of early tracking was 1997 Eight-Year Compulsory Education Enforcement Law (Law no. 4306).[5] The law required that 6.9 million students who were at that time enrolled between the first and the fifth grades of primary schools and all children who would start school in the future would continue schooling until completion of the eight grade. The program essentially aimed at expanding the opportunities of children who normally would have left schooling after the completion of the fifth grade, in particular all children from poor villages and poorer suburbs of metropolitan areas and girls.

From the early 1970s until the end of the 1990s, the successive governments of Turkey sought to increase the years of compulsory education. However, they experienced various difficulties over time. Dulger (2004) argue that the government in 1997 took a fast approach and because they were afraid that the reform could be overturned or it took time to develop quality-enhancing components of the program, the legislation was prepared by the education ministry administrators with no public consultation or debate and the program started up shorty after the law.

The implementation of the program was heavily relied on construction. The first stage was to construct Eight-Year Primary Education Schools. These schools brought primary level and lower-secondary level education under one administration which would then facilitate the use of all available school buildings in the districts. The second step was to build new classrooms to create additional capacity. Moreover, in order to improve access to education for the children in rural areas, some additional measures were taken e.g. the establishments of boarding schools, free of charge transportation and lunches, books, etc. The third step was to address the teacher constraint. In order to do that, the Ministry recruited additional teachers. Finally, the primary education curriculum was merged with the existing lower-secondary curriculum. This implies that the curriculum across all the Eight-Year Primary Education Schools was made uniform. It is important to note that there are both private and state schools which provide pre-primary, primary and secondary education in Turkey under the regulations of MONE. However, state schools do not charge any fees for education and this applies to all type of primary and secondary state schools (Smits and Hosgor (2006)).

Figure 3.1 illustrates the state schools in lower-secondary level before and after the policy change. The upper part of the figure shows that before the policy change took

[5] Dulger (2004) provides an overview of this regulation. The description of the program presented here is mainly based on his work.

place in 1997, there were two group of state schools for the students who proceeded to lower-secondary schools after completing the 5th grade: High-ranked state schools and standard state schools. High-ranked state schools admitted students depending on their academic achievement via a nationally held exam. The standard lower-secondary schools, in turn, admitted students depending on non-academic criteria, e.g. geographic proximity. Each year, MONE announced the number of places available in each high-ranked schools. The applicants first chose the preferred high-ranked schools located all around Turkey during term time and then took the exam during summer break. Once all individual scores were calculated, the highest scored students were accommodated into the available places in the chosen high-ranked schools from the central system (Dincer and Uysal (2010)).[6] On the other hand, the students who did not take the exam or did not get any place in the high-ranked schools admitted to the standard (lower-secondary) schools.

Before the policy change, the high-ranked schools provided 7 years of (lower and upper-secondary) schooling including one year English preparatory class. These schools were more academic and foreign language (English in particular) teaching oriented than the standard state schools. In addition, there was a selection process while assigning teachers into these schools. After the regulation, because the compulsory years of education was increased to eight years, students had eight years of uninterrupted schooling starting from September 1997 onwards. Therefore, all the standard[7] primary and lower-secondary schools started providing eight years of education.This resulted in the removal of early tracking.

In 1995, 25% [8] of all the 5th grade graduates took the nationally held exam.[9] Among the students who took the exam, around 13% of them scored high enough to get a place in one of the high-ranked schools. In the late 1990s, these students consisted of on average 5% of all lower-secondary school graduates (8th grade students) who form of the treatment group in this study. This implies that although the policy change removed the early tracking after 1997, the students who were tracked before 1997 studied in the high-ranked schools until they graduated. This allows us to construct the treatment group in the TIMMS 1999 sample.

[6] Dincer and Uysal (2010) describe this mechanism for the secondary schools after the policy change when the tracking started taking place in the secondary school level.

[7] The schools which admit students depending on non-academic criteria, e.g. geographic proximity

[8] The statistics given here are my own calculations based on the various newspaper articles and Ministry of National Education statistics. Due to lack of consistent information over the years, they are only approximations of the real numbers.

[9] The exam was called Anatolian High School Exam.

3.3 Data

3.3.1 Description

This chapter exploits cross-sectional data from the TIMMS and the PISA. TIMMS is conducted by the International Association for the Evaluation of Educational Achievement (IAE) and PISA is conducted by The Organisation for Economic Co-operation and Development(OECD). Turkey took part in TIMMS in 1999, 2007 and 2011 and participated in PISA in 2003, 2006 and 2009. We only employ 1999 and 2007 TIMMS and 2003 PISA cross-section data samples where the number of observations is 7 841, 4 855 and 4 498 students respectively.

TIMMS and PISA are regarded as the two main cross-national studies which provide insight into the mathematics and science competencies of the students below the higher education level. They share common traits such as they are both large scale surveys, their samples are designed to be the representative of the population; they both collect student and school background characteristics information as well as cognitive skills data, and they process the data gathered using similar methods, most importantly they are repeated studies which aim to measure trends over time (see Gronmo and Olsen (2006)).[10]

The TIMMS and PISA both assesses the mathematics and science achievements of the students, the former tests students in the 8th (and 4th) grades whereas latter examines 15-year-old students only. Both of the surveys produce the reported achievement scores in mathematics and science using item response theory (IRT) scaling methods. Since, item pool in each subject is too wide to be administered entirely to any one student given the limited testing time[11], each student is given one test booklet for each mathematics and science items among several booklets which contains only a part of the complete assessments. The IRT method is then utilised to generate comparable estimates of performance for all students by taking into consideration of the difficulty of the items solved by different students. The TIMMS and PISA IRT scaling employ the multiple imputation or plausible value technology where five separate estimates known as plausible values of each student's score is produced on each scale in accordance with the responses to the items in the student's booklet and the student's background characteristics.

[10] Appendix B.1 provides a brief comparison of the two surveys and verify that the two studies are comparable and hence substitutable for Turkey in 2003.

[11] If the testing time was extended, students would start to be affected by fatigue and this would hence bias the outcomes of the surveys. In addition, school principals would not be willing to let their students go for a very long testing period. This would decrease the school participation rate, that in turn might considerably bias the outcomes of the results (see e.g. PISA and TIMMS technical reports)

This study mainly concentrates on the mathematics performance results since the mathematics curricula is more standard across schools than the science curricula. In addition, achievement in mathematics is more of a signal of future wages (see e.g., Murnane et al. (1995)).[12]

The students who are tested also complete a questionnaire regarding their attitudes towards mathematics, classroom activities, activities outside school and family demographic and socio-economic background in both surveys.[13] In addition, the heads of sampled schools respond to questions regarding the management of the school, school staff and resources.[14]

Table 3.2 displays some descriptive statistics for the whole sample of students in 1999, 2003 and 2007. The table demonstrates that some of the family socio-economic status indicators, particularly parents level of highest education, slightly improved in the data from 1999 to 2007. This is expected since the change in compulsory schooling law took place in 1997. In addition, home resources such as computers become more abundant. Finally, most of the indicators for the school resource limitations show an improvement over the periods.

3.4 Identification Strategy

This section initially introduces the identification strategy to investigate the causal effect of the removal of early tracking on the students' mathematics test scores who are eligible. Further, the definition of treatment and control groups is explained. Finally, the threats to identification are discussed.

Estimating the causal effect of early tracking using the observational data has difficulties since tracking is an endogenous treatment and potentially correlated with some factors that could not be controlled for. For instance, it is known that socio economically better off parents highly value their children being tracked and going to the high-ranked schools. This results in them spending more money on private tutoring, etc. to prepare their children for the tracking exam (WorldBankReport (2013)). In order to estimate the causal impact, the treatment should be treated as exogenous. This is possible when an exogenous intervention such as a policy change alters the treatment status of individuals as in a natural experiment or in a quasi-experimental setting.

[12] Figlio and Page (2002) also use similar reasoning to examine the mathematics test scores.

[13] Table 3.1 displays the TIMMS and PISA student and school characteristics variables. In addition, Appendix B.2 provides more detailed description of these variables.

[14] In the TIMMS questionnaire, the mathematics teachers of the sampled students also answer questions related to the their training, qualification and experience as well as the instructional practices in the TIMMS class.

The identification strategy in this chapter is based on the regulation described above in the education policy which (indirectly) resulted in the removal of early tracking opportunity for 8th grade students. By changing the tracking status exogenously, the regulation provides the exogenous intervention needed to estimate the causal impact of the removal of early tracking on the students who were streamed.

Program evaluation (treatment evaluation), also called as Rubin Causal Model, provides a framework for the identification in this context. The potential outcome model makes an assumption that every unit of the population is potentially subjected to the treatment. Following the notation of Cameron and Trivedi (2005), the treatment evaluation can then be explained using Equation 3.1:

$$y_i = \begin{cases} y_{1i} & \text{if } D_i{=}1 \\ y_{0i} & \text{if } D_i{=}0. \end{cases} \tag{3.1}$$

with $i{=}1,\ldots,N$ where the binary variable D_i takes the value 1 when individual i is treated and 0 otherwise; y_i is the potential outcome. y_{1i} denotes the outcome for individual i when i is subjected to the treatment, and y_{0i} denotes the outcome when i is not subjected to the treatment. However, for any individual ,i, only one of the test scores is measured since being exposed to and not being exposed to the treatment are mutually exclusive situations. Here, the unavailable state's measure is called the counterfactual. The causal effect of D on the individual i's outcome is given by (y_{1i}-y_{0i}) and the average causal impact of $D_i = 1$ compared to $D_i = 0$ is given by the average treatment effect(ATE):

$$ATE = E[y|D = 1] - E[y|D = 0] \tag{3.2}$$

Within this framework, the exogenous intervention provides an opportunity to estimate ATE-type parameters and evaluate the causal effect by making a comparison of the behaviour of the impacted group both before and after an intervention in comparison to a non-impacted group after the intervention, provided certain other conditions are met. Under the treatment being the 'removal of early tracking', the potential outcome model in the Equation 3.1 becomes:

$$\text{Potential Mathematics Test Score} = \begin{cases} y_{1i} & \text{if } D_i{=}1 \\ y_{0i} & \text{if } D_i{=}0. \end{cases} \tag{3.3}$$

with i=*1,...,N* where the binary variable D_i denotes 'the removal of early tracking' and takes the value 1 when a student i is no longer tracked and does not study in high-ranked schools and 0 otherwise; y_{1i} denotes the mathematics test score for a student, i, when i is no longer tracked, and y_{0i} denotes the test score when i is tracked. The causal effect of D (the removal of early tracking) on the student i's mathematics test score is given by (y_{1i}-y_{0i}) and the average causal impact of $D_i = 1$, in comparison to $D_i = 0$ is in this case:

$$\text{Average Causal Effect of Removal of Tracking} = E[y|D = 1] - E[y|D = 0] \tag{3.4}$$

3.4.1 The Definition of Treatment and Control Groups

The TIMMS 1999, 2007 and PISA 2003 samples convey information on the treatment status and the outcomes of the students. We define the 1999 period as the pre-intervention and 2003 and 2007 periods as the post-intervention periods for the ease of the problem.

The treatment group (treated students) in 1999 consists of students who were studying in the high-ranked state schools during the pre-intervention period (1999). The students in the treatment group in 2003 and 2007 were, in turn, impacted from the policy change -they were exposed to the removal of early tracking- by having lost the opportunity to study in the high-ranked streams (during the post-intervention periods).

In the TIMMS 1999 sample, treatment group is constructed by grouping the 8th grade students who were admitted into their schools depending on their performance on the nationally held examination or the standardised test after completing the 5th grade. A control group is constructed within rest of the students in 1999. A control group would ideally be formed by students who have similar family socio economic background and personal characteristics with the treatment group students. This would be important since some students in 1999 sample took the 5th grade exam but not succeed to enter whereas some of the students did not take it. This would create an intention to treat bias. Therefore, a matching method is used to form a control group which has similar observable characteristics to the treatment group.[15] To find the matches initially a probit model is fitted, of the following form:

$$Y_i^* = \beta_0 + \beta_1 Book_i + \beta_2 Calculator_i + \beta_3 Desk_i + \beta_4 Dictionary_i + \beta_5 Computer_i$$

[15] See e.g, Machin (2008) and OECD (2011) for the use of matching methods with similar reasoning.

$$+\beta_6 Mother'sEduc_i + \beta_7 Father'sEduc._i + \beta_8 AttitudeMath_i + \beta_9 PerceptionMath_i + \epsilon_i \tag{3.5}$$

$$Y_i^* = \begin{cases} 1 & \text{if } D_i\text{=1} \\ 0 & \text{if } D_i\text{=0.} \end{cases} \tag{3.6}$$

Where Y_i^* is a binary outcome which takes '1' for the treated students ($D_i = 1$) in 1999 and take '0' for rest of the students in 1999. The outcome variable is regressed on the set of student's family socio-economic status indicators namely number of books and whether have a dictionary, a calculator, a desk and a computer at home, mother's and father's education. This is reasonable considering taking the exam is a choice and some socio-economically advantaged parents see the high-ranked streams as an investment in education of their children. On the other hand, in order to capture the possible unobserved heterogeneity within the streamed students, attitudes towards mathematics and perceived importance of mathematics to the students are also controlled for. Table 3.5 presents the results in column (I). Second, using the probit regression results, all students' predicted probability of being treated is calculated. Finally, students with the lowest 25%[16] of the predicted probabilities are dropped to form a control group in 1999.

In the PISA 2003 and TIMMS 2007 samples the treatment and control groups are constructed using the same approach by matching the observable and possibly capturing some unobservable characteristics of the treatment and control group students in 1999. In order to find the matches in later cohorts, initially a probit regression model is fit using Equation 3.5 from the 1999 TIMMS sample. Table 3.5 presents the results in column (II). The results show that in comparison to column (I), only father's university diploma varible remains significant at the 5% level. This might be resulted from that after the matching in 1999, observable differences, which can be explained by the given characteristics, between treatment and control group students decrease. Further, using coefficient estimates of the probit regression in column (II), predicted probabilities of being treated in 2003 (2007) are computed. Finally, students with the highest 5% of predicted probabilities are formed a treatment group. A control group is, in turn, formed by rest of the students in 2003 (2007) after dropping students with the lowest 25% of predicted probabilities.

Table 3.3 and Table 3.4 show the descriptive statistics for the students who were exposed to the removal of early tracking (treatment group) and the students who were not subject to the treatment (control group) in 1999, 2003 and 2007. In addition, Figures 3.2 and

[16] Due to missing values in the observable student characteristics, size of the sample could not be limited more.

3.3 display the kernel density estimation of the mathematics test scores for these two groups of students.

Table 3.3 and Table 3.4 compare the descriptive statistics for the treatment and control groups over the periods. The number of treated students are 358, 211 and 196; whereas number of untreated students are 4112, 2938 and 2745 in 1999, 2003 and 2007, respectively. The number of boys is higher than girls among both the treated students and untreated students throughout the period. There is no significant age difference between the control and treatment groups. Moreover, although the level of parents' education is slightly higher among the students who were in treatment group than in the control group, the distribution of socio-economic indicators are balanced between the two groups in all periods. When the students' attitudes and perception towards mathematics are taken into consideration, there was not any meaningful difference between the two groups. Further, more than 80% of the students study more populated areas in all three years. Finally, school related variables neither appear to be very different for both groups. The tables also compare statistics of treated students in 1999 to constructed treatment group students in 2003 and 2007. Although there is a slight improvement over the periods in line with the time trend, distribution of the socio-economic factors as well as other student characteristics across groups are balanced.

Figures 3.2 and 3.3 plot the kernel density distribution of the mathematics test scores for the treatment and control groups respectively. The figures imply that the students in the treatment group tend to score higher than the students in the control group in 1999. However, estimated scores of treatment group has dropped between 1997 and 2007 whereas estimated scores of control group has not varied considerably.

3.4.2 Threats to Identification

First of all, since the education reform was implemented nationwide simultaneously, a matching method is employed to combine the treated and untreated students in 1999 to the students with similar observable characteristics in 2003 and 2007. Fortunately, TIMMS and PISA samples provide student characteristics and family background variables to do a matching as successfully as possible to reduce any bias caused by the matching process. However, this approach has two possible threats to identification. First, as for any matching on observable methods, constructing treatment and control groups by using observable family and student characteristics variables would be subject to some measurement error. The measurement error problem would increase with unobservable factors and weak observable controls. Furthermore, when predicted probabilities of being in treatment and control groups are calculated in 2003 and 2007, the effect of observable measures on the probabilities are kept constant at 1999 level. This implies that any change in how observable student and family characteristics relates to the probability of being treated across years, is not taken into account by the model.

Second of all, the impact of the compulsory schooling law adds an extra complexity on the identification. In particular, as explained in the previous part the curriculum was not changed in the standard schools and teaching quality would not have expected to vary due to the regulation. However, since it was an objective of the regulation, the most disadvantaged students remained at school in later periods until the end of the eight grade which potentially might have affected the peer quality. Nevertheless, this is assumed to affect the both groups in the same way. In order to control for any policy effect other than the removal of early tacking e.g. change in peer quality, school resources, etc., we add a trend variable which captures the common 'other policy effect' for the treatment and control group.

3.5 Evaluation Method

The goal of this analysis is to estimate the direct impact of the removal of early academic tracking on the students' test scores who were in the treatment group. The difference-in-differences (DD) method is commonly used to estimate the policy effects in the literature (see e.g., Duflo (2001), Meghir and Palme (2005)).

The common identifying assumption in difference-in-differences method is that in the absence of the policy change the average outcomes would change at the same rate for the treatment and control groups. However, a time trend which exists in a treatment group might not exist in the control group. Meyer (1995) recognises this issue as omitted interactions and he suggests that omitted interactions present a threat to internal validity (causal interpretations).
When omitted interactions exist a difference-in-differences (DD) estimate with two periods gives a biased estimate of the treatment as the following :

$$[E(Y_{i,m}|d_i = 1) - E(Y_{i,m-k}|d_i = 1)] = \beta + \iota + \tau_1 + \tau_2, \tag{3.7}$$

and

$$[E(Y_{i,m}|d_i = 0) - E(Y_{i,m-k}|d_i = 0)] = \iota + \tau_2. \tag{3.8}$$

The difference-in-differences estimates:

$$[E(Y_{i,m}|d_i = 1) - E(Y_{i,m-k}|d_i = 1)] - [E(Y_{i,m}|d_i = 0) - E(Y_{i,m-k}|d_i = 0)] = \beta + \tau_1. \tag{3.9}$$

In Equations 3.7, 3.8 and 3.9, 'm' is the first period after the treatment (i.e. 2003), 'm-k' is the previous period before the treatment (i.e. 1999) and 'k' is the number of years in between (and in the subsequent equations, 'm+k' is the second period after treatment (i.e. 2007)). ι[17]is the 'other policy effect' which is common to both groups, τ_1[18] is the specific time trend for the treatment group and finally τ_2[19]is the time trend for the control group which is shared by both groups (see Figure 3.5).

Assuming that $E(\epsilon_{it}|d) = 0$, the DD method gives $\beta + \tau_1$ which is a biased estimate of β and the bias arises from the specific time trend of treatment group. In fact, given the observable and unobservable characteristics of the students in the high-ranked and standard state schools, I acknowledge the possible omitted interactions and do not assume the common time trend for both group of students.
Moreover, if I use Equation 3.15 with three periods including one pre-intervention (1999) and two post interventions (2003 and 2007), a difference-in-difference-in-differences(DDD) estimator yields an unbiased estimate of the treatment as the following :

$$[E(Y_{i,m+k}|d_i = 1) - E(Y_{i,m}|d_i = 1)] = \tau_1 + \tau_2, \tag{3.10}$$

and

$$[E(Y_{i,m}|d_i = 1) - E(Y_{i,m-k}|d_i = 1)] = \beta + \iota + \tau_1 + \tau_2, \tag{3.11}$$

and

$$[E(Y_{i,m+k}|d_i = 0) - E(Y_{i,m}|d_i = 0)] = \tau_2, \tag{3.12}$$

and

$$[E(Y_{i,m}|d_i = 0) - E(Y_{i,m-k}|d_i = 0)] = \iota + \tau_2. \tag{3.13}$$

The difference-in-difference-in-differences (DDD) estimates:

$$\begin{aligned} &\{[E(Y_{i,m+k}|d_i = 1) - E(Y_{i,m}|d_i = 1)] - [E(Y_{i,m}|d_i = 1) - E(Y_{i,m-k}|d_i = 1)]\} \\ &- \{[E(Y_{i,m+k}|d_i = 0) - E(Y_{i,m}|d_i = 0)] - [E(Y_{i,m}|d_i = 0) - E(Y_{i,m-k}|d_i = 0)]\} = -\beta, \end{aligned} \tag{3.14}$$

assuming that $E(\epsilon_{it}|d) = 0$, the DDD estimator gives an unbiased estimate of β (see also Figure 3.5).
The identifying assumption is that without a policy change the trends in control groups and treatment groups are different from each other yet equal across time periods i.e. between 'm+k and m', 'm and m-k' (see Figure 3.4).

[17]This represents α_4 in Equation 3.15.
[18]This represents $\alpha_{32}k$ in Equation 3.15.
[19]This represents $\alpha_{31}k$ in Equation 3.15.

In order to achieve that I motivate my econometric specification using an empirical policy evaluation model presented in Francesconi and van der Klaauw (2004). In Equation 3.15, the mathematics achievement scores of the students, Y_{it}[20] is predicted to be the following:

$$Y_i = \alpha_1 + \alpha_2 d_i + (\alpha_{31} + \alpha_{32} d_i)t + \alpha_4 I(t \geq m) + \beta d_i I(t \geq m) + \epsilon_{it} \tag{3.15}$$

where d_i is a binary variable which is 1 if individual i is in the treatment group and 0 otherwise and α_2 captures the group specific effect for the treated students. The parameter α_{31} represents a linear time trend which is shared by both treatment and control groups, α_{32} in turn shows the time trend which is specific to the treatment group.[21] $I(t \geq m)$ is a dummy variable which is 1 for the periods after treatment (i.e 2003, 2007) and zero otherwise and α_4 reflects any change in the average test scores that is common for both treated and not treated students due to the 'other policy effects'. The treatment effect is captured by β. It is assumed that treatment effect is constant over the periods after treatment to be able to identify the effect. The assumption indicates that treated students would suffer from the absence of the high-ranked schools equally over the periods due to difference in peer, teacher and school factors. We acknowledge that this would generate a bias in the results if students recover from the absence of the treatment between 2003 and 2007. Finally, ϵ_{it} is the residual and assumed to be an i.i.d.(independently and identically distributed) term.

My main evaluation strategy and the basic regression model (which implements the DDD estimator) are given by Equation 3.15. I also extend Equation 3.15 in the augmented regression models, in line with the education production function literature, by adding the set of observable variables $X \equiv (S, F, SCH)$ including student traits, S, family socio-economic status indicators, F, and school characteristic variables, SCH. The set of student traits, S, covers student age, attitudes towards mathematics and perceived importance of mathematics. The family socio-economic status indicators, F, are as follows: mother's highest education dummies, father's highest education dummies and dummies indicating possession at home namely number of books, a computer, a study desk, a dictionary and calculator. The school characteristics, SCH, include dummy variables which show the limitations of school resources and the dummy variables which indicate the community where the school is located.
The augmented regression models are represented by Equation 3.16 as the following:

$$Y_{it} = \alpha_1 + \alpha_2 d_i + (\alpha_{31} + \alpha_{32} d_i)t + \alpha_4 I(t \geq m) + \beta d_i I(t \geq m) + \delta \mathbf{X}'_{it} + u_{it}, \tag{3.16}$$

[20] i denotes the observations, N is the sample size, $i = 1, ..., N$

[21] Common trends between treatment and control groups are generally tested before the policy change. However, we do not have two periods before the treatment. Therefore, we distinguish between a shared and a specific time trend and control in the model.

where $\mathbf{X}'_{it}$ is the vector of the added controls and u_{it} is the residual and assumed to be an i.i.d. term.

3.6 The Effect of Early Tracking on Mathematics Test Scores

The DDD estimator can be interpreted as the causal effect of the removal of early tracking under the identification strategy presented in section 3.4.
The identifying assumption is, in the absence of the treatment, the increase in the mathematics test scores would have been different for the students who had little or no exposure to the removal of tracking (the control group); than for those students who were subjected to the removal of tracking (the treatment group) by having lost the opportunity to study in the high-ranked state schools. However it is assumed that these trends remain same for both groups of students across the time periods as illustrated in Figure 3.4.
Table 3.6 presents the mean mathematics test scores with standard errors for the treatment and control groups in 1999, 2003 and 2007. It shows that the mean mathematics test scores have risen only for control group from 1999 to 2007. This is consistent with the increasing trend in the test scores within the period for whole sample of students in Turkey (shown in Table 3.2). The differences on the third row, in turn, indicates that average mathematics score of the treatment group was higher than control group in 1999 but it has reversed in the following periods. Plugging the mean values into Equation 3.14, the DDD estimator is found to be 106.4 which is the negative treatment effect ($-\beta$). This result suggests that the students who were exposed to the removal of early tracking experienced 13%[22] decrease in mathematics test scores during the post intervention periods.

Table 3.7 presents the estimates for the basic and augmented regression models in four columns.[23] The regression model in column (I) implements the basic DDD estimator without any other controls added. This provides the coefficient estimates of Equation 3.15 where β shows the effect of removal of early tracking, by measuring the additional mathematics test score change for the students who were subjected to the treatment relative to the students who were not subjected it -when the group specific time trend cancels out-. α_2 denotes the estimated coefficient for the treatment dummy which measures the mean test score difference between the students in the treatment and control groups in 1999, α_{31} and α_{32} capture the time trends for the control and treatment

[22] 106.4 is divided by the maximum test mathematics score.
[23] The full regression estimates are presented in Table 3.12.

group respectively -although the former is the time trend shared by both groups, the latter is the group specific time trend for the students in treatment group only-, α_4 in turn measures any "other policy effect" which is shared by both groups and finally the constant term, α_1, shows the mean test scores for students in the control group in 1999.

Column (I) displays that when the possibility of the time varying covariates are not taken into account, the estimated effect of the removal of early tracking on the mathematics test scores is -106.4 points and this implies an additional 13% decrease in the mathematics test scores. The post policy effect is found to be positive but not different than zero. This suggests that there is not a policy effect in test scores shared by both group of students which is caused by the other policy implications in the post intervention periods. The coefficient of treated students specific time trend is positive and significant at the 5% significance level whereas the common time trend is not different than zero. This might provide evidence that my identifying assumption on the distinct time trends for both groups is in fact appropriate.

The regression models in columns (II) to (IV) augment the basic DDD regression model by controlling for the student, family socio-economic status and school characteristics variables. Column (II) introduces eight socio-economic status indicator variables, student age and sex to the basic regression model. The estimated effect of the removal of early tracking is still negative and significant. The magnitude of the treatment effect drops to 98.64 points and implies an additional 12% decrease on the mathematics test score of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods. This suggests that the effect of the removal of early tracking found in column (I) might be picking up part of the specific compositional change, over time, in socio-economic status of the students in the treatment group.

Column (III) adds the four student characteristics variables which proxy for the students' attitudes towards mathematics and the perceived importance of mathematics by them. The estimated effect of the removal of early tracking on the test scores is negative and significant at the 10% level. The magnitude of the treatment effect drops to -43.86 points and implies an additional 5% decrease on the mathematics test score of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods.

Finally, column (IV) introduces eleven school characteristics variables which indicate the community where the school is located and the limitations of various school resources. The inclusion of these variables moderately increases the effect of the removal of early tracking on the mathematics test scores. It is seen that there are 50.30 points of additional fall in the average test scores experienced by the students who were exposed to the treatment when all the observable student, family background and school characteristics are controlled for. However, the results of this model is very likely to suffer from the decrease in the number of observations.

3.6.1 Robustness Checks

In this subsection, three robustness checks are performed to test the sensitivity of the regression results- in particular the effect of the removal of early tracking- over the changes in the construction of treatment and control groups and various plausible values. In addition, the model is run using the science score of the students to examine whether there are any drops in science scores stem from the policy change.

First, sensitivity of the variables included in the matching model over the OLS results is tested. A probit model is fit controlling only for mother's education, father's education, attitudes towards mathematics and perceived importance of mathematics to the students. The model excludes the family wealth indicators from the original regresin equation. Table 3.9 presents the probit regression results. Table 3.8 displays estimates of the basic DDD and augmented regression models with new set of treated and untreated groups. In Column (I), the estimated effect of the removal of early tracking on the mathematics test scores is still negative and significant at the 5% level. It indicates an additional 9% decrease in the mathematics test scores which is slightly smaller than the original estimate. In Column (II) the estimated effect of the removal of early tracking is still negative and significant when student and family controls are also included to the model. The magnitude of the treatment effect implies an additional 9% decrease on the mathematics test score of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods. This estimate is also slightly smaller than the estimate in Table 3.7. In Column (III) the estimated effect of the removal of early tracking is still negative but not different than zero. This exercise shows that estimated effect of the removal of early tracking is not considerably sensitive to the change in the matching model.

Second, basic DDD and augmented regression models are run using science scores of the students to examine whether estimated effects of the removal of early tracking on mathematics scores could apply to science scores as well. Table 3.10 displays the regression results. In Column (I), estimated effect of the removal of early tracking on science test scores is negative and significant at the 5% level. It indicates an additional 9% decrease in the science test scores of treated students which is slightly smaller than the estimated effect on mathematics test scores. In Column (II) the estimated effect of the removal of early tracking on science scores is still negative and significant. The magnitude of the treatment effect implies an additional 8% decrease on the science test scores of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods. In Column (III) the estimated effect of the removal of early tracking on science scores is still negative and significant at the 10% level. This exercise indicate that there is a negative and significant effect of the removal of early tracking on science as well as mathematics test scores during the post-intervention periods.

Finally, Table 3.11 presents estimates for the basic DDD and augmented regression models using other three plausible mathematics scores. As described in section 3.3, there are five sets of plausible values identified for the overall mathematics score in both data sets. Each of these sets is designed to provide equally good population parameter estimates. Although, the estimates might be slightly different due to the error involving the imputation process, they should not vary substantially. Therefore, I replicate the results five times.[24]The results reveal that the effect of the removal of early tracking is negative for all models. The estimates only differ in the magnitude. The effect is estimated slightly lower by the second and third plausible values (PV3 and PV4 respectively). The significance of the effect over the different specifications does not show much difference from the results presented earlier.

3.7 Summary and Conclusion

The design of the education system plays a crucial role over the determination of cognitive development and achievement. By creating variations in peer group, teaching quality and academic curriculum across schools/classes, in particular, the choice between selective versus comprehensive schooling policies has important outcomes regarding efficiency and equality.

In this chapter, our aim is to assess the overall efficiency gains from tracking by measuring the effect of a policy change which 'removes the early tracking' for the 8th grade students in Turkey. The education regulation change which took place in 1997 provides the exogenous variation in the early tracking status of the students (who were eligible) to evaluate the causal impact of the early academic tracking on the achievement levels.

The evaluation methodology relies on the difference-in-difference-in-differences (DDD) estimates which can be argued to be more appropriate in this context than the conventional difference-in-differences (DD) method. The common identifying assumption in DD method is the common time trend for treatment and control groups in the absence

[24]The results with the fifth plausible values are not presented here due to the lack of space but can be provided upon request.

of the policy change. However, a time trend which exists in a treatment group might not exist in the control group. My identifying assumption hence is, in the absence of the regulation change, the increase in the mathematics test scores would have been different for the students who had little or no exposure to the removal of tracking (the control group); than for those students who were subjected to the removal of tracking (the treatment group). However it is assumed that these trends remain same for both groups of students across the time periods observed.

IThe results show that estimated effect of the removal of early tracking is negative and significant, even when potential variation in group specific composition changes, particularly in the student characteristics and family socio-economic background are controlled for. This alone suggests that there was a significant decrease in the mathematics test score of the students who were exposed to the removal of early tracking and lost the opportunity to go to high-ranked schools during post-intervention periods. Nevertheless, caution still should be taken that some bias may spring particularly from three sources. Firstly, as for any matching on observable methods, constructing treatment and control groups by using observable family and student characteristics variables would be subject to some measurement error. Secondly, as acknowledged before, substituting PISA 2003 for TIMMS 2003 is still an uncertain projection. Thirdly, the increasing compulsory schooling law adds more complication to the analysis and despite the 'other policy effect' control in the regression model, there might remain some other effects. Finally, there might be some observable factors which can not be controlled for with the available data such as the effect of private tutoring on the achievement levels.

The results presented complement the earlier two important findings in the literature: Hanushek and Wobmann (2006) apply the DD method and compare the test score changes in a tracked grade to an untracked grade between countries which implement ability tracking policies and do not implement those policies. Their findings suggest that early tracking does not significantly contribute to the mathematics test score of the students. On the other hand, Akyol and Krishna (2014) provide evidence for the efficiency of the high-ranked secondary schools in Turkey. Estimating the value-added of the selective secondary schools on the students' performance on the university entrance exam, they find that these schools do not significantly contribute to the students' academic performance. Since these two studies apply different methodologies and use a different definition of tracking, the results presented here only complement them.

Although we could measure the overall efficiency gains from tracking from the available data, we were not able to disentangle the sources in terms of peer quality, teaching quality or curriculum. Therefore, an interesting question that can not be addressed here is to what extent these factors individually contribute to the estimated effect of tracking.

3.8 Tables and Figures

3.8.1 Figures

FIGURE 3.1: Early Tracking Policy in Turkey

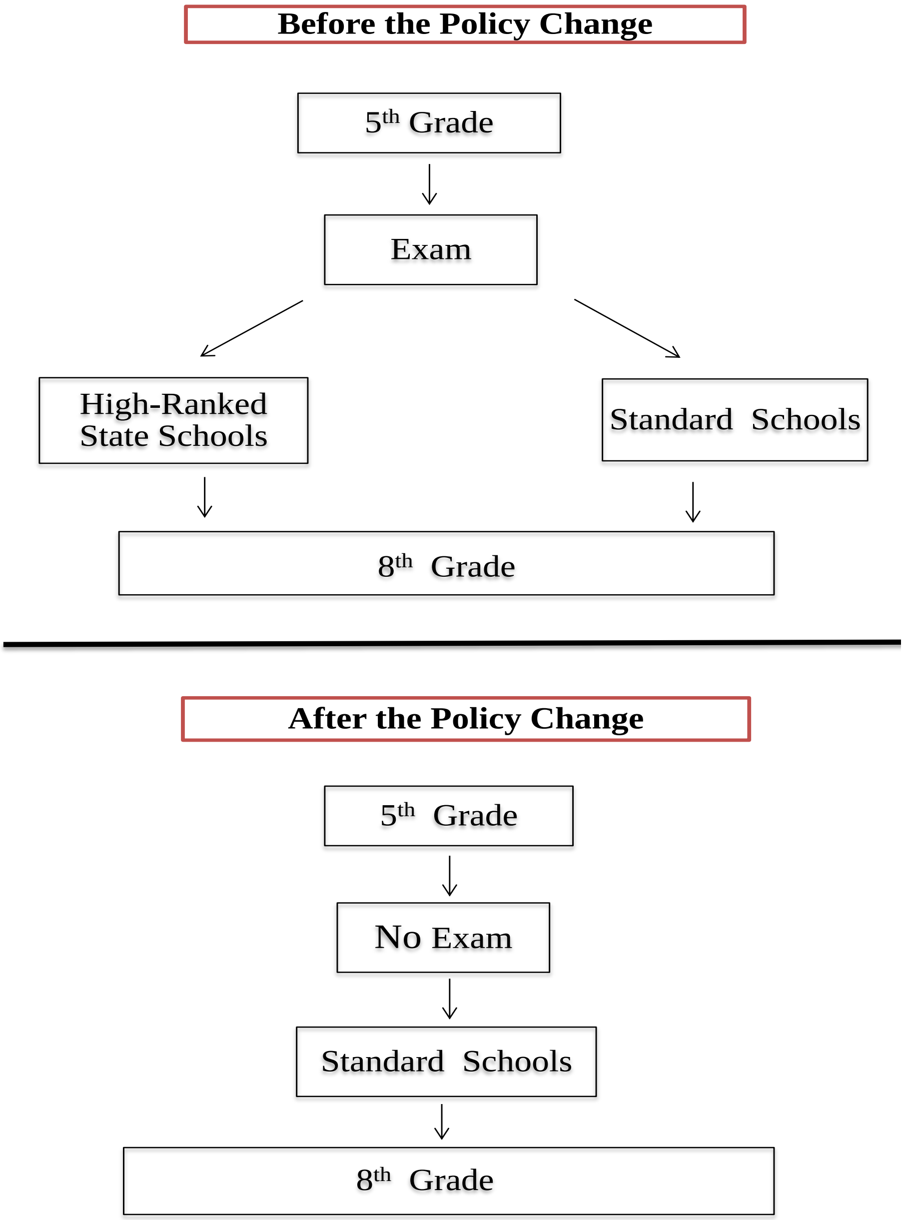


Figure 3.2: Kernel Density Estimation of Mathematics Test Scores for Treatment Group

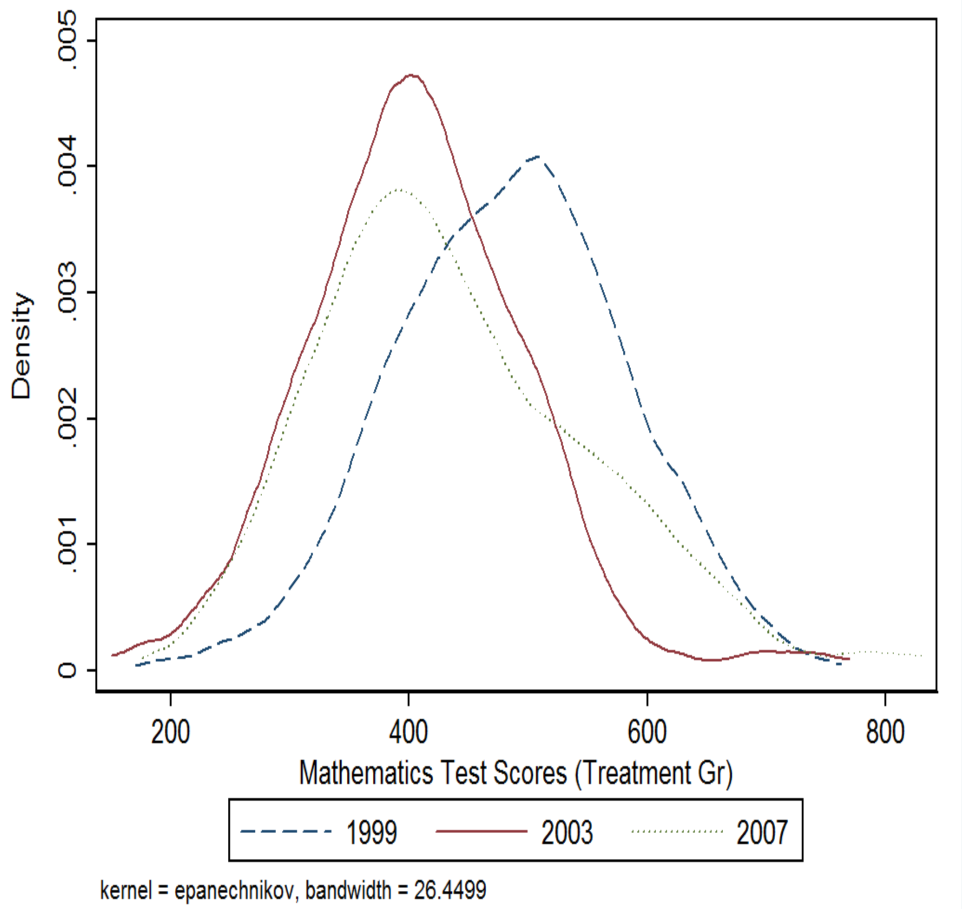


Figure 3.3: Kernel Density Estimation of Mathematics Test Scores for Control Group

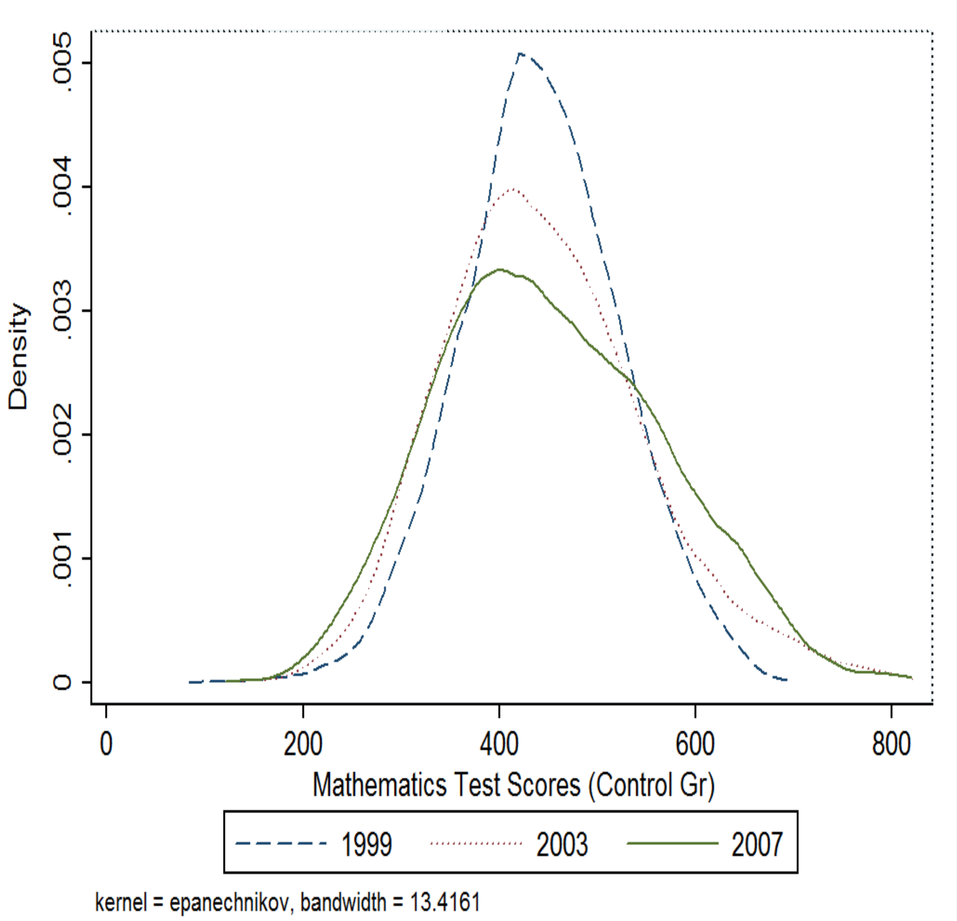


Figure 3.4: Trends in the Average Outcome Without a Policy Change

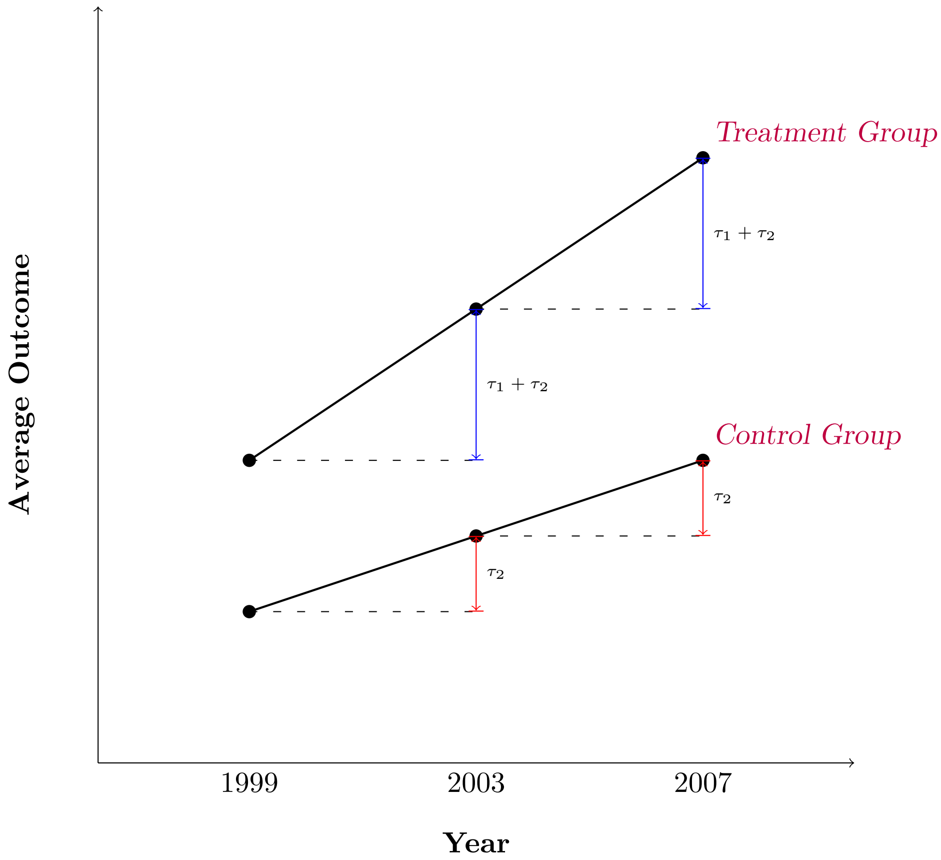
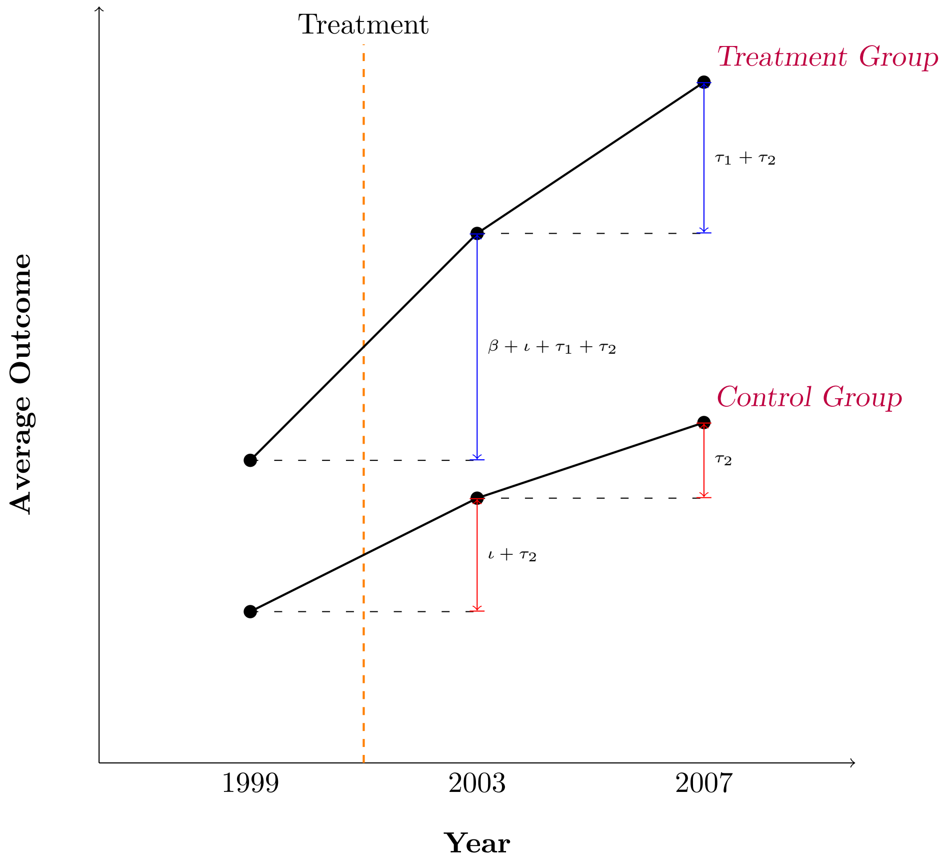


FIGURE 3.5: Causal Effects in the DDD Model



3.8.2 Tables

Table 3.1: TIMMS and PISA Variables

Variables	Description
Student Characteristics	
Maths score	The first overall mathematics plausible value
Age	Age when completed the assessment
Socio-economic Status Indicators:	
Mother's highest education	How far the mother went at school
Father's highest education	How far the father went at school
Number of books	Number of books have at home
Computer at home	Whether computer is possessed at home
Internet at home	Whether internet is possessed at home
Desk at home	Whether desk is possessed at home
Dictionary at home	Whether dictionary is possessed at home
Calculator at home	Whether calculator is possessed at home
Attitudes towards maths	Various questions on attitudes towards maths
Perceived importance of maths	Various questions on perceived importance of maths
School Characteristics	
Community	How many people live in the area where the school is located
Limitations in school resources	Index of inadequacy of school resources

Notes: Appendix B.2 provides detailed information on these variables.

Table 3.2: Descriptive Statistics

Panel A: Number of Observations	1999	2003	2007
Schools	479	159	150
Students	7841	4855	4498
Boys	4540	2765	2405
Girls	3301	2090	2093
Panel B: Student Characteristics			
Mean Maths Score	429	423	432
	(4.3)	(6.7)	(4.8)
Mean Age	14.2	15.9	14.03
	(0.0)	(0.0)	(0.0)
Socio-economic Indicators:			
Mother's highest educ (%)			
Below secondary education	88.2(0.4)	76.7(0.7)	85.3(0.5)
Secondary education	8.4(0.3)	14.03(0.6)	10.6(0.4)
Tertiary education	3.3(0.2)	9.2 (0.3)	4.1(0.1)
Father's highest educ (%)			
Below secondary education	71.7(0.6)	58.8(0.8)	71.3(0.7)
Secondary education	15.6(0.5)	22.7(0.7)	18.8(0.6)
Tertiary education	12.5(0.3)	18.4(0.3)	9.8 (0.3)
Resources at home:			
Number of books (%)			
0-25	58.2(0.7)	51.6(0.7)	63.5(0.8)
26-100	27.6(0.5)	30.1(0.5)	22.7(0.6)
More than 100	15(0.3)	18.1(0.4)	13.6(0.3)
computer at home (Yes, %)	9.7(0.3)	23.2(0.6)	42.6(0.7)
her own study desk at home (Yes, %)	68.9(0.6)	80.9 (0.7)	64.5(0.8)
Dictionary (Yes, %)	89.2(0.4)	92(0.4)	93.9(0.4)
Calculator (Yes, %)	82.9(0.5)	75.2(0.7)	84.3(0.6)
Attitudes towards Mathematics (agree, %)			
I do well in mathematics	45.6(0.7)	38.6(0.8)	52.1(0.8)
I enjoy learning mathematics	46.6(0.7)	36.6(0.8)	24.5(0.7)
Perceived Importance of Maths (agree, %)			
I need mathematics to get preferred school	43.8(0.6)	48.9(0.8)	30.1(0.7)
I need mathematics to get a job	37.7(0.6)	45.3(0.8)	21.8(0.7)
Panel C: School Characteristics			
School's community (%)			
3000 People or Fewer	5.9(0.3)	0.5(0.1)	13.2(0.4)
3001 to 15000 People	15.3(0.4)	10.9(0.4)	11.8 (0.4)
More than 15000	78.8(0.4)	88.5(0.4)	74.9(0.6)
Limitations in school resources (A lot, %)			
Instructional materials	39.8(0.5)	51.4(0.7)	37.9(0.7)
Budget for supplies	19.7(0.4)	42.05(0.7)	29.1(0.6)
School buildings and grounds	48.8(0.6)	48.1(0.7)	33.9(0.7)
Heating and lighting system	40.4(0.6)	49.9(0.7)	26.2 (0.6)
Instructional space	42.9(0.6)	45.2(0.7)	30.2 (0.7)
Equipment for handicapped pupils	30.6(0.5)	22.2(0.5)	14.4(0.5)
Computers for maths instruction	33.2(0.5)	44.6(0.7)	29.5(0.6)
Software for maths instruction	30.7(0.5)	45.4(0.7)	36.7(0.7)
Calculators for maths instruction	11.4(6.3)	10.5(0.4)	17.2(0.5)
Library tools for maths instruction	35.02(0.5)	49.1(0.7)	20.8 (0.6)
A-V resources for maths instruction	41.4(0.5)	65(0.6)	33.7(0.6)

Notes: The descriptive statistics are weighted using the final student weights provided by TIMMS and PISA. The standard errors are in parenthesis.

TABLE 3.3: Descriptive Statistics for the Treatment and the Control Groups

	1999		2003		2007	
	Teatment	**Control**	**Treatment**	**Control**	**Treatment**	**Control**
Panel A: Number of Observations						
Students	358	4112	211	2938	196	2745
Boys	215	2305	135	1628	112	1446
Girls	143	1806	76	1310	84	1299
Panel B: Student Characteristics						
Age	14.2(0.1)	14.2(0.0)	15.9(0.0)	15.9(0.0)	14.1(0.1)	14.0(0.0)
Socio-economic Indicators:						
Mother's highest educ (%)						
Below secondary education	82.6(5.1)	88.4(1.5)	63.3(4.7)	69.4(2.6)	78.2(4.4)	81.7(2.0)
Secondary education	11.7(3.8)	7.2(0.9)	22.1(3.5)	17.8(1.3)	12.7(2.9)	13.0(1.4)
Tertiary education	5.7(1.9)	4.4(0.5)	14.6(2.6)	12.8(1.7)	9.1(2.1)	5.3(0.8)
Father's highest educ (%)						
Below secondary education	61.5(7.5)	68.5(1.8)	43.3(4.6)	50.1(2.5)	56.7(5.0)	66.7(2.4)
Secondary education	13.7(2.9)	14.9(0.8)	29.4(4.0)	22.9(1.1)	14.8(2.8)	20.2(1.3)
Tertiary education	24.8(4.5)	16.6	27.3(3.8)	27.0(2.3)	28.5(3.8)	13.1(1.2)
Resources at home (%):						
Number of books						
0-25	48.9(5.1)	50.0(1.2)	51.0(3.5)	49.1(1.6)	57.3(4.3)	62.5(4.4)
26-100	30.9(3.4)	32.2(1.1)	24.9(2.9)	25.3(1.3)	13.7(3.2)	19.4(2.3)
More than 100	20.2(3.1)	17.8(1.1)	24.1(2.8)	26.4(1.6)	30.0(3.8)	18.1(2.3)
computer at home (Yes)	8.6(2.1)	8.4(0.8)	31.6(4.4)	28.6(2.6)	53.2(4.5)	46.9(2.1)

TABLE 3.4: Descriptive Statistics for the Treatment and the Control Groups

	1999		2003		2007	
	Teatment	**Control**	**Treatment**	**Control**	**Treatment**	**Control**
her own study desk at home (Yes)	70.7(2.6)	73.4(1.5)	80.3(3.6)	82.3(1.5)	60.8(1.5)	67.6(2.0)
Dictionary (Yes)	89.3(2.5)	91.3(0.8)	91.0(2.3)	93.5(0.8)	92.1(2.3)	95.5(0.5)
Calculator (Yes)	82.7(2.9)	86.8(0.8)	74.2(3.4)	72.9(1.9)	85.9(3.2)	82.1(1.4)
Attitudes towards Maths (agree, %)						
I do well in mathematics	45.5(1.8)	46.7(1.1)	13.2(2.6)	38.3(1.3)	44.4(3.6)	50.8(1.1)
I enjoy learning mathematics	51.8(4.1)	51.5(1.0)	5.6(1.7)	34.5(1.1)	17.9(2.7)	24.4(1.0)
Perceived Importance of Maths		53.9(0.9)	1.3(0.9)	37.8(1.2)	1.6(0.9)	13.2(0.7)
I need mathematics to get preferred sch.	60.4(5.1)	42.6(0.9)	10.9(2.2)	38.7(1.2)	22.2(3.4)	15.7(0.9)
I need mathematics to get a job	38.9(4.9)					
Panel C: School Characteristics						
School's community (%)						
3000 People or Fewer	-	4.9(0.3)	-	0.2(0.0)	10.2(2.1)	10.6(0.6)
3001 to 15000 People	10.3(1.6)	13.4(0.5)	9.0(1.9)	7(0.4)	6.1(1.7)	7.8(0.5)
More than 15000	89.7(1.6)	81.7(0.6)	91.0(1.9)	92.8(4.7)	83.7(2.6)	81.6(0.7)
Limitations in school resources (A lot, %)						
Instructional materials	32.7(2.4)	43.6(0.7)	50.2(3.4)	51.9(0.9)	42.8(3.5)	36.6(0.9)
Budget for supplies	64.0(1.3)	18.6(0.6)	43.8(3.4)	41.3(0.9)	30.1(3.3)	27.3(0.8)
School buildings and grounds	39.6(2.6)	50.7(0.8)	40.7(3.3)	44.6(0.9)	34.5(3.4)	35.1(0.9)
Heating and lighting system	51.1(2.6)	44.4(0.7)	46.7(3.4)	46.3(0.9)	27(3.2)	25.8(0.8)
Instructional space	39.6(2.6)	44.9(0.7)	42.6(3.4)	42.7(0.9)	34.9(3.4)	31.8(0.9)
Equipment for handicapped pupils	41.8(2.6)	29.6(0.7)	21.0(2.8)	20.9(0.7)	14.9(2.5)	17(0.7)
Computers for maths instruction	16.7(1.9)	31.6(0.7)	42.6(3.4)	44.2(0.9)	29.6(3.3)	29.5(0.8)
Software for maths instruction	18.4(2.1)	28.8(0.7)	39.8(3.3)	43.1(0.9)	31.1(3.3)	31.5(0.8)
Calculators for maths instruction	16.7(1.9)	10.6(0.4)	9.5(2.0)	85.9(0.5)	18.4(2.8)	15.9(0.6)
Library tools for maths instruction	41.8(2.6)	32.5(0.7)	44.1(3.4)	42.5(0.9)	22.4(2.9)	20.4(0.7)
A-V resources for maths instruction	43.2(2.6)	40.5(0.7)	62.5(3.3)	60.9(0.9)	35.7(3.4)	29.2(0.8)

Notes: Standard errors are in parenthesis.

Table 3.5: Probit Results

Regressors	(I)	(II)
11-25 books	0.0160(0.0980)	-0.00274(0.0936)
26-100 books	0.0829(0.0832)	-0.0522(0.0996)
101-200 books	0.314**(0.145)	0.118(0.121)
More than 200 books	0.205(0.195)	0.0255(0.136)
Calculator	0.0363(0.105)	-0.0453(0.0898)
Computer	-0.120(0.109)	0.0158(0.109)
Desk	0.0292(0.0933)	-0.0130(0.0728)
Dictionary	-0.152(0.174)	0.0162(0.111)
Mother Secondary School Educ.	-0.125(0.102)	0.0246(0.115)
Mother First Stage Tertiary Educ.	-0.0452(0.318)	-0.0228(0.255)
Mother Tertiary Educ.	0.00216(0.214)	-0.00570(0.165)
Father Secondary School Educ.	-0.00695(0.0754)	0.0115(0.0915)
Father First Stage Tertiary Educ.	0.302**(0.144)	0.153(0.137)
Father Tertiary Educ.	0.450***(0.135)	0.289***(0.100)
Do well in mathematics1	0.0374(0.169)	-0.0422 (0.198)
Do well in mathematics2	0.0522(0.155)	-0.0606(0.200)
Do well in mathematics3	0.165(0.152)	-0.0756(0.212)
Enjoy learning mathematics1	0.406**(0.203)	-0.275(0.320)
Enjoy learning mathematics2	0.439**(0.189)	-0.253(0.318)
Enjoy learning mathematics3	0.374**(0.190)	-0.246(0.322)
Need maths to get a job1	0.948** (0.406)	-0.584(0.765)
Need maths to get a job2	0.886**(0.379)	-0.610(0.762)
Need maths to get a job3	0.760**(0.369)	-0.509(0.762)
Need maths to get prefer. school1	-0.240(0.245)	-0.108(0.245)
Need maths to get prefer. school2	-0.259 (0.181)	-0.128(0.215)
Need maths to get prefer. school3	-0.242(0.191)	-0.135(0.214)
Constant	-2.761***(0.418)	-0.544(0.823)
Observations	5,764	4,390

Notes: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: DDD Estimator for the Removal of Early Tracking

	1999	**2003**	**2007**
Treatment Group	**485.10**	**407.19**	**439.32**
	(5.04)	(6.35)	(8.22)
Control Group	**424.05**	**445.60**	**452.77**
	(1.27)	(1.92)	(2.19)
Differences	43.05	-38.41	-13.4
Diff-in-Diff-in-Diff	**106.47**		

Notes: TIMMS and PISA samples. Standard errors are in parenthesis.

Table 3.7: The Effect of Early Tracking on Mathematics Test Scores

	(I)	(II)	(III)	(IV)
Removal of Early Tracking (β)	-106.4***	-98.64***	-43.86*	-50.30**
	(25.41)	(19.88)	(23.31)	(23.86)
Treatment (α_2)	43.04**	44.31***	48.95***	49.64***
	(19.70)	(14.73)	(15.47)	(17.30)
Post Policy (α_4)	-3.644	13.75	36.79***	44.91***
	(16.16)	(11.97)	(12.17)	(13.91)
Treated Students Specific Time Trend (α_{32})	24.93**	14.75*	-2.848	-0.0809
	(11.04)	(8.346)	(8.749)	(8.437)
Common Time Trend (α_{31})	7.192	-7.736	-19.89***	-26.72***
	(9.918)	(7.161)	(7.271)	(8.564)
Family Background Controls	No	Yes	Yes	Yes
Student Characteristics Controls	No	No	Yes	Yes
School Characteristics Controls	No	No	No	Yes
Constant	442.1***	475.6***	382.2***	439.6***
	(3.295)	(24.83)	(27.39)	(29.96)
Observations	10,560	10,512	10,263	9,630
R-squared	0.010	0.237	0.316	0.330

Notes: The dependent variable is the mathematics test scores from TIMMS and PISA. Clustered robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Robustness Checks 1

	(I)	(II)	(III)
Removal of Early Tracking (β)	-74.69***	-65.85***	-11.23
	(25.89)	(20.38)	(27.40)
Treatment (α_2)	44.08**	42.97***	48.92***
	(19.69)	(14.77)	(15.53)
Post Policy (α_4)	-7.315	5.841	41.50***
	(16.13)	(11.94)	(12.09)
Treated Students Specific Time Trend (α_{32})	-7.768	-8.493	-14.82
	(10.23)	(8.748)	(9.262)
Common Time Trend (α_{31})	10.16	-3.363	-21.09***
	(9.856)	(7.141)	(7.240)
Family Background Controls	No	Yes	Yes
Student Characteristics Controls	No	No	Yes
Constant	441.0***	474.9***	367.7***
	(3.239)	(24.27)	(28.98)
Observations	10,896	10,599	10,332
R-squared	0.014	0.234	0.316

Notes: The dependent variable is the mathematics test scores from TIMMS and PISA. Clustered robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.9: Robust Probit Results

Regressors	(a)	(b)
Mother Secondary School Educ.	-0.116	0.0820
	(0.0991)	(0.117)
Mother First Stage Tertiary Educ.	-0.0379	-0.0425
	(0.313)	(0.345)
Mother Tertiary Educ.	-0.00126	0.0313
	(0.215)	(0.215)
Father Secondary School Educ.	0.00872	0.0401
	(0.0791)	(0.0856)
Father First Stage Tertiary Educ.	0.355**	0.123
	(0.148)	(0.136)
Father Tertiary Educ.	0.517***	0.261*
	(0.142)	(0.140)
Do well in mathematics1	0.0464	-0.0993
	(0.176)	(0.190)
Do well in mathematics2	0.0408	-0.101
	(0.160)	(0.179)
Do well in mathematics3	0.157	-0.229
	(0.158)	(0.179)
Enjoy learning mathematics1	0.413**	-0.316
	(0.192)	(0.253)
Enjoy learning mathematics2	0.453**	-0.401*
	(0.189)	(0.242)
Enjoy learning mathematics3	0.405**	-0.242
	(0.194)	(0.255)
Need maths to get a job1	0.905**	-1.400
	(0.412)	(0.957)
Need maths to get a job2	0.846**	-1.428
	(0.386)	(0.941)
Need maths to get a job3	0.713*	-1.256
	(0.378)	(0.929)
Need maths to get prefer. school1	-0.229	-0.104
	(0.248)	(0.266)
Need maths to get prefer. school2	-0.251	-0.127
	(0.183)	(0.200)
Need maths to get prefer. school3	-0.219	-0.177
	(0.193)	(0.210)
Constant	-2.785***	0.386
	(0.392)	(0.967)
Observations	5,881	4,481

Notes: Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.10: Robustness Checks 2

	(I)	(II)	(III)	(IV)
Removal of Early Tracking (β)	-76.28***	-66.48***	-39.70*	-45.07**
	(24.70)	(19.18)	(22.52)	(22.31)
Treatment (α_2)	29.99	30.45**	34.57**	32.73**
	(19.53)	(14.94)	(15.12)	(15.32)
Post Policy (α_4)	-4.613	-12.42	4.984	14.99
	(14.26)	(10.52)	(10.78)	(12.34)
Treated Students Specific Time Trend (α_{32})	16.34	5.570	-4.891	-2.477
	(10.08)	(7.567)	(8.256)	(7.994)
Common Time Trend (α_{31})	17.99**	16.55***	7.639	0.958
	(8.430)	(6.093)	(6.279)	(7.378)
Family Background Controls	No	Yes	Yes	Yes
Student Characteristics Controls	No	No	Yes	Yes
School Characteristics Controls	No	No	No	Yes
Constant	439.2***	386.8***	341.1***	390.1***
	(2.988)	(21.06)	(25.43)	(27.95)
Observations	10,560	10,512	10,263	9,630
R-squared	0.022	0.236	0.274	0.287

Notes: The dependent variable is the science test scores from TIMMS and PISA. Clustered robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.11: Robustness Checks 3

	(1) PV 2	(2) PV 2	(3) PV 2	(1) PV 3	(2) PV 3	(3) PV 3	(1) PV 4	(2) PV 4	(3) PV 4
Removal of Early Tracking	-106.3***	-98.23***	-39.93*	-101.2***	-92.18***	-35.38	-97.12***	-88.58***	-23.44
	(25.98)	(20.22)	(23.50)	(26.39)	(20.20)	(23.93)	(26.01)	(20.05)	(23.04)
Treatment	49.37**	51.25***	56.37***	43.99**	44.45***	49.65***	45.64**	46.81***	50.69***
	(20.19)	(14.84)	(15.55)	(20.95)	(15.48)	(16.51)	(20.04)	(14.52)	(15.22)
Post Policy	-2.233	9.449	33.26***	-4.660	8.698	31.22***	-1.475	8.764	32.16***
	(15.98)	(11.78)	(12.10)	(16.11)	(11.49)	(11.76)	(16.08)	(11.74)	(12.03)
Treated Students Time Trend	22.66*	11.73	-6.929	22.74**	11.83	-7.235	16.45	5.653	-13.19
	(11.84)	(8.989)	(9.288)	(11.17)	(8.304)	(8.684)	(11.80)	(8.800)	(9.111)
Common Time Trend	6.888	-4.800	-17.54**	6.391	-6.353	-17.91**	7.210	-4.474	-17.31**
	(9.877)	(7.072)	(7.219)	(9.929)	(6.863)	(6.970)	(9.866)	(7.016)	(7.153)
Family Background Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Student Characteristics Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Constant	439.5***	450.3***	355.2***	443.0***	470.1***	378.0***	439.1***	446.0***	348.2***
	(3.541)	(25.30)	(28.64)	(3.490)	(23.58)	(27.39)	(3.628)	(24.75)	(28.37)
Observations	10,560	10,512	10,263	10,560	10,512	10,263	10,560	10,512	10,263
R-squared	0.011	0.242	0.320	0.009	0.250	0.321	0.011	0.241	0.317

Notes: The dependent variable is the mathematics test scores from TIMMS and PISA. Clustered robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.12: Full Regression Results

	(I)	(II)	(III)	(IV)
Removal of Early Tracking (β)	-106.4***	-98.64***	-43.86*	-50.30**
	(25.41)	(19.88)	(23.31)	(23.86)
Treatment (α_2)	43.04**	44.31***	48.95***	49.64***
	(19.70)	(14.73)	(15.47)	(17.30)
Post Policy (α_4)	-3.644	13.75	36.79***	44.91***
	(16.16)	(11.97)	(12.17)	(13.91)
Treated Students Specific Time Trend (α_{32})	24.93**	14.75*	-2.848	-0.0809
	(11.04)	(8.346)	(8.749)	(8.437)
Common Time Trend (α_{31})	7.192	-7.736	-19.89***	-26.72***
	(9.918)	(7.161)	(7.271)	(8.564)
Age		-10.45***	-8.778***	-9.164***
		(1.677)	(1.609)	(1.641)
Sex		15.38***	12.33***	12.03***
		(2.318)	(2.204)	(2.094)
Mother Secondary School Educ.		24.26***	20.91***	18.69***
		(3.527)	(3.352)	(3.166)
Mother First Stage Tertiary Educ		8.639	5.109	5.008
		(7.300)	(6.658)	(6.380)
Mother Tertiary Educ.		61.14***	56.86***	42.74***
		(10.61)	(10.13)	(8.206)
Father Secondary School Educ.		15.91***	14.08***	13.56***
		(2.756)	(2.645)	(2.634)
Father First Stage Tertiary Educ.		9.711**	7.928*	7.470*
		(4.565)	(4.429)	(4.283)
Father Tertiary Educ.		45.15***	37.78***	34.77***
		(3.886)	(3.591)	(3.577)
11-25 books		17.45***	13.54***	12.63***
		(2.690)	(2.533)	(2.549)
26-100 books		31.07***	25.64***	22.84***
		(3.183)	(3.072)	(3.044)
101-200 books		35.87***	28.07***	24.36***
		(3.757)	(3.634)	(3.686)
more than 200 books		43.26***	35.86***	30.57***
		(5.425)	(5.263)	(5.122)
Desk		18.42***	15.35***	15.65***
		(2.521)	(2.346)	(2.285)
Computer		23.75***	20.29***	18.98***
		(3.157)	(3.060)	(2.854)
Calculator		11.51***	11.95***	11.15***
		(2.831)	(2.797)	(2.790)
Dictionary		33.46***	29.57***	28.94***
		(3.696)	(3.620)	(3.657)

Table 3.12 Continued

	(I)	**(II)**	**(III)**	**(IV)**
	(1)	(2)	(3)	(4)
outskirts of a town/city			-3.799	2.672
			(8.852)	(8.985)
a town/city			16.55**	16.88**
			(7.775)	(8.175)
do well in mathematics1			14.84***	13.80***
			(3.717)	(3.651)
do well in mathematics2			32.22***	31.88***
			(3.771)	(3.645)
do well in mathematics3			71.15***	71.38***
			(4.810)	(4.661)
enjoy learning mathematics1			-0.456	0.106
			(4.550)	(4.366)
enjoy learning mathematics2			16.42***	15.92***
			(4.432)	(4.251)
enjoy learning mathematics3			25.77***	25.42***
			(4.748)	(4.601)
need maths to get a job1			19.31*	13.96
			(9.957)	(9.412)
need maths to get a job2			7.707	3.981
			(10.02)	(9.486)
need maths to get a job3			-1.388	-4.775
			(9.757)	(9.215)
need maths to get prefer. school1			-3.442	-1.586
			(5.843)	(5.534)
need maths to get prefer. school2			13.21**	10.91**
			(5.684)	(5.248)
need maths to get prefer. school3			19.10***	17.79***
			(5.854)	(5.444)
Instruction Materials 1				-12.85
				(10.75)
Instruction Materials 2				-23.13**
				(10.70)
Instruction Materials 3				-27.56**
				(10.74)
budget1				-19.64***
				(7.115)
budget2				-9.495
				(7.558)
budget3				-3.821
				(8.419)

Table 3.12 Continued

	(I)	(II)	(III)	(IV)
buildings and grounds1				-11.44
				(10.02)
buildings and grounds2				-5.484
				(10.81)
buildings and grounds3				-0.521
				(10.96)
heating and lighting1				5.303
				(7.998)
heating and lighting2				0.208
				(7.935)
heating and lighting3				4.584
				(7.743)
instructional space1				2.290
				(8.805)
instructional space2				-5.374
				(9.570)
instructional space3				-9.495
				(10.16)
equipment for handicapped pupils1				2.493
				(5.895)
equipment for handicapped pupils2				5.149
				(6.167)
equipment for handicapped pupils3				8.695
				(7.046)
computers1				12.19
				(9.914)
computers2				-3.690
				(9.867)
computers3				-5.285
				(11.00)
software1				3.753
				(9.834)
software2				9.884
				(10.28)
software3				11.14
				(10.91)
calculators1				-9.337*
				(5.602)
calculators2				-9.896
				(6.789)
calculators3				-20.00**
				(8.680)
library tools1				-5.050
				(9.546)
library tools2				-0.927
				(8.952)
library tools3				-1.459
				(10.09)

Table 3.12 Continued

	(I)	(II)	(III)	(IV)
A-V resources1				-6.008
				(10.39)
A-V resources2				-3.799
				(9.705)
A-V resources3				-9.709
				(9.657)
Constant	442.1***	475.6***	382.2***	439.6***
	(3.295)	(24.83)	(27.39)	(29.96)
Observations	10,560	10,512	10,263	9,630
R-squared	0.010	0.237	0.316	0.330

Notes: The dependent variable is the mathematics test scores from TIMMS and PISA. Clustered robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Chapter 4

How Do Returns to Skills Vary Across Occupations in the UK? A Task-Based Approach

4.1 Introduction

The human capital investment model developed by Becker (1964) treats human capital as either general or firm specific. The former is useful across all firms, whereas the latter is only useful at the firm which was acquired. Over time, because this view has not been found to be very realistic and has been challenged by many (e.g. Heckman and Sedlacek (1985), Lazear (2009)), the literature has tended to favour models with partially transferable heterogeneous human capital (labour market skills).[1]

The empirical works on heterogeneous human capital have investigated aspects such as firm specificity (e.g. Altonji and Shakotko (1987)), occupation specificity (e.g. Kambourov and Manovskii (2009), Sullivan (2010)), industry specificity (e.g.Parent (1995)), and, more recently, task specificity of human capital. Although the papers which employ the first three approaches provide some insight into the modelling of the accumulation of labour market skills and wage losses after job displacement; the human capital measures used (e.g. occupation tenure) capture the similarities of the tasks that workers perform which are largely tied to specific occupations and industries. Therefore, with the recent increase in the data availability of task measures which workers perform in their jobs, a

[1]See Sanders and Taber (2012) for a review of empirical heterogeneous human capital literature.

task-based approach to modelling labour market skills has become a promising area of research particularly for analysing the transferability of labour market skills and wages.[2]

This chapter aims to explore the task-based channels of male workers' wage growth and human capital accumulation in the UK labour market. For this purpose, we test one of the implications of the heterogeneous human capital model by Yamaguchi (2012) by asking the question: To what extent are there varying returns to cognitive and motor skills across occupations? In this framework, each occupation is defined as a vector of cognitive[3] and motor[4] task complexity where cognitive (motor) task complexity indices measures how intensely cognitive (motor) tasks are performed. The model's key prediction is that, when a worker is employed in an occupation characterised by complex cognitive (motor) tasks, the more the worker uses his cognitive (motor) skills, the more task-specific cognitive (motor) skills acquired, thereby increasing productivity. This process, in turn, results in heterogeneous cognitive (motor) skills and wage profiles over time.

Using this framework as an intuition, we conduct an exploratory empirical analysis employing data from the Skills Survey of Britain (SS) and the British Household Panel Survey (BHPS). My empirical strategy relies on treating education, general labour market experience and accumulated task-specific labour market skills as indicators for the workers' level of cognitive and motor skills given that they are not measured directly. Using self-reported cognitive and motor task information from the SS, we first calculate the cognitive and motor task complexity vector of occupations at the 3-digit level. We then merge this information with the same 3-digit occupation variable in the BHPS. And then finally, by employing a fixed effects estimator, we quantify heterogeneous rewards to education, experience and accumulated cognitive and motor skills across different levels of task complexity.

The results suggest that there are heterogeneous rewards to cognitive skills across occupations (with varying degrees of cognitive task complexities) for male workers in the UK. For instance, if a highly educated worker moves from an occupation with one standard deviation below the mean cognitive task complexity to another occupation with one standard deviation above the mean task complexity, his expected wage increases up to 18% when all other characteristics are held constant at their means. Moreover, the rate

[2]Task-based approach with data is widely employed for modelling the relationship between technological change (computerisation) and employment and wage inequality trends (e.g. Autor et al. (2003), Goos and Manning (2007) and Acemoglu and Autor (2010); see Autor (2013) for a review of this literature).

[3]Cognitive skills imply an ability to process thoughts and examples of cognitive tasks, including analysing complex problems in-depth and instructing people.

[4]Motor skills imply an ability to do intentional movements with muscles; examples of motor tasks include operating tools and using one's hands/fingers.

of the wage increase of a worker with just one standard deviation above the mean accumulated task-specific cognitive skills is up to 16% when he moves from an occupation with simple cognitive tasks to complex cognitive tasks. However, the results also show that when a low cognitive skilled worker switches from an occupation characterised with simple cognitive tasks to complex cognitive tasks, his wages drops. On the other hand, the findings regarding motor skills indicate that overall motor skills do not have much explanatory power alone on wages in this analysis once the cognitive skill measures are controlled.

The results of this study also can be explained in relation to a mismatch between workers' skill level and their jobs. In particular, if a mismatch between a worker's skills and his job is defined as being that of a highly cognitive skilled worker and he is employed in an occupation characterised by simple cognitive tasks (e.g. retail assistants) rather than complex cognitive tasks (e.g. a sales manager), the results imply that he experiences wage losses not to mention the fact that he accumulates less cognitive skills in the labour market. The wage losses are, in turn, rationalised in the model by the assumption that when task complexity increases, output is more sensitive to the skills of workers. Therefore, this framework can also provide an insight into why there is a pay penalty for highly skilled workers when they are overqualified for their jobs.

This chapter proceeds as follows: Section 4.2 provides a brief literature review; Section 4.3 explains the conceptual framework; Section 4.4 introduces the data sources with some descriptive statistics; Section 4.5 provides the empirical strategy; Section 4.6 presents the econometric specification and results with some robustness checks; and finally in Section 4.7 concluding remarks are made.

4.2 Related Literature

Recent studies have shown that a task-based approach to modelling labour market skills provides a valuable means of explaining wage growth, mobility and the human capital accumulation of workers in the labour market.

Gathmann and Schonberg (2010) provided one of the first papers, which studied the importance of task specific human capital for occupational mobility and quantified the contribution of these labour market skills to wage growth. Their empirical results[5] show that task specific human capital explains up to more than half of the wage growth of workers. They also found that the likelihood of experiencing significant wage losses in the case of job displacement and after job reallocation is much lower if individuals

[5]They used German Qualification and Career Survey as well as the German Employee Panel.

are employed in an occupation with similar skill requirements to their previous job. These results suggest that highly skilled workers accumulate more task specific human capital on the job. This, in turn, explains the distance of their moves, in terms of task similarities, between their jobs over the life cycle.

On the other hand, Autor and Handel (2013) have attempted to fill the gap in this part of the literature regarding the lack of a conceptual framework which explicitly models[6] the relationship between workers' skills, their occupation, the tasks they perform on the job and their wages. The results of their exploratory empirical analyses[7] suggest that task returns vary across occupations[8] and workers self-select themselves into occupations depending on their comparative advantage.

As an attempt to provide an explanation as to why task-based labour market skills are transferable across occupations as previous papers imply (e.g.Poletaev and Robinson (2008) and Gathmann and Schonberg (2010)) as well as how returns to skills vary across occupations, Yamaguchi (2012) presents a theoretical framework on the relationship between task complexity, skill growth and wages. His model is a Roy type model with a distinct feature that occupations are characterised in the task space. He structurally estimated of the model by using data from the Dictionary of Occupational Titles (DOT) and the National Longitudinal Survey of Youth 1979. The results suggest that returns to skills grow faster when workers are employed in an occupation with more complex tasks. He also finds that cognitive skills can explain all of the wage growth for college and high school graduates.

This chapter uses the conceptual framework of Yamaguchi (2014) whose empirical wage model is based on Yamaguchi (2012). Yamaguchi (2014) explores the relationship between changes in returns to task specific cognitive and motor skills and the gender wage gap in the U.S. from 1979 to 1996. Nevertheless, his framework is mainly intended to build an intuition rather than a guide.

Our contribution to the literature is three-fold: First, we test one of the implications of Yamaguchi (2012) and Yamaguchi (2014) conducting an exploratory empirical analysis utilising the Skills Survey of Britain and the British Household Panel Survey. In a way, we extend the empirical implementation of the model by quantifying varying rewards to education categories, experience and accumulated cognitive and motor skills across task complexities. Second, by using data from the Skills Survey which provides self-reported task measures, our work does not share some of the common shortcomings of other studies that exploit occupational task data sources like the Dictionary of Occupation

[6]They use a Roy-type model where workers simply have different skills in different occupations.

[7]They use data from Occupational Information Network (O*NET) and Princeton Data Improvement Initiative (PSII).

[8]Gibbons et al. (2005) find a similar result with occupation and industry measures.

Titles (DOT) and the Occupational Information Network (O*NET). For instance, Autor (2013) states that since these data sources are not developed for the purpose of providing task measures, job measures become mostly unclear, repetitive and have ambiguous scales. Finally, we improve upon Zangelidis (2008)'s work, who assessed the contribution of occupation and industry specific human capital on wages, as well as examining the heterogeneity of returns to labour market skills in different occupations using the BHPS. Although his work contributes to the literature by suggesting any assumption of homogeneity of returns to labour market skills across occupations (in the UK) is misleading, this chapter approaches the issue in a more sophisticated way. Firstly, as supported by the literature discussed above, a task-based analysis to human capital and varying returns to skills provides a better fit to the data. Furthermore, his occupation and industry specific human capital measures are not transferable across different occupations something which has been challenged by recent studies that find that specific human capital is not completely lost if a worker changes occupation.

4.3 Conceptual Framework

The framework for empirical analysis is based on Yamaguchi (2014).[9] In his model, skill is defined as a worker's endowment to perform tasks and a task indicates a unit of job activity which produces output. Workers' skill sets comprise cognitive (c) and motor (m) skills (also called as task-specific skills). $S_i = (S_{c,i}, S_{m,i})$ denotes the skill vector of worker i where $S_{c,i}$ is cognitive skills and $S_{m,i}$ is motor skills. As the key feature of the model, occupations (j=1,..., J) are defined as task bundles. $X_j = (X_{c,j}, X_{m,j})$, denotes the task complexity index vector of occupation j where $X_{c,j}$ is a cognitive task complexity index and $X_{m,j}$ a motor task complexity index. Task complexity measures how intensely a task is performed. By varying in each occupation j, $X_{c,j}$ and $X_{m,j}$ characterise (each) occupation j. Higher values of task complexity indices imply higher task complexity in occupation j. For example, Plumbers' task complexity index can be denoted as $X_{plumbers}$=($X_{cognitive,plumbers}$, $X_{motor,plumbers}$) and Solicitors' is $X_{solicitors}$=($X_{cognitive,solicitors}$, $X_{motor,solicitors}$).
If $X_{c,plumbers}$<$X_{c,solicitors}$ and $X_{m,plumbers}$>$X_{m,solicitors}$, this implies that although both occupation groups involve some degree of motor and cognitive skills, Solicitors perform more complex cognitive tasks than Plumbers but Plumbers perform more complex motor tasks than Solicitors.

Workers' initial cognitive (motor) skill level is a function of time-invariant individual characteristics (i.e.race, gender), unobserved permanent cognitive (motor) skills and

[9]This model is based on heterogeneous human capital model of Yamaguchi (2012).

skill shock. Workers' skills grow through learning-by-doing. Therefore, the cognitive (motor) skill level of worker i in year t in a long panel can be expressed as[10]

$$S_{k,it} = f(educ_{it}, exp_{it}, exp_{it}^2, AS_{k,it}(X_{k,j})) + \sigma_{i,k} + \epsilon_{k,it}, \quad k \in \{c, m\}, \tag{4.1}$$

where $educ_{it}$, exp_{it} and exp_{it}^2 are education, experience and experience-squared. In the case where k=cognitive (motor), $AS_{k,it}(X_{k,j})$ denotes acquired cognitive (motor) skills in the labour market through performing cognitive (motor) tasks and they are measured by summing up the past cognitive (motor) task complexities of the workers since they entered in the labour market. The model predicts that cognitive (motor) skill acquisition increases more if workers perform more complex cognitive (motor) tasks.[11] For instance, when Solicitors engage in greater cognitive task complexity than Plumbers ($X_{c,plumbers}$<$X_{c,solicitors}$), Solicitor's cognitive skill growth will be bigger than Plumbers' where as it would be the contrary for motor skill growth. $\sigma_{i,k}$ is unobserved permanent cognitive (motor) skills and $\epsilon_{k,it}$ is skill shock.
In this equation, the accumulated cognitive (motor) skills capture the skills which workers acquire by performing the cognitive (motor) tasks in their jobs. Experience indicates the other general skills acquired in the labour market which contributes to the cognitive (motor) ability of workers regardless of the cognitive (motor) task complexity. Finally, the workers' level of education is also assumed to contribute to the level of cognitive (motor) ability of the workers.

The key prediction of the model is when the tasks are complex, skills are used more; the acquisition of the skills and increase in productivity becomes larger. This results in heterogeneous skill and wage profiles over time.

The hourly wage ($W_{i,jt}$) of worker i in year t who is employed in occupation j is then given by

$$\begin{aligned} W_{i,jt} = g(&S_{c,it}(educ_{it}, exp_{it}, exp_{it}^2, AS_{c,it}), S_{m,it}(educ_{it}, exp_{it}, exp_{it}^2, AS_{m,it}), \\ &educ_{it}, exp_{it}, exp_{it}^2) + \omega_{i,kjt}, \quad k \in \{c, m\}, \end{aligned} \tag{4.2}$$

where the wages are a function of cognitive and motor skill levels of workers, education, experience and experience-squared.[12] In the wage model, returns to skills vary across

[10] This is the case when there is only males and race is not considered.

[11] The level that workers learn skills from their job decreases their work experience. This implies that skills grow with a decreasing rate.

[12] These variables are likely to have independent effect on wages other than their indirect effect through cognitive and motor skills.

occupations depending on the task complexities.[13][14] The reason is that depending on the characterised task complexities, to what extent the skills are used changes and so the productivity. Consequently, this result in different wage levels.

4.4 Data

This study employs two data sets: Skills Survey of Britain and British Household Panel Survey.

4.4.1 Measuring Task Complexities

We use data from the Skills Survey of Britain to calculate cognitive and motor task complexity index vector that characterise occupations. The Skills Surveys[15] are conducted in 1997, 2001, 2006 and 2012[16] to investigate the employed workforce and in particular to provide information on the distribution of the skills, skills requirements and a description of the work preferences and work motivation of the employed individuals in Britain. We employ all four cross-section data series where number of observations are 2467, 4470, 7787, 3200 respectively.[17]

The self-reported motor and cognitive task information is extracted from the 'Detailed Job Analysis Section' of the surveys. This section is composed of over 30 different questions related to the type of task that workers perform at work. In each job task questions, respondents are asked "*How important is ...[each job task] in your job?*" For example, **how important is analysing complex problems in depth in your job?** The choices are "Essential ", "Very important ", "Fairly important", "Not very important" and "Not at all important/Does not apply". These answers are given numerical values between 0(not at all important) and 4(essential).

In order to construct the cognitive and motor task complexity indices, we first choose job activity variables related to these two tasks in line with Yamaguchi (2014). Table 4.3 compares the cognitive and motor task measures which Yamaguchi (2014) has employed from the Dictionary of Occupational Titles and the task measures used from the Skills

[13]In the model, the return to skills are function of task complexities (i.e. $b_{cognitive,t}(X_{c,j})$ and $b_{motor,t}(X_{m,j})$ where b is return to skills) and the change in returns over time represent the change in the technology because return to skills are in the production function.

[14]This is similar to Teulings (1995), whose model has the property that return to skills increase more in complex jobs.

[15]Felstead,A. et al. , Skills and Employment Surveys Series Dataset, 1986, 1992, 1997, 2001, 2006 and 2012 [computer file]. 2nd Edition. Colchester, Essex: UK Data Archive [distributor], May 2014. SN: 7467 , http://dx.doi.org/10.5255/UKDA-SN-7467-2

[16]The surveys are renamed as Skills and Employment Survey in 2012.

[17]Table A.2 in Appendix A presents the summary statistics for all four subsequent Skills Surveys.

Survey. The cognitive task inputs in both surveys show a similarity. In the analysis, analysing complex problems, counselling, advising or caring for clients, instructing, training or teaching people, making speeches or presentations, thinking of solutions to problems, three mathematical and six language skills measurement, influencing others, planning activities of others, dealing with people are chosen from the SS as cognitive task measures (see Table 4.1).[18] On the other hand, the table reveals that motor task measures from the SS are not as adequate and detailed as they are in the DOT.[19]In the analysis, knowledge of how to operate tools, skills or accuracy using hands or fingers, spotting problems or faults and physical stamina are chosen as motor task measures. Among the four task inputs, spotting problems or faults are included due to lacking of motor tasks measures and unlike most of other tasks it is positively correlated with three tasks.[20]

Second, following the literature (e.g. Ingram and Neumann (2006), Poletaev and Robinson (2008), Yamaguchi (2012)), principal component analysis (PCA) is employed to generate composite task (complexity) measures which retain the highest variation possible in the data. To run a principal component analysis, initially cognitive and motor task measures are given numerical values between 0-4. Using all observations from four waves of the Skills Survey[21], PCA is run separately for cognitive and motor tasks. Table 4.4 presents the PCA results for both cognitive and motor task indices. The the first column in each part shows the job task items included in the analysis. The values in the columns with principal components shows how much of the variation in task inputs can be explained by the retained principal component. The last column namely uniqueness, in turn, represents the variance which is unexplained. Regression scores are used to predict individuals' raw scores as cognitive and motor task complexity indices.[22]

Figure 4.1 plots the occupations in the task space, where the standardised mean cognitive and motor task complexities (indices) for nine (one digit) occupation classes are shown.[23] Here, I aggregate the individual task indices at the one digit occupation classification using the Skill Survey sample weights. the graph demonstrates the cognitive

[18]Table C.2 presents the correlation coefficients of cognitive task measures which are all positive.

[19]It would be because the DOT is a job dictionary and purposefully prepared to guide the job seekers.

[20]see Table C.1

[21]Since predicted cognitive and motor task complexities are averaged over 3-digit occupational level in the econometric analysis, the number of observations become significantly smaller due to the sample size. However, pooling all periods may become a threat for identification of the true cognitive and motor task complexities. First, we can not capture any change in cognitive and motor complexities of occupations over time. Therefore, the wage regression results do not capture any occupational time effect on wages. Second, the sample includes female workers as well as male. Although, degree of the performed task intensity by men and women may not change within an occupation, this may bias the results.

[22]Yamaguchi (2012) converts the PCA cognitive and motor indices into percentile scores. Nevertheless, he reports that using raw scores do not change his results significantly.

[23]The raw mean scores are standardised such that the mean of the both indices becomes 0 and the standard deviations become 1.

and motor task complexity vectors of occupations at one digit level, for instance, professionals' task complexity vector is $X_{Professionals}$=(1.4($cognitive$), −0.4($motor$)). The figure also allows us to compare the cognitive and motor complexity indices across occupations. For instance, the workers who are employed in professional, managerial and associate professional occupations involve some degree of complex cognitive tasks above the average cognitive task index. On the other hand, the workers who are employed in personal service, elementary, operatives and skilled trades occupations involve some degree of complex motor tasks above the average motor task index. This finding is also largely in line with what Yamaguchi (2014) finds for the US.

Since, PCA is also a data reduction method, it would share the shortcomings of factor analysis. Therefore, some robustness checks are run. First, in order to test the sensitivity of results to inclusion of different cognitive task inputs, PCA is run using more task inputs [24]. Figure C.2 plots 1-digit occupations in the updated cognitive and motor task space. It is illustrated that the results are significantly similar to the results from Figure 4.1. Second, in order to test sensitivity of the results to choice of motor task inputs, PCA is run excluding spotting fault task. Figure C.1 plots 1- digit occupations in the cognitive and updated motor task space. It is shown that the results are significantly similar to the results from Figure 4.1.

4.4.2 British Household Panel Survey

We use repeated cross-section data from the BHPS for the empirical analysis. The data sample contains an unbalanced panel and covers all 18 waves from 1991 to 2008. The sample contains 5850 male full time workers with 43767 observations. The BHPS[25] was conducted between 1991 to 2008 [26] to understand and then identify the causes and consequences of social and economic changes in Britain at the individual and household level. It was designed as a nationally representative annual survey which covers more than 5000 households and approximately 10000 adults over 16 years old. The same individuals were re-interviewed during 18 waves and if they had left the original households, their new households would have interviewed. Although additional sub-samples were included to the BHPS in 1997 and 1999, the sample remained broadly representative of the population (see Taylor et al. (2010)).

[24] Using all task inputs of the analysis from Chapter 2

[25] It carried out by the ESRC UK Longitudinal Studies Centre with the Institute for Social and Economic Research at the University of Essex.

[26] From 2009 onward, the BHPS became part of the study called Understanding Society conducted by ISER.

The data set has been processed to obtain wage series of male full-time workers over 18 waves. The wage series which consist of gross hourly pay[27] of workers are then deflated by CPI (Consumer Price Index). Since, the cognitive and motor task information is not readily available in the BHPS, this information is obtained from the Skills Survey. First the individual cognitive and motor task indices which are calculated using the Skills Survey are aggregated into the occupation level by averaging the indices of 348 3-digit occupations (standard occupational version 90-SOC90) using the Skills Survey sample weights. We then merge this information with the same 3 digit SOC90 variable in the BHPS.[28]

Table 4.5 presents some summary statistics and Figures 4.2, Figures 4.3, and Figures 4.4 display some descriptive statistics for BHPS data sample.

Figure 4.2 plots the occupations in the task space, where the standardised mean cognitive and motor task complexities (indices) for seven (one digit) occupation are shown.[29] Here, we aggregate the 3-digit occupational cognitive and motor task indices at the one digit occupation level using the BHPS sample weights. The figure shows that the workers who are employed in higher and lower service classes and routine manual occupations perform some degree of complex cognitive tasks above the average cognitive task index. On the other hand, the workers who are employed in skilled manual, technical and semi unskilled manual occupations perform some degree of complex motor tasks above the average.

Figure 4.3 illustrates the mean log hourly wages by one digit occupations with their characterised cognitive task complexity index. The graph shows that there is a positive correlation between mean log wages in each occupation and their characterised cognitive task complexity. The mean wages are the highest for higher and lower service class occupations which are characterised by the most complex cognitive tasks. In addition, the mean wages are the lowest for semi unskilled manual and personal service occupations which are characterised by the simple cognitive tasks.

Figure 4.4 plots the mean log hourly wages by one digit occupations with their characterised motor task complexity index. On the contrary to cognitive task complexity case, the highest waged higher and lower service class occupations are characterised by the most simple motor tasks. Among the occupations which are characterised by above average motor complexity, technicians earn the highest.

[27] In order to find gross hourly wage, gross monthly wage in current job is divided by the gross hours of work multiplied by 4.33.

[28] There were 362 3 digit SOC90 occupations in the BHPS sample. Therefore workers who are employed in rest of 14 occupations which did not have any cognitive and motor task indices are dropped.

[29] The raw mean scores are standardised such that the mean of the both index becomes 0 and the standard deviations become 1.

4.5 Empirical Strategy

In this chapter, we investigate to what extent reward to cognitive and motor skills are heterogeneous across cognitive and motor task complexities of occupations. In the conceptual framework, occupations are defined by cognitive and task complexity indices and the model predicts that return to skills would vary across occupations depending on the characterised cognitive and motor task complexity.

In order to test predictions of the model, we operationalise the conceptual wage model of Yamaguchi (2014) in (2) as follows:

$$lnW_{i,jt} = X_{c,j}\mathbf{S}'_{it}\lambda_c + \theta_c X_{c,j} AS_{i,ct} + X_{m,j}\mathbf{S}'_{it}\lambda_m + \theta_m X_{m,j} AS_{i,mt}$$
$$+ \mathbf{S}'_{it}\beta + \gamma_{c,1} AS_{i,ct} + \gamma_{c,2} X_{c,j} + \gamma_{m,1} AS_{i,mt} + \gamma_{m,2} X_{m,j} + u_{i,kjt}, \quad k \in \{c, m\}, \quad (4.3)$$

where $lnW_{i,jt}$ denotes loh hourly wage of individual i who is employed in occupation j in year t, $X_{c,j}$ ($X_{m,j}$) cognitive (motor) task complexity index in occupation j, S'_{it} denotes education, experience[30] and experience-squared. $AS_{i,ct}$ ($AS_{i,mt}$) denotes accumulated cognitive (motor) skills in the labour market through performing cognitive (motor) tasks since worker i appeared in the survey. They are calculated by summing up the past cognitive (motor) task complexities of workers in their past occupations[31] and $u_{i,kjt}$ denotes the error term.

Education, experience (and experience-squared) and accumulated skills in the labour market all contribute to the workers' level of cognitive and motor skills. Since the cognitive (motor) skill level of workers are not measured directly, these variables are each indicators to cognitive and motor skill level of the workers. Therefore, in order to capture the heterogeneous returns to cognitive and motor skills across occupations (task complexities), each indicator of cognitive and motor skills (S'_{it}, $AS_{i,ct}$, $AS_{i,mt}$) are interacted by cognitive and motor task indices.[32] This suggests that λ_c, θ_c, λ_m and θ_m are vectors of varying returns to skills across occupations. For instance, estimated θ_c shows whether rewards to accumulated cognitive skills in the labour market vary across occupations(task complexities). In the mean time, the estimated coefficient allows me to quantify to what extent reward to accumulated cognitive skills change across different

[30]Age is proxied for years of general labour market experience due to lacking of direct information in BHPS to calculate years of experience. Hence, age is replaced by general labour market experience throughout the document.

[31]The employment spells are taken to be equal across all waves and workers. This would create a bias on the results if workers have breaks between the survey interviews since it would inflate the accumulated skills.

[32]Zangelidis (2008) also uses interaction terms of occupations with occupation tenure to capture the heterogeneous returns to occupation tenure.

level of cognitive task complexity that workers perform in their jobs. On the other hand, β, γ_c and γ_m represents the direct(or main) effects of the skill measures.[33]

4.5.1 Estimation Methods

First, as a benchmark, we estimate the wage model in Equation 4.3 by pooled ordinary least squares(OLS) estimation as follows:

$$lnW_{i,jt} = z'_{i,kjt}\rho + \underbrace{h_{i,kj} + \phi_{i,jt}}_{u_{i,kjt}}, \quad k \in \{c, m\}, \tag{4.4}$$

where $z_{i,kjt}$ denotes all of the explanatory variables. The error term $u_{i,kjt}$ consist of unobserved individual heterogeneity $h_{i,kj}$ and idiosyncratic errors $\phi_{i,jt}$. We assume strict exogeneity throughout where idiosyncratic errors are uncorrelated with regressors (i.e. E($\phi_{i,jt}\backslash$z$_{ikj1}...z_{ikjT}$, $h_{i,kj} = 0$)). The unobserved heterogeneity can be decomposed into four parts:

$$h_{i,kj} = \sigma_{i,c} + \sigma_{i,m} + \tau_{i,cj} + \tau_{i,mj}, \quad k \in \{c, m\}, \tag{4.5}$$

where $\sigma_{i,c}$ and $\sigma_{i,m}$ denote unobserved permanent cognitive and motor skills respectively. Following Gibbons et al. (2005), it can be said that these unobserved skills represent the part of workers' productive ability which is equally valued in all occupations (regardless of the task complexities). On the other hand, $\tau_{i,cj}$ and $\tau_{i,mj}$ denote unobserved cognitive and motor task-specific match (see Gathmann and Schonberg (2010)) between workers and the task complexity they involve in their occupations. These unobserved factors would stem from comparative advantage of workers across cognitive and motor task complexities. If the regressors ($z_{i,kjt}$) are uncorrelated with the unobserved characteristics and matches (i.e $cov(z_{i,kjt}, h_{i,kj}) = 0, t = 1...T$) then the coefficients (ρ) can be consistently estimated using pooled OLS.[34]

However, if the two unobserved characteristics and matches are correlated with observed skill and task complexity measures, there would likely to be two types of potential endogeneity bias. The first type of bias is an ability bias that occurs when workers with high unobserved ability (high $\sigma_{i,c}$ and $\sigma_{i,m}$), acquire more skills and are more productive

[33] In Yamaguchi (2014)'s framework, because tasks measures are not productive themselves, they are not included in the wage equation 4.2 alone. However, I include them as main effects because of the interaction terms. If they are not included, main effects and interaction effects get confounded (?? (Aik)).

[34] Nevertheless, the likely correlation of regression model errors ($h_{i,kj} + \phi_{i,jt}$) over time for each individual is required to be controlled because in this case standard errors for pooled OLS are underestimated and t-statistics can be overstated.

and earn higher wages. Second type of bias is selection-bias.[35] For instance, Yamaguchi (2014)'s framework, the wages are not very different for high and low skilled workers when both type are involved in simple tasks. However, the reward is increasing for high skilled workers when they are involved in complex tasks i.e. high skilled workers have a comparative advantage in complex tasks. On the other hand, the reward is higher for low skilled workers when they perform simple tasks (see Figure 4.5). Therefore workers would choose an occupation (in the task space) which offer the highest returns. This implies that tasks are not randomly assigned to workers but workers self-select into occupations which then leads to a bias from self-selection into occupations (task complexities). In the wage regression, the sign of the self-selection bias for interaction terms, which show heterogeneity of returns to skills across occupations, might be positive or negative depending on the workers' skill level and level of task complexity. For instance, the endogeneity bias is likely to move the estimates upwards for high skilled workers (in terms of education, experience and accumulated labour market skills) who perform more complex tasks. However, estimates would be downward biased for low skilled workers who perform complex tasks rather than simple tasks.

As a second method, we use a fixed effects (within) estimator to allow the correlation between the unobserved permanent cognitive and motor skills and the observed skill measures.[36] Within estimator treats unobserved constant heterogeneity as parameters to be estimated. The estimator then measures the relationship between individual-specific departures of predictor variables from their time-averaged values and individual specific departures of the outcome variable from its time-averaged value (Cameron and Trivedi (2005)).

A fixed effects estimator is used to eliminate the bias which springs from the correlation between observed skill measures and unobserved permanent cognitive and motor ability. However, the bias that stems from the self-selection of workers into task complexities would remain because the unobserved task-specific matches are valued differently across occupations, e.g. not constant over time. Therefore, the fixed effect estimates will provide consistent estimates for no comparative advantage case, however they may not provide consistent estimates for under comparative advantage. Nonetheless, Gibbons et al. (2005) imply that their fixed effects results in the no comparative advantage case are still informative for their analysis.

[35]The works in occupation and industry specific human capital literature which use occupation and industry tenure as proxies for skills commonly suffer selection bias as well despite employing instrumental variables approach. Keane and Wolpin (1997) and successors apply structural approach to tackle this selection bias.

[36]Because the BHPS sample is unbalanced panel, we only use complete cases (i.e $s_{it} = 1$. Selection indicators for each individual i,$\{s_{i1}, ...s_{iT}\}$,where $s_{it} = 1$ if ($z_{i,kjt}$, $lnW_{i,jt}$) is fully observed, otherwise $s_{it} = 0$) and in order to have consistent estimates, we further assume that observing a data point is not systematically related to error (i.e. $E(u_{i,kjt} \backslash z_{i,kjt}, lnW_{i,jt}, s_i = 0)$.

In addition to standard pooled OLS and fixed effects estimator, we run Mundlak (1978)'s correlated random effects model (CRE)[37] for two reasons. First, this device allows the researcher to control for the time invariant variables and also provides fixed effect estimates on the time-varying covariates under appropriate assumptions. We use this feature of the model on my robustness checks. Second, CRE provides a way to test the correlation between regressors and the unobserved heterogeneity (i.e $cov(z_{i,kjt}, h_{i,kjt}, s_i) = 0, t = 1...T$). In this case, the fixed effects estimator are estimated as a pooled OLS estimator by adding the time averages of the (time varying) covariates including time dummies and any aggregate time variables.[38] Using the estimates for the time averages of the covariates (herein Mundlak averages), the null hypothesis of the absence of correlation between the regressors and unobserved permanent cognitive and motor skills can be tested[39] (see Wooldridge (2013), Ciani (2012), Socio and Nigro (2012)).

4.6 Econometric Wage Specification and Results

The estimated wage model in Equation 4.3 which is augmented with time dummies and Mundlak averages as follows:

$$lnW_{i,jt} = \beta_0 + \lambda_{c,1} higheduc_{it} * X_{c,j} + \lambda_{c,2} mideduc_{it} * X_{c,j} + \lambda_{c,3} loweduc_{it} * X_{c,j} + \lambda_{c,4} exp_{it} * X_{c,j} + \lambda_{c,5} expsq_{it} * X_{c,j} + \lambda_{c,6} AS_{i,ct} * X_{c,j} + \lambda_{m,1} higheduc_{it} * X_{m,j} + \lambda_{m,2} mideduc_{it} * X_{m,j} + \lambda_{m,3} loweduc_{it} * X_{m,j} + \lambda_{m,4} exp_{it} * X_{m,j} + \lambda_{m,5} expsq_{it} * X_{m,j} + \lambda_{m,6} AS_{i,mt} * X_{m,j} + \beta_1 higheduc_{it} + \beta_2 mideduc_{it} + \beta_3 loweduc_{it} + \beta_4 exp_{it} + \beta_5 expsq_{it} + \gamma_{c,1} AS_{i,ct} + \gamma_{m,1} AS_{i,mt} + \gamma_{c,2} X_{c,j} + \gamma_{m,2} X_{m,j} + timedummies_t{}'\theta + Mundlakaverages_i{}'\delta + u_{i,kjt}, \quad k \in \{c, m\}, \tag{4.6}$$

where, $higheduc_{it}$, $mideduc_{it}$ and $loweduc_{it}$ are education category [40] dummies for imdividual i in year t.[41] exp_{it}, $expsq_{it}$, $AS_{c,it}$ and $AS_{m,it}$ denote years of experience, experience squared, accumulated cognitive and motor skills in the labour market respectively.

[37] This model is introduced by Mundlak (1978) and relaxed by Chamberlain (1980) (see also Wooldridge (2010))

[38] This is because the time average of time dummies and other aggregate time variables varies across individuals in the unbalanced panel.

[39] This is also called variable addition test or regression based Hausman test.

[40] Education categories in BHPS are grouped in accordance with Redwood and Tudela (2004) as follows: High: teaching, first or higher degree; Middle: A Level, nursing or other higher; Low: CSE, GCSE or commercial qualification; None: no or other qualification or apprenticeship.

[41] Education category dummy=1 if individual is in that category, 0 otherwise. None education group is the reference category.

$X_{c,j}$ and $X_{m,j}$ denote cognitive and motor task complexities in occupation j which individual i is employed at time t.[42] In addition, $higheduc_{it} * X_{c(m),j}$, $mideduc_{it} * X_{c(m),j}$ and $loweduc_{it} * X_{c(m),j}$ are categorical by continuous interaction terms and they suggest the different slope of the cognitive (motor) task complexity ($X_{c(m),j}$) on log wages for different education levels. Hence, $\lambda_{c(m),1}$, $\lambda_{c(m),2}$ and $\lambda_{c(m),3}$ capture heterogeneous returns to different education levels across cognitive and motor task complexities. Further, $exp_{it} * X_{c(m),j}$, $expsq_{it} * X_{c(m),j}$ and $AS_{i,c(m)t} * X_{c(m),j}$ are continuous by continuous interaction terms and they imply that the slope of experience, experience squared and accumulated cognitive (motor) skills on log wages differs as the cognitive (motor) task complexity ($X_{c(m),j}$) changes. Therefore, $\lambda_{c(m),4}$, $\lambda_{c(m),5}$ and $\lambda_{c(m),6}$ capture the heterogeneous reward to general labour market experience, experience squared and accumulated cognitive (motor) skills across cognitive (motor) task index. On the other hand, β_1 to β_5 denote direct effect of education and experience (and experience squared) on log wages where as $\gamma_{c,1}$,$\gamma_{c,2}$,$\gamma_{m,1}$ and $\gamma_{m,2}$ are the main effects of task related regressors. Time dummies also included to capture the year effects. Finally, Mundlak averages denote the time averages of all the regressors including time dummies.

The results are presented in Table 4.6 and Figures 4.6, 4.7, 4.8 and 4.9. Table 4.6 introduces the results from all linear wage regression models. In addition, Figures 4.6, 4.7, 4.8 and 4.9 are used to interpret the magnitude of the estimated coefficients of interaction terms in the wage models.

As a benchmark, the pooled OLS results are presented in column (I), the fixed effects results are presented in column (II) and correlated random effects result are presented in column (III). Here, the estimated coefficients of interaction terms are my main interests.

The pooled OLS results show that among the three estimated education categories only the interaction term of the middle education category with cognitive task complexity is significant. This implies that there are heterogeneous rewards only to the middle education group across cognitive task complexities. Further, the interaction terms of experience and experience squared with cognitive task complexity are significant. These suggest that returns to general labour market experience varies across occupations. The estimate for accumulated cognitive skills with cognitive task complexity interaction is also significant. This implies two things. First, the reward to accumulated cognitive skills in the labour market also vary across occupations. Secondly, this finding is in line with Yamaguchi (2014) who also found the effect of accumulated cognitive skills positive and significant. He further suggests that accumulated task-specific measures should be included in the standard wage models. On the other hand, the reward for having low

[42] All of the continuous explanatory variables are standardised with mean 0 and standard deviation 1 including cognitive and motor task complexities. This is necessary to meaningfully interpret multiple continuous by continuous interactions.

level of education is the only education level which varies across motor task complexities. Further, there are heterogeneous returns to general labour market experience across motor task complexities. Finally, the estimate for accumulated motor skills with motor task complexity interaction is also significant and this implies that accumulated motor skills in the labour market also vary across occupations. Although, the coefficients of single explanatory variables are not the main interest, the standard skill measures like experience and education categories are significant with expected signs. Furthermore, the estimates for accumulated cognitive skills and cognitive task index are positive and significant. An interesting point to note that, the cognitive task related regressors are positive whereas the motor task related regressors are largely negative (though mostly not different than zero). The reason might be that the correlation between motor and cognitive skills of workers are not high as shown in Figure 4.1 and Figure 4.2 (see Autor and Handel (2013)). In addition, high waged occupations are mostly cognitive task intense whereas, low waged occupations are motor task intense as shown in Figure 4.3 and Figure 4.4.

As explained in the previous section, these results are very likely to suffer from ability bias due to correlation between unobserved permanent abilities (cognitive and motor) and regressors in the wage equation. To test this assumption, we add Mundlak averages to pooled OLS regression model in column (III). This correlated random effects model provides the fixed effects estimates in column (II). Using the estimates from the CRE model, we test the null hypothesis that the Mundlak averages (δ) are jointly equal to zero. The p-value of the test suggests that the null is rejected and there is evidence for the correlation between unobserved permanent cognitive and motor abilities and regressors. Therefore, fixed effects estimates are used to tackle this issue.

The fixed effects estimates in column (II) show that the interaction terms of all three education categories with cognitive task complexity are positive and significant. This suggests that there is a heterogeneous reward to education regardless of level across cognitive task complexities. Likewise, the interaction of experience and experience squared with cognitive task complexity is significant and suggest that return to general labour market experience varies across occupations. Further, although the magnitude is smaller than pooled OLS, the fixed effects estimate of accumulated cognitive skills with cognitive task complexity interaction is positive and significant. Therefore, the heterogeneous returns to accumulated cognitive skills and transferability of cognitive skills are still valid conclusions. On the other hand, fixed effects estimate of the interaction terms of motor task complexity with education categories, experience and experience squared are not different than zero. This implies that motor skills, when measured as education and general labour market experience, do not vary across occupations. Nevertheless, the estimate for accumulated motor skills with motor task complexity interaction is negative and significant at the 10% level. This is the only evidence of heterogeneous reward to motor skills across motor task complexities. Finally, the standard skill measures like experience and education categories are still significant with expected signs, although their effect seem lower comparing with pooled OLS estimates.

Figures 4.6, 4.7, 4.8 and 4.9 are produced from fixed effects estimates and demonstrate to what extent reward to skills are heterogeneous across task complexities. Since, all of the cognitive skill interactions with cognitive task index and accumulated motor skill interaction with motor task index are significant, we only plot these interaction effects. In order to illustrate and explain the interaction terms in the wage regression, we use simple slopes approach. For continuous by continuous interactions, simple slopes compute the amount of change in log wages with one unit change in skill indicators (i.e. experience (experience-squared), accumulated cognitive and accumulated motor skills) when the value of cognitive (motor) task complexity is held constant at running from low (one standard deviation below the mean) to high (two standard deviation above the mean) values and the value of other explanatory variables is held constant at their mean values. For continuous by categorical interactions (i.e. education categories with cognitive task complexity), simple slopes compute log wage differences of education categories for various values of cognitive task complexity constant at running from low (one standard deviation below the mean) to high (three standard deviation above the mean) values and holding the value of other explanatory variables constant at their mean values.

Figure 4.6 displays the log wage differences of education categories across various values of cognitive task complexity. It further shows that the return to all education levels increases across more complex cognitive task complexity. Nevertheless, the log wage differences across tasks are greatest (i.e. the slope is the steepest) for the highly educated group. In fact, if a highly educated worker moves from an occupation with a task complexity one standard deviation below the mean (i.e. Xc=mean-1sd) to another occupation with a task complexity one standard deviation above the mean (i.e. Xc=mean+1sd), his expected wage increases around 18% when all other characteristics are held constant at their means. In line with Yamaguchi (2014)'s framework, it can be rationalised as when a highly educated worker who is employed in an occupation characterised by more complex cognitive tasks, he uses his human capital more and his productivity increases more and he earns more. Moreover, if a low educated worker switches from simple (i.e. Xc=mean-1sd) to complex tasks (i.e. Xc=mean+1sd), his expected wage also increases around 10% when all other characteristics are held constant at their means.

Figure 4.7 demonstrates how rewards to general labour market experience changes across cognitive task complexities. This suggests that, a worker with general labour market experience up to 0.5 standard deviation above the mean switches from his occupation with one standard deviation below the mean (i.e. Xc=mean-1sd) cognitive task complexity to an occupation with one standard deviation above the mean (i.e. Xc=mean+1sd), the expected wage increase when all other characteristics are held constant at their means. On the other hand, when experience increase over one standard deviation above the mean, the reward for experience is more for simple cognitive tasks (i.e. Xc=m-1sd) than for more complex tasks (i.e. Xc=m+1sd).

Figure 4.8 illustrates the heterogeneous returns to accumulated cognitive skills in the labour market by cognitive task complexities. It further reveals that log wages increase with accumulated cognitive skills but the slope is steeper for more complex cognitive tasks. In fact, if a skilled worker (i.e. accumulated cognitive skills=mean+1sd) switches from his occupation with one standard deviation below the mean cognitive task complexity (i.e. Xc=mean-1sd) to another occupation with one standard deviation above the mean task complexity (i.e. Xc=mean+1sd), his expected wage increase is around 16% when all other characteristics are held constant at their means. Moreover, the trade off between intercept and slope also exists for accumulated cognitive skills. When an unskilled worker (i.e. accumulated cognitive skills<mean-3sd) moves from simple (i.e. Xc=mean-1sd) to complex tasks (i.e. Xc=mean+1sd), his expected wage drops.

Finally, Figure 4.9 demonstrates how reward to accumulated motor skills in the labour market changes across different level of task complexities. However, the simple slope is only significant for motor task complexity one standard deviation below the mean (the dotted line, Xm=m-1sd). The dotted line shows that log wages decrease with accumulated motor skills in the labour market. In fact, if an average skilled worker (i.e. accumulated motor skills=mean) who is employed in an occupation which is characterised by simple motor tasks (Xm=m-1sd) increase his accumulated motor skills two standard deviation above the mean (i.e. accumulated motor skills=mean+2sd), his predicted wage drops around 1.5%. This finding is in contrast to those of Yamaguchi (2014) who found that accumulated motor skills had a positive effect on wages. However, the reason might be that as shown in Table 4.2, Skills Survey do not have as detailed task measures as the Dictionary of Occupation Titles. This results in less variation in the data for better estimates. In addition, motor tasks provided by skills survey heavily on manual dexterity and hence might not be adequate to capture motor tasks that high skilled workers i.e. dentist, surgeons perform on the job.

4.6.1 Robustness Checks

Tables 4.7 and 4.8 present some robustness checks to assess the sensitivity of the (fixed effects) results particularly the estimated coefficients of the interaction terms by adding and removing regressors. The results show that the interaction terms for cognitive task complexity are largely robust to the different econometric model specifications. However, the interaction terms for motor task complexity are sensitive to the change in model specification.

In Table 4.7, we add two interaction terms in the Mundlak model in column (II) to compare the results with original fixed effects estimates in column (I). In column (II), the two added regressors are the average cognitive and motor task complexity indices[43] which are interacted with cognitive and motor task indices respectively. Yamaguchi (2014) suggests that adding these two terms in the wage model would provide a way to tackle the endogeneity bias (self-selection bias) by putting restrictions on the conditional distribution of the unobserved heterogeneity (unobserved task-specific matches) given the sufficient history of the covariates. The results show that the estimated coefficient of interaction term for average cognitive task complexity with cognitive task complexity index is positive and significant where as the coefficient of interaction term for average motor task complexity with motor task complexity index is positive but not different than zero. In addition, the coefficients of cognitive and motor interaction terms which capture the heterogeneous rewards to skills largely unaffected by these additions apart from the interaction terms of education levels with cognitive task index. By the addition of average cognitive terms, the cognitive interaction terms of middle and low education level become insignificant and the cognitive interaction term with high education level is still significant but the estimated coefficient becomes significant at the 10% level.

In Table 4.8, column (I) presents the original fixed effects estimates, column (II) introduces the estimates from the wage regression where there is only cognitive skill and task measures are present whereas motor task measure are dropped, finally column (III) only controls for the motor skill and task measures. Column (II) shows that the results are almost unchanged when the motor task measures are removed. Column (III) indicates that when the cognitive skill and task measures are dropped, the effect of these terms largely increase. This implies that motor task skill and task measures are sensitive to the change in model specification.

[43]Since the averages are constant, they can not be added to the fixed effects model. Mundlak model then provides a way to compare the two set of results.

4.7 Concluding Remarks

This chapter builds on the recent works in the literature which suggest that a task-based approach to modelling labour market skills enhance our understanding of the life time wage growth and accumulation of labour market skills. This chapter attempted to test to what extent rewards to cognitive and motor skills are heterogeneous across cognitive and motor task complexities, using Yamaguchi (2014) as an intuition for both the analysis and the results.

The results of our exploratory empirical analysis imply that the returns to education, general labour market experience and accumulated cognitive labour market skills vary across occupations. In particular, when a highly cognitive skilled worker switches from an occupation with simple cognitive tasks to an occupation with complex cognitive tasks, his expected wage increases when all other characteristics are held constant. In line with Yamaguchi (2014), these findings can be rationalised as being similar to when a highly educated worker who is employed in an occupation is characterised by having more complex cognitive tasks, uses more human capital, his productivity is higher, and earns more. However, when a low cognitive skilled worker moves from an occupation with simple cognitive tasks to an occupation with complex cognitive tasks, his expected wage drops when all other characteristics are held constant at their means. This can also be rationalised in terms of the trade off between intercept and slope: When the tasks are complex, the output is more sensitive to the skill level and, hence, the guaranteed wage is lower for complex tasks and higher for simple tasks. On the other hand, as discussed in Section 4.6 the results regarding motor skills do not correspond to those which Yamaguchi (2014) finds.

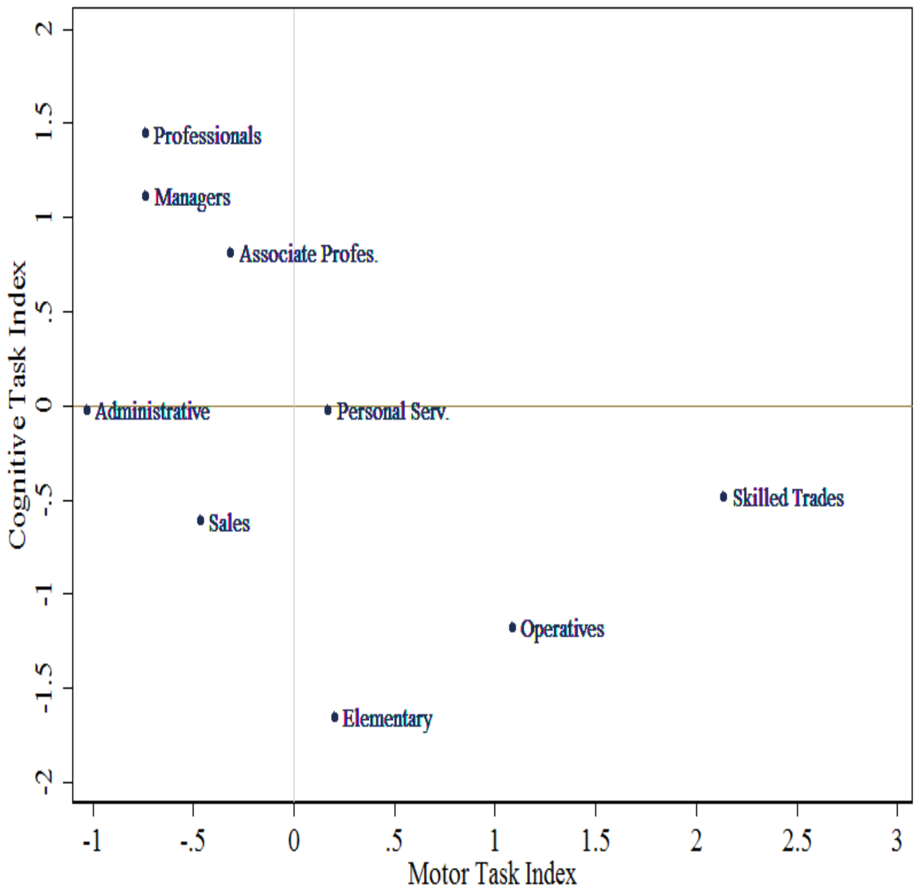
On a methodological note, endogeneity bias is a common issue in the empirical specific human capital literature due to the likely correlation between workers' unobserved match quality (i.e. occupation specific, industry specific, and task specific matches) with observed human capital measures (see Sanders and Taber (2012)). For instance, the results in Section 4.6 indicate that the rewards are increasing for highly skilled workers when they perform complex tasks. Therefore, these workers would self-select themselves into occupations which are characterised by complex cognitive tasks. This also implies that there exists a comparative advantage for highly cognitive skilled workers for complex cognitive tasks. As was discussed in Section 4.5, fixed effect estimates provide a benchmark for no comparative advantage cases; they may not, however, provide consistent estimates under comparative advantage cases either. Nevertheless, under comparative advantage, the results would provide a upper bound for the true effect on highly skilled workers (in terms of education, experience and accumulated labour market skills) who perform more complex tasks. Moreover, the estimates would provide a lower bound for the true effect on low skilled workers who perform complex tasks. Furthermore, due to lacking of detailed motor task measures in the Skills Survey, estimates on motor tasks would be biased. Furthermore, the results would be subject to some biases which stem from data limitations. First, due to lacking of detailed motor task measures in the Skills Survey, estimates on motor tasks would be biased. Second, using full employment histories of workers would have improved the estimates.

While not without limitations, the findings of this study provide insights into the importance of task-based channels of human capital accumulation and wage growth in the labour market, a topic with potential implications on why there is a pay penalty for highly skilled workers (particularly for highly skilled immigrant workers) when they are overqualified for their jobs. On the other hand, developing more tools for tackling endogeneity bias could improve the quality of future empirical research on heterogeneous human capital.

4.8 Tables and Figures

4.8.1 Figures

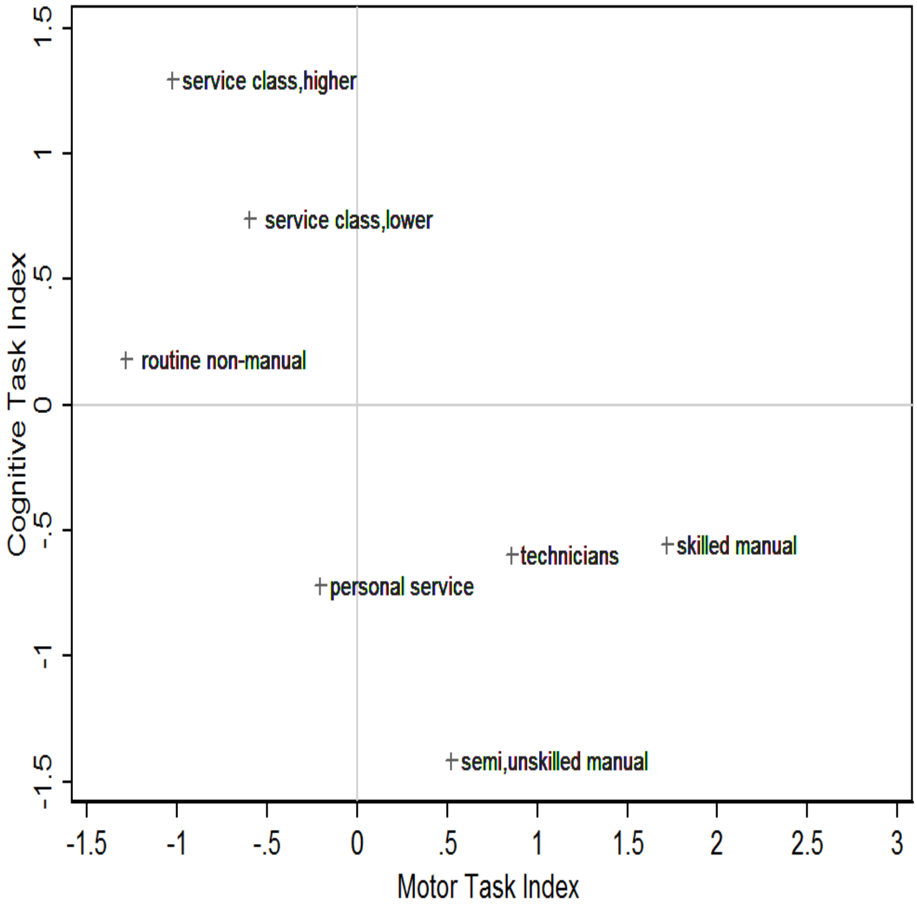
FIGURE 4.1: Occupations in the Task Space (SS)



Notes: The raw mean scores from pooled Skills Survey in 1997, 2001, 2006 and 2012 are standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average values.

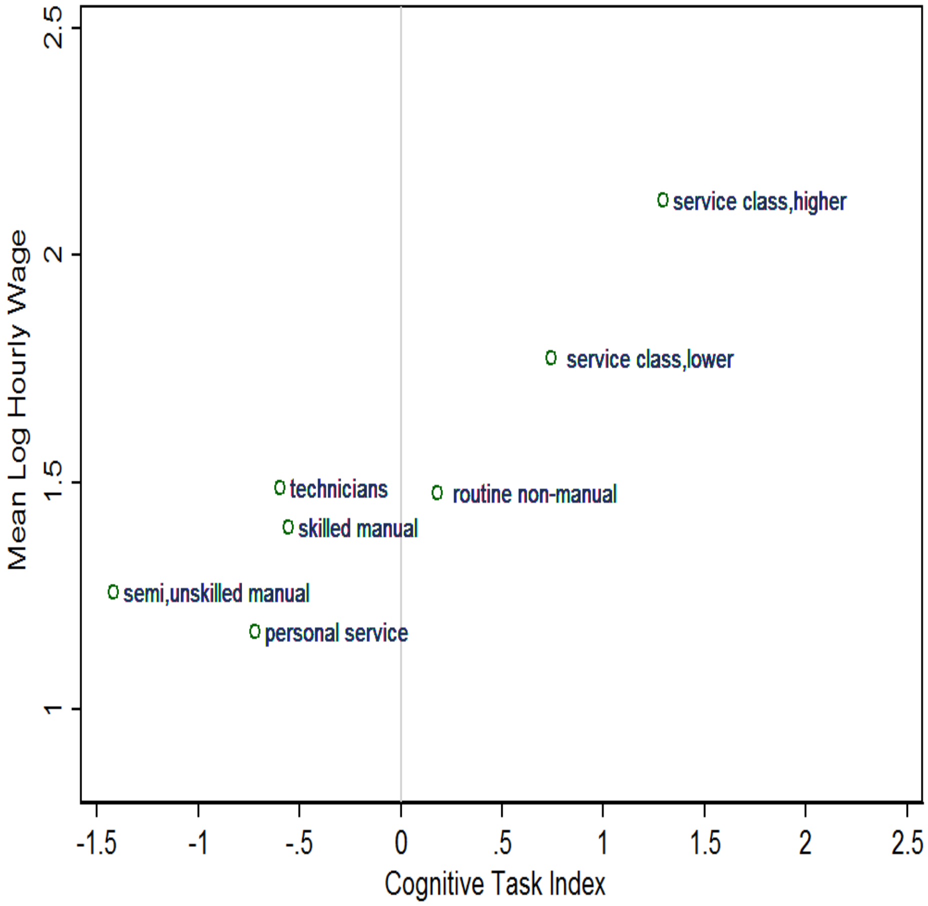
Standard Occupational Classification 2000; 1 Managers, e.g. All kind of managers, senior officials in national government 2 Professionals, e.g. Solicitors, chemist, civil engineers, doctors, researchers 3 Associate Professional and Technical, e.g. IT technicians, nurses, paramedics, artists, writers, sports players, air traffic controllers, musicians 4 Administrative, e.g. Civil service officers, assistants, clerks, receptionists 5 Skilled Trades, e.g. Plumbers, bakers, electricians, chefs 6 Personal Serv., e.g. Travel agents, hairdressers 7 Sales, e.g. Telephone salesperson, retail assistants 8 Operatives, e.g. Assemblers, clothing cutters, road construction operatives, van drivers 9 Elementary, e.g. Farm workers, labourers, couriers, waitress, cleaners

Figure 4.2: Occupations in the Task Space (BHPS)



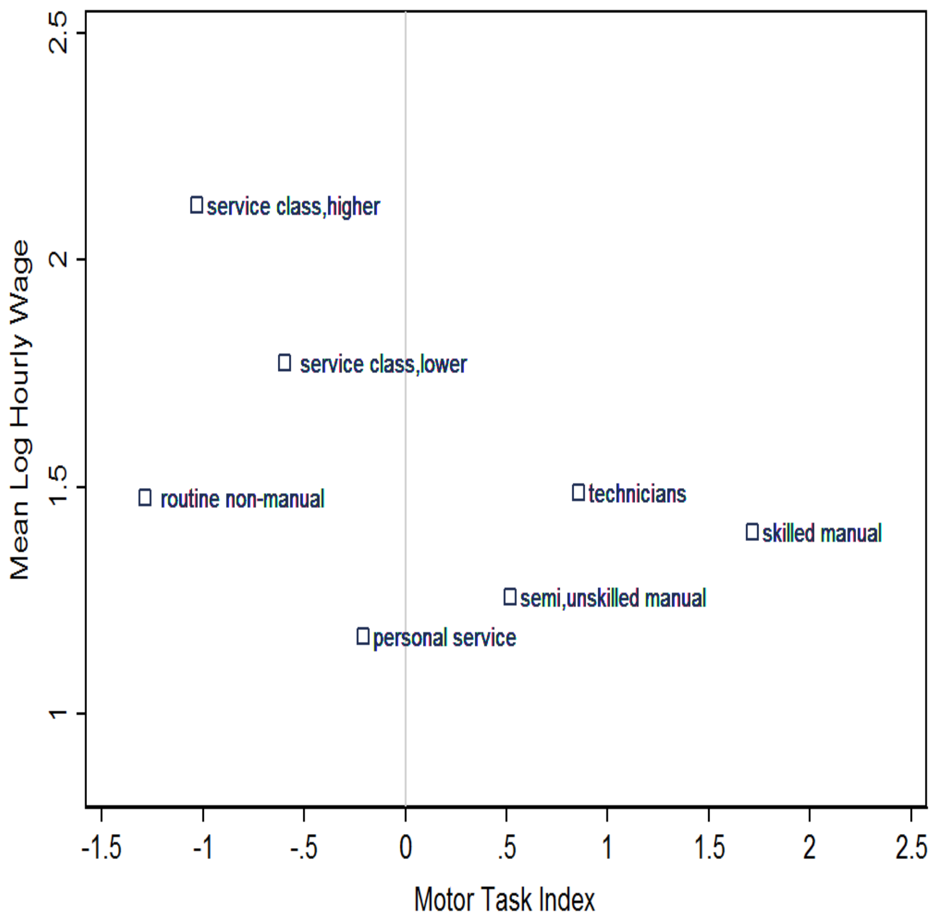
Notes: The 3-digit occupation cognitive and motor task complexity indices from pooled BHPS 1991-2008 are aggregated in one digit occupation level (Goldthorpe social class in present job) using BHPS sample weights and then standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average values.

Figure 4.3: Mean Log Hourly Wages by Cognitive Task Index



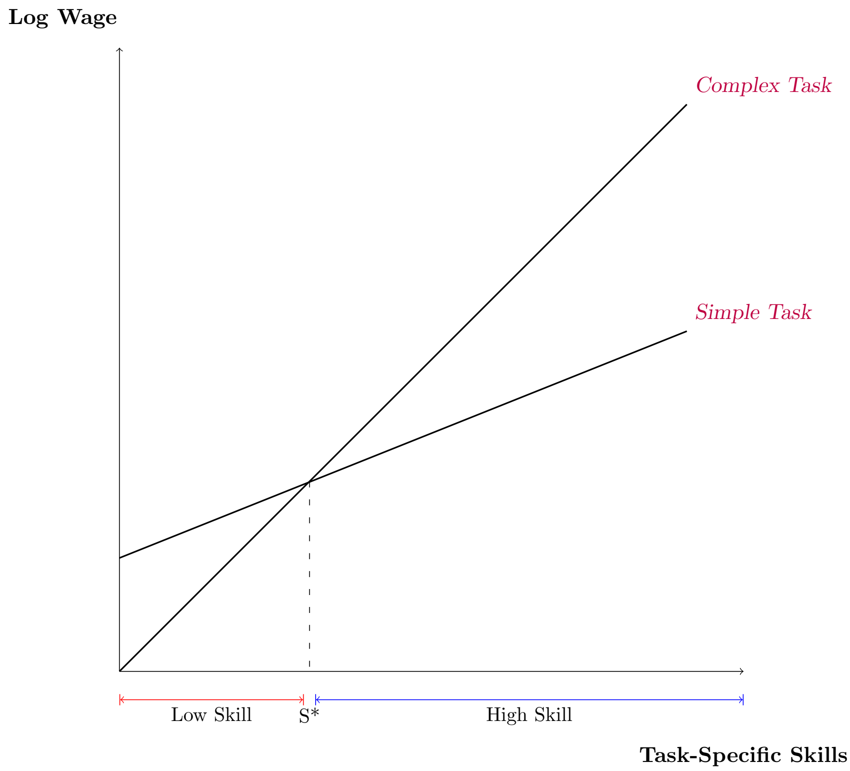
Notes: The 3-digit occupation cognitive task complexity index from pooled BHPS 1991-2008 are aggregated in one digit occupation level (Goldthorpe social class in present job) using BHPS sample weights and then standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average value for cognitive index.

FIGURE 4.4: Mean Log Hourly Wages by Motor Task Index



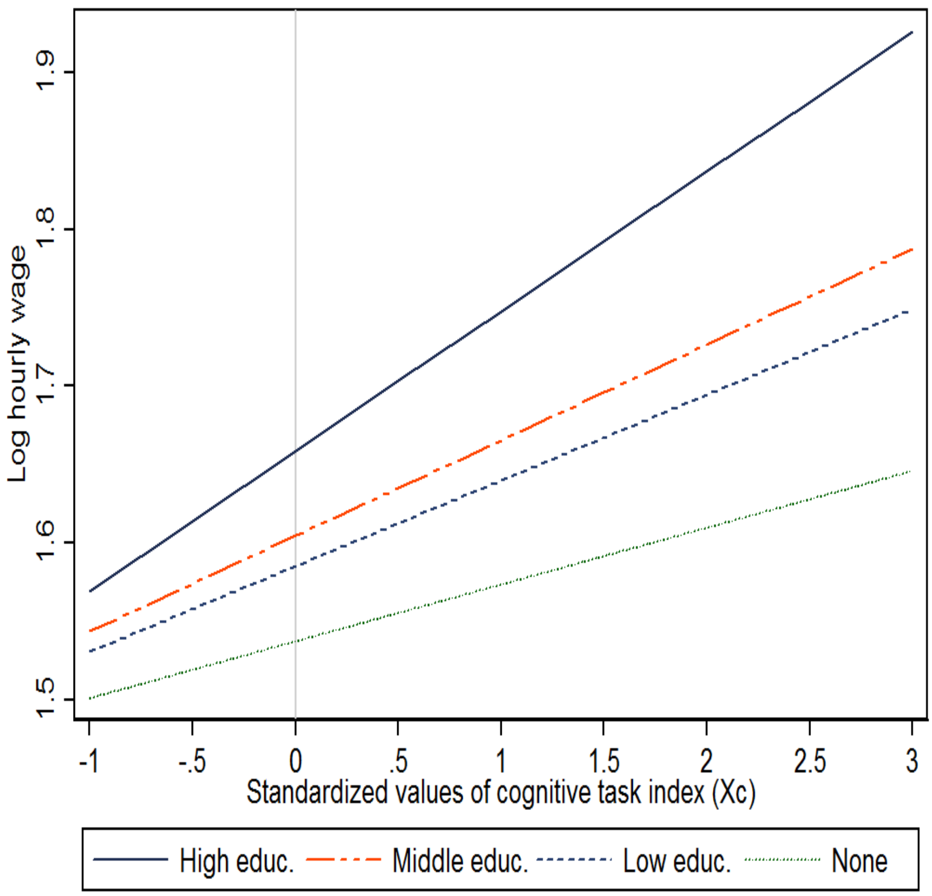
Notes: The 3-digit occupation motor task complexity index from pooled BHPS 1991-2008 are aggregated in one digit occupation level (Goldthorpe social class in present job) using BHPS sample weights and then standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average value for motor index.

Figure 4.5: Occupational Choice



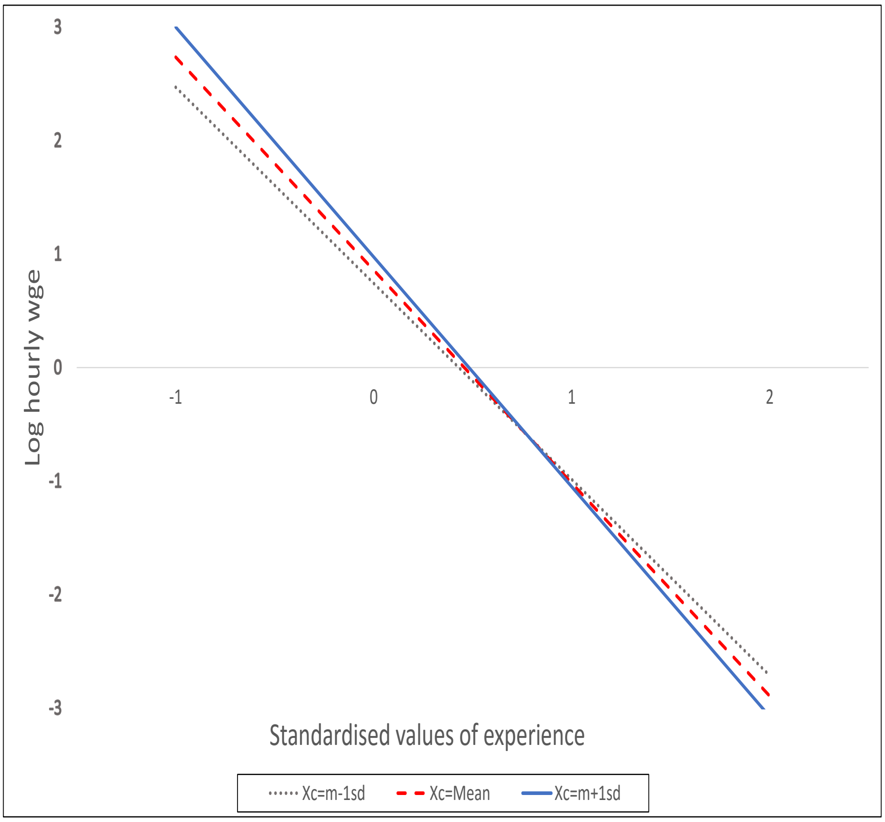
Notes: The graphs is taken from Yamaguchi (2014) and illustrates the 'trade off between intercept (guaranteed wage) and slope'. It shows that workers with skill level less than s* get higher wages in the simple task than in complex tasks, where as workers with skill level more than s* get higher wages in the complex task than in simple task.

Figure 4.6: Predicted Returns to Education Categories Across Cognitive Task Complexities



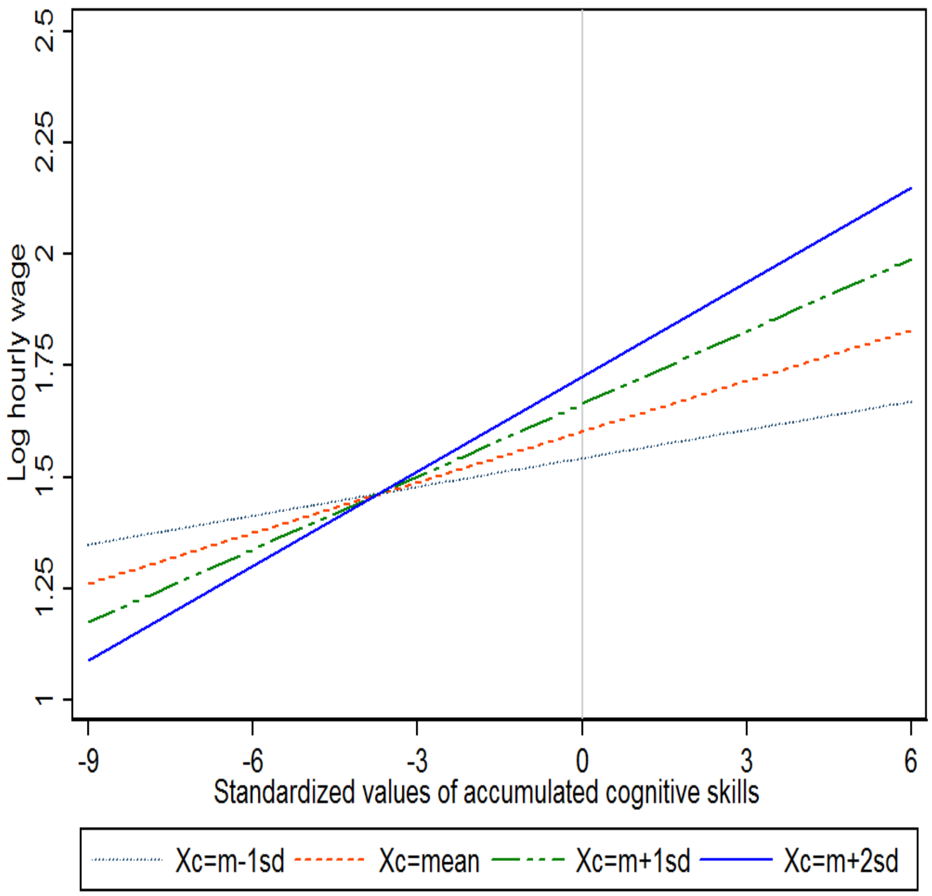
Notes: Cognitive task complexity index(Xc) is standardised such that the mean(m) and standard deviation(sd) are 0 and 1 respectively (The vertical line indicate the average value). The figure is plotted using Stata *margins* and *marginsplot* commands. Stata margins command computes log wage differences of education categories for various values of standardised cognitive task complexities running from mean-1sd to mean+3sd when other explanatory variables are held constant at their mean values. The simple slopes are significant for all levels. Education categories are as follows: High: teaching, first or higher degree; Middle: A Level, nursing or other higher; Low: CSE, GCSE or commercial qualification; None: no or other qualification or apprenticeship.

Figure 4.7: Predicted Returns to Experience Across Cognitive Task Complexities



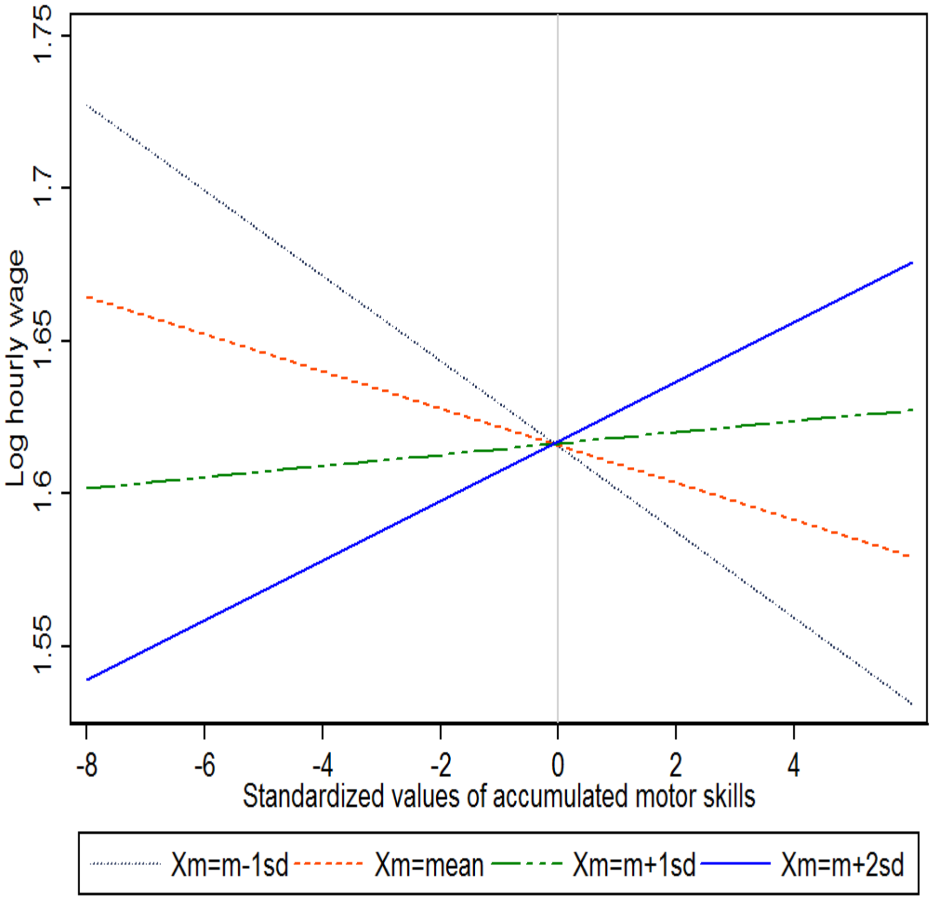
Notes: Cognitive task complexity index(Xc) and experience are standardised such that the mean(m) and standard deviation(sd) are 0 and 1 respectively.The figure is plotted by the amount of change in log wages with one unit change in experience when the value of cognitive task complexity is held constant at running from mean-1sd to mean+1sd and the value of other explanatory variables are held at their mean values.

Figure 4.8: Predicted Returns to Accumulated Cognitive Skills Across Cognitive Task Complexities



Notes: Cognitive task complexity index(Xc) and accumulated cognitive skills are standardised such that the mean(m) and standard deviation(sd) are 0 and 1 respectively (The vertical line indicate the average value). The figure is plotted using Stata *margins* and *marginsplot* commands. Stata margins command computes the amount of change in log wages with one unit change in accumulated cognitive skills when the value of cognitive task complexity is held constant at running from mean-1sd to mean+2sd and the value of other explanatory variables are held constant at their mean values. Intercepts for each of the simple regression lines are log wages when standardised accumulated cognitive skills is equal to -9 (mean-9sd). The simple slopes are significant for all values. The line indicate the average value.

Figure 4.9: Predicted Returns to Accumulated Motor Skills Across Motor Task Complexities



Notes: Motor task complexity index(Xm) and accumulated motor skills are standardised such that the mean(m) and standard deviation(sd) are 0 and 1 respectively (The vertical line indicate the average value). The figure is plotted using Stata *margins* and *marginsplot* commands. Stata margins command computes the amount of change in log wages with one unit change in accumulated motor skills when the value of motor task complexity is held constant at running from mean-1sd to mean+2sd and the value of other explanatory variables are held constant at their mean values. Intercepts for each of the simple regression lines are log wages when standardised accumulated motor skills is equal to -8 (mean-8sd). The simple slopes are only significant for Xm=m-1sd

4.8.2 Tables

Table 4.1: Cognitive and Motor Tasks in Skill Survey of Britain

COGNITIVE TASKS

ReadShort: Reading short documents such as short reports, letters or memos
ReadForm: Reading written information such as forms, notices or signs
ReadLong: Reading long documents such as long reports, manuals, articles or books
WriteForm: Writing material such as forms, notices or signs
WriteShort: Writing short documents (for example, short reports, letters or memos)
WriteLong: Writing long documents with correct spelling and grammar
Maths1: Adding, subtracting, multiplying or dividing numbers
Maths2: Calculations using decimals, percentages or fractions
Maths3: Calculations using more advanced mathematical or statistical procedures
Instruct: Instructing, training or teaching people, individually or in groups
Speech: Making speeches or presentations
Persuade: Persuading or influencing others
Client: Counselling, advising or caring for customers or clients
People: Dealing with people
ProbSolve: Thinking of solutions to problems
Analyse: Analysing complex problems in depth
Planoth: Planning the activities of others

MOTOR TASKS

Hands: Skill or accuracy in using the hands or fingers
Tools: Knowledge of how to use or operate tools/equipment/machinery
Stamina: Physical stamina (to work for long periods on physical activities)
Fault: Spotting problems or faults

Notes: SS data sample aged between 20-60.

TABLE 4.2: Cognitive Task Measures in the DOT and the SS

Dictionary of Occupation Titles Cognitive Task Measures	**Skills Survey** Cognitive Task Measures
DATA	
Synthesizing	Analysing Complex Problems in Depth
Coordinating	Counselling, advising or caring for clients
Analyzing	Instructing, Training or Teaching People
Compiling	Making Speeches or Presentations
Computing	Thinking of solutions to problems
Copying	Adding, subtracting, dividing numbers
Comparing	Calculations using decimals,percentages
PEOPLE	Calculations using more advanced maths
Mentoring	Reading forms, notices, etc
Negotiating	Reading short docs
Instructing	Reading long docs
Supervising	Writing forms, notices, etc
Diverting	Writing short docs
Persuading	Writing long docs
Speaking-Signalling	Persuading or Influencing Others
Serving	Dealing with People
Taking Instructions-Helping	Planning the activities of others
General Educational Development	
Reasoning	
Mathematics	
Language	
Aptitude	
Intelligence	
Verbal	
Numerical	
Temperament	
Influencing People	
Dealing With People	

TABLE 4.3: Motor Task Measures in the DOT and the SS

Dictionary of Occupation Titles **Motor Tasks Measures**	**Skills Survey** **Motor Task Measures**
THINGS	
Setting Up	Knowledge of how to operate tools
Precision Working	Skills or accuracy in using hands or fingers
Operating-Controlling	Physical stamina
Driving-Operating	Spotting problems or faults
Manipulating	
Tending	
Feeding-Offbearing	
Handling	
Aptitude	
Motor Coordination	
Finger Dexterity	
Manual Dexterity	
Eye-Hand-Foot Coordination	
Spatial	
Form Perception	
Color Discrimination	

Table 4.4: Principal Component Analysis Results

Cognitive Task Complexity		
Variable	Principal Component	Unexplained
Instruct	0.2216	0.6693
People	0.1839	0.7723
Speech	0.2492	0.5821
Persuade	0.2558	0.5596
Caring	0.1917	0.7527
ProbSolve	0.2298	0.6444
Analyse	0.268	0.5166
ReadForm	0.2275	0.6515
ReadShort	0.2875	0.4435
ReadLong	0.2998	0.3948
WriteForm	0.2561	0.5585
WriteShort	0.3028	0.3829
WriteLong	0.2862	0.4488
Maths1	0.1773	0.7884
Maths2	0.2047	0.7179
Maths3	0.1974	0.7377
Planoth	0.2289	0.6472
Motor Task Complexity		
Variable	Principal Component	Unexplained
Tools	0.5714	0.3234
Hands	0.5913	0.2755
Stamina	0.4812	0.5202
Faults	0.3038	0.8088

Notes: All observations from four waves of the Skills Survey 1997-2012 is used. PCA is run separately for cognitive and motor tasks.

Table 4.5: Summary Statistics, BHPS Sample

No of individuals	5850			
No of observations	43767			

	Mean	**Standard dev.**	**Min**	**Max**
Log hourly wages	1.623	0.004	0.001	4.969
Age (Experience)	38.590	0.078	16	64
Cognitive Task Index	-0.557	0.012	-6.918	4.183
Motor Task Index	0.212	0.006	-2.520	2.352
Accumulated Cognitive Skills	-3.380	0.082	-93.318	56.470
Accumulated Motor Skills	1.402	0.042	-37.799	32.873
Distribution of 1 digit occupations(%)				
Service class,higher	21.73			
Service class,lower	21.84			
Routine non-manual	7.66			
Personal service	1.74			
Technicians	11.94			
Skilled manual	14.33			
Semi,unskilled manual	20.76			
Distribution of Highest Qualifications (%)				
Higher degree (high educ)	3.69			
First degree (high educ)	13.77			
Teaching (high educ)	1.31			
Other higher qf (middle educ)	31.67			
Nursing qf (middle educ)	0.17			
Gce a levels (middle educ)	13.8			
Gce o levels or equiv (low educ)	17.62			
Commercial qf, no o levels (low educ)	0.22			
Cse grade 2-5,scot grade 4-5(low educ)	4.88			
Apprenticeship (none)	1.65			
Other qf (none)	0.56			
No qf (none)	10.66			

Notes: British Household Panel Survey 1991-2008. These statistics are based on the used sample of male full-time employees. Age is proxied for years of general labour market experience throughout the analysis. The BHPS sample weights are used.

Table 4.6: Linear Regression Models

Regressors	Pooled OLS (I)	Fixed Effects (II)	Mundlak(CRE) (III)
Xc*high educ	0.0110 (0.0203)	**0.0547***** (0.0159)	0.0547*** (0.0159)
Xc*mid educ	0.0599*** (0.0138)	**0.0271***** (0.00953)	0.0271*** (0.00953)
Xc*low educ	0.00963 (0.0149)	**0.0196*** (0.0114)	0.0196* (0.0114)
Xc*exp	0.139*** (0.0217)	**0.0819***** (0.0205)	0.0819*** (0.0205)
Xc*exp-squared	-0.125*** (0.0221)	**-0.0743***** (0.0210)	-0.0743*** (0.0210)
Xc*accumulated cognitive s.	0.0532*** (0.00562)	**0.0174***** (0.00310)	0.0174*** (0.00310)
Xm*high educ	-0.0283 (0.0204)	-0.00613 (0.0150)	-0.00613 (0.0150)
Xm*mid educ	-0.0208 (0.0138)	-0.00263 (0.00998)	-0.00263 (0.00998)
Xm*low educ	-0.0246* (0.0149)	-0.00593 (0.0117)	-0.00593 (0.0117)
Xm*exp	-0.0627*** (0.0223)	-0.0268 (0.0214)	-0.0268 (0.0214)
Xm*exp-squared	0.0663*** (0.0232)	0.0289 (0.0216)	0.0289 (0.0216)
Xm*accumulated motor s.	-0.0357*** (0.00552)	**-0.00675*** (0.00346)	-0.00675* (0.00346)
Cognitive Task Index (Xc)	0.131*** (0.0118)	0.0347*** (0.00861)	0.0347*** (0.00861)
Motor Task Index (Xm)	0.00688 (0.0117)	0.00499 (0.00927)	0.00499 (0.00927)
Experience	0.907*** (0.0242)	0.859*** (0.0669)	0.859*** (0.0670)
Exp-squared	-0.798*** (0.0248)	-0.938*** (0.0300)	-0.938*** (0.0300)
Accumulated cognitive s.	0.0771*** (0.00792)	0.0376*** (0.00580)	0.0376*** (0.00580)
Accumulated motor s.	-0.00304 (0.00658)	-0.00619 (0.00534)	-0.00619 (0.00534)
High educ.	0.372*** (0.0244)	0.120*** (0.0371)	0.120*** (0.0371)
Middle educ.	0.224*** (0.0182)	0.0658*** (0.0212)	0.0658*** (0.0212)
Low educ.	0.138*** (0.0194)	0.0460** (0.0234)	0.0460** (0.0234)
Year Dummies	Yes	Yes	Yes
Mundlak averages	No	No	Yes
Constant	1.362*** (0.0178)	1.287*** (0.0525)	0.893*** (0.123)
Observations	43,767	43,767	43,767
R-squared	0.495		0.516
Number of individuals		5,850	
H_0:Mundlak averages(δ)=0, p-value			0.000

Notes: British Household Panel Survey 1991-2008. The dependent variable is log hourly wages of male full-time workers aged 16-65. Robust (clustered) standard errors are in parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.6 Continued

Regressors	Pooled OLS (I)	Fixed Effects (II)	Mundlak(CRE) (III)
1992.year	0.00623	0.0323***	0.0323***
	(0.00710)	(0.00779)	(0.00779)
1993.year	-0.00431	0.0431***	0.0431***
	(0.00815)	(0.0124)	(0.0124)
1994.year	-0.0104	0.0628***	0.0628***
	(0.00892)	(0.0174)	(0.0174)
1995.year	-0.0294***	0.0688***	0.0688***
	(0.00933)	(0.0226)	(0.0226)
1996.year	-0.0246***	0.0995***	0.0995***
	(0.00943)	(0.0276)	(0.0276)
1997.year	-0.0443***	0.122***	0.122***
	(0.00954)	(0.0328)	(0.0328)
1998.year	-0.0451***	0.151***	0.151***
	(0.00996)	(0.0381)	(0.0381)
1999.year	-0.0199**	0.206***	0.206***
	(0.00976)	(0.0432)	(0.0433)
2000.year	-0.0127	0.244***	0.244***
	(0.0101)	(0.0484)	(0.0484)
2001.year	0.0128	0.295***	0.295***
	(0.0102)	(0.0540)	(0.0540)
2002.year	0.0387***	0.334***	0.334***
	(0.0107)	(0.0595)	(0.0595)
2003.year	0.0327***	0.357***	0.357***
	(0.0108)	(0.0650)	(0.0651)
2004.year	0.0301***	0.386***	0.386***
	(0.0111)	(0.0702)	(0.0702)
2005.year	0.0311***	0.410***	0.410***
	(0.0116)	(0.0756)	(0.0756)
2006.year	0.0308***	0.439***	0.439***
	(0.0116)	(0.0809)	(0.0810)
2007.year	0.0275**	0.459***	0.459***
	(0.0121)	(0.0862)	(0.0862)
2008.year	0.0198	0.476***	0.476***
	(0.0125)	(0.0916)	(0.0917)

Table 4.6 Continued

Regressors	Pooled OLS (I)	Fixed Effects (II)	Mundlak(CRE) (III)
mean(Xc*high educ)			0.117***
			(0.0302)
mean(Xc*mid educ)			0.233***
			(0.0137)
mean(Xc*low educ)			0.158***
			(0.0165)
mean(Xc*no educ)			0.170***
			(0.0207)
mean(Xc*exp)			0.109***
			(0.0415)
mean(Xc*exp-squared)			-0.0982**
			(0.0413)
mean(Xc*accumulated cognitive s.)			0.0366***
			(0.00998)
mean(Xm*high educ)			0.00346
			(0.0274)
mean(Xm*mid educ)			0.0223
			(0.0138)
mean(Xm*low educ)			0.0101
			(0.0166)
mean(Xm*no educ)			0.0205
			(0.0209)
mean(Xm*exp)			-0.0405
			(0.0442)
mean(Xm*exp-squared)			0.0455
			(0.0454)
mean(Xm*accumulated motor s.)			-0.0468***
			(0.0106)
mean(High educ.)			0.221***
			(0.0478)
mean(Middle educ.)			0.138***
			(0.0304)
mean(Low educ.)			0.0819**
			(0.0329)
mean(Exp)			-0.0412
			(0.0761)
mean(Exp-squared)			0.218***
			(0.0463)
mean(Accumulated cognitive s.)			-0.0230
			(0.0153)
mean(Accumulated motor s.)			-0.0293**
			(0.0147)

Table 4.6 Continued

Regressors	Pooled OLS (I)	Fixed Effects (II)	Mundlak(CRE) (III)
meanyeardum1			0.637***
			(0.148)
meanyeardum2			0.389***
			(0.148)
meanyeardum3			0.476***
			(0.137)
meanyeardum4			0.405***
			(0.140)
meanyeardum5			0.440***
			(0.136)
meanyeardum6			0.497***
			(0.132)
meanyeardum7			0.209*
			(0.120)
meanyeardum8			0.269**
			(0.124)
meanyeardum9			0.341***
			(0.108)
meanyeardum10			0.132
			(0.109)
meanyeardum11			0.129
			(0.104)
meanyeardum12			0.366***
			(0.106)
meanyeardum13			0.128
			(0.105)
meanyeardum14			0.0483
			(0.106)
meanyeardum15			0.0416
			(0.109)
meanyeardum16			0.00144
			(0.107)
meanyeardum17			0.0446
			(0.144)
Constant	1.362***	1.287***	0.893***
	(0.0178)	(0.0525)	(0.123)
Observations	43,767	43,767	43,767
R-squared	0.495	0.272	0.516
Number of individuals		5,850	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4.7: Robustness Checks (1) by Adding Mean Task Complexities

Regressors	Fixed Effects (I)	Mundlak(CRE) (II)
Xc*high educ	0.0547***(0.0159)	**0.0324***(0.0170)
Xc*mid educ	0.0271***(0.00953)	**0.0163**(0.00997)
Xc*low educ	0.0196*(0.0114)	**0.0125**(0.0114)
Xc*exp	0.0819***(0.0205)	**0.0776*****(0.0208)
Xc*exp-squared	-0.0743***(0.0210)	**-0.0708*****(0.0212)
Xc*accumulated cognitive s.	0.0174***(0.00310)	**0.0127*****(0.00340)
Xm*high educ	-0.00613(0.0150)	**-0.00598**(0.0155)
Xm*mid educ	-0.00263(0.00998)	**-0.00386**(0.0101)
Xm*low educ	-0.00593(0.0117)	**-0.00744**(0.0117)
Xm*exp	-0.0268(0.0214)	**-0.0252**(0.0214)
Xm*exp-squared	0.0289(0.0216)	**0.0272**(0.0216)
Xm*accumulated motor s.	-0.00675*(0.00346)	**-0.00702****(0.00341)
Cognitive Task Index (Xc)	0.0347***(0.00861)	0.0482***(0.00954)
Motor Task Index (Xm)	0.00499(0.00927)	0.00795(0.00951)
Experience	0.859***(0.0669)	0.852***(0.0669)
Exp-squared	-0.938***(0.0300)	-0.930***(0.0301)
Accumulated cognitive s.	0.0376***(0.00580)	0.0353***(0.00580)
Accumulated motor s.	-0.00619(0.00534)	-0.00656(0.00529)
High educ.	0.120***(0.0371)	0.118***(0.0370)
Middle educ.	0.0658***(0.0212)	0.0590***(0.0214)
Low educ.	0.0460**(0.0234)	0.0412*(0.0236)
Xc*meanXc		**0.0197*****(0.00601)
Xm*meanXm		**0.00800**(0.00559)
Year Dummies	Yes	Yes
Mundlak averages	No	Yes
Constant	1.287***(0.0525)	0.880***(0.123)
Observations	43,767	43,767
R-squared		0.517
Number of individuals	5,850	

Notes: British Household Panel Survey 1991-2008. The dependent variable is log hourly wages of male full-time workers aged 16-65. Robust (clustered) standard errors are in parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.8: Robustness Checks 2

Regressors	(I)	(II)	(III)
Xc*high educ	0.0547***(0.0159)	**0.0534*****(0.0153)	
Xc*mid educ	0.0271***(0.00953)	**0.0246*****(0.00942)	
Xc*low educ	0.0196*(0.0114)	**0.0186***(0.0111)	
Xc*exp	0.0819***(0.0205)	**0.0897*****(0.0199)	
Xc*exp-squared	-0.0743***(0.0210)	**-0.0825*****(0.0204)	
Xc*accumulated cognitive s.	0.0174***(0.00310)	**0.0185*****(0.00300)	
Xm*high educ	-0.00613(0.0150)		**-0.0228**(0.0150)
Xm*mid educ	-0.00263(0.00998)		**-0.00861**(0.0103)
Xm*low educ	-0.00593(0.0117)		**-0.0115**(0.0122)
Xm*exp	-0.0268(0.0214)		**-0.0628*****(0.0214)
Xm*exp-squared	0.0289(0.0216)		**0.0630*****(0.0217)
Xm*accumulated motor s.	-0.00675*(0.00346)		**-0.0117*****(0.00371)
Cognitive Task Index (Xc)	0.0347***(0.00861)	0.0372***(0.00854)	
Motor Task Index (Xm)	0.00499(0.00927)		-0.00359(0.00958)
Experience	0.859***(0.0669)	0.860***(0.0670)	0.867***(0.0674)
Exp-squared	-0.938***(0.0300)	-0.938***(0.0301)	-0.954***(0.0303)
Accumulated cognitive s.	0.0376***(0.00580)	0.0411***(0.00510)	
Accumulated motor s.	-0.00619(0.00534)		-0.0281***(0.00480)
High educ.	0.120***(0.0371)	0.118***(0.0367)	0.124***(0.0373)
Middle educ.	0.0658***(0.0212)	0.0635***(0.0205)	0.0399*(0.0209)
Low educ.	0.0460**(0.0234)	0.0446**(0.0227)	0.0311(0.0232)
Year Dummies	Yes	Yes	Yes
Constant	1.287***(0.0525)	1.290***(0.0520)	1.299***(0.0527)
Observations	43,767	43,767	43,767
Number of individuals	5,850	5,850	5,850

Notes: British Household Panel Survey 1991-2008. The dependent variable is log hourly wages of male full-time workers aged 16-65. Robust (clustered) standard errors are in parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Column (I) presents the original fixed effects estimates, column (II) introduces the estimates from the wage regression where there is only cognitive skill and task complexity measures are present whereas motor task measures are dropped, finally column (III) only controls for the motor skill and task measures.

Chapter 5

Conclusion

This thesis combined three applied essays (Chapters 2, 3 and 4) in the area of labour economics.

Chapter 2 explored the link between the increasing wage dispersion within the male workers with university degrees and the job skills that they apply in the workplace using data from the British Skill Survey. The residual wage gap analysis results demonstrate that a substantial part of the wage dispersion of university graduates is not attributed to standard skill measures. Moreover, they show that the task-based job skills approach could provide a promising way towards addressing the unexplained part of wage dispersion. On the other hand, if there existed a self selection of workers to occupations, estimates would provide a benchmark for no comparative advantage cases; they would not, however, provide consistent estimates under comparative advantage cases. This implies that the estimated effect of job skills would be bigger than its true value.

Chapter 3 aimed at estimating the direct impact of the removal of early academic tracking on the test performance of students who could have been (early) tracked if there had been no policy changes in Turkey. We found that when the potential variation in group-specific composition changes (particularly with regards to student characteristics and family socio-economic background) are not controlled for, there are an additional 13% decrease on the mathematics test scores of students who were exposed to the removal of early tracking. Although we could measure the overall efficiency gains from tracking from the available data, we were not able to disentangle the effect of the individual sources namely peer and teaching quality, and curriculum. Therefore, future research could address an interesting question which could not be addressed here (mainly due to data limitations): To what extent does peer quality, teaching quality, and academic curriculum individually contribute to the estimated effect of tracking?

Chapter 4 examined whether returns to cognitive and motor skills vary across occupations in the UK by employing the heterogeneous human capital framework of Yamaguchi (2014), who defines occupations as a bundle of cognitive and motor task indices. The results suggest that there are heterogeneous rewards to education, general labour market experience, and accumulated cognitive labour market skills across occupations. This implies that, when a highly cognitive skilled worker switches from an occupation with simple cognitive tasks to an occupation with complex cognitive tasks, his expected wage increases when all other characteristics are held constant. This can be rationalised with the following mechanism in the model: If a highly educated worker is employed in an occupation characterised by more complex cognitive tasks, he uses his human capital more, thereby increasing his productivity; and this, in turn, leads to him earning more. These results prove the importance of task-based channels of human capital accumulation and wage growth in the labour market, a topic with potential implications on why there is a pay penalty for highly skilled workers (particularly, for highly skilled immigrant workers) when they are overqualified for their jobs.

Overall, the findings in this thesis provide insights into human capital accumulation during formal education (through education policies), as well as in the labour market. In addition, the findings shed more light on the extent to which accumulated human capital translates into wage growth for workers.

Appendix A

A.1 Basic processing of the Labour Force Survey(LFS) and the Skills Survey(SS)

We use all four quarters of the LFS survey from 1997 to 2012. The LFS sample used in the analyses consists of male workers aged between 16-65 who are not self-employed but primarily employees and very few government employment&training programme attendees.

Education categories i.e. university and high school graduates are constructed from the variable reports the age workers left full-time education. University graduates are those who left full-time education at age 21 or later. High school graduates are those who left full-time education at age 16 to 20.

LFS questionnaire does not contain a question on the years of experience. Therefore, the experience variable is created by individual's age minus the variable '*the age when completed full-time education*' (Bell and Hart (1999)).
The years of education is generated by the variable '*the age when completed full-time education*' minus six.

We have the cross sectional data of the Skills Survey conducted in 1997, 2001, 2006 and 2012. The cross-section survey sample comprises of male workers aged between 20-60 in 1997 and 2001 and between 20-65 in 2006 and 2012. The self-employed respondents are excluded.
The occupation dummies created by '*One digit SOC (Standard Occupation Classification) in 2000*' variable. The nine occupation dummies are as follows: 'Managers', 'Professional Occupations', 'Associate Prof. and Technical Occupations', 'Administrative and Secretarial Occupations', 'Skilled Trades', 'Personal Service Occupations', 'Sales Occupations', 'Operatives', 'Elementary Occupations'.
The region dummies created by '*Region of Work*' variable. The twelve region dummies are as follows: 'North East', 'North West', 'Yorkshire and the Humber', 'East Midlands', 'West Midlands', 'East of England', 'London', 'South East', 'South West', 'Wales', 'Scottish Lowlands', 'Highlands and Islands.

Native-born workers are the worker who were born in the UK.

Table A.1: No of Observations by Education, LFS sample

Year	High school	University
1997	19,360	6,134
1998	21,405	6,972
1999	20,529	6,833
2000	19,362	6,487
2001	14,435	5,022
2002	18,943	6,798
2003	18,078	6,595
2004	17,198	6,412
2005	16,485	6,320
2006	15,826	6,295
2007	16,180	6,711
2008	15,808	6,584
2009	14,646	6,257
2010	13,981	6,287
2011	12,866	5,934
2012	12,898	5,939

Notes: LFS data sample of male full-time workers (excluding self-employed) aged between 16-65.

A.2 Construction of the Real Hourly Wage Series in the LFS and the SS

The LFS hourly wage series are constructed from the ‘ *hourpay*’ variable which is derived from ‘*gross weekly pay in main job*’ variable , ‘*usual hours of work*’ and ‘*usual hours of paid overtime*’ variables.[1] The*hourpay* variable applies to all employees and those on government scheme. In order to find the real hourly wages, initially in each year (four quarters) from 1997 to 2012, the hourly wage series are deflated by the quarterly CPI(Consumer Price Index). Secondly, the natural logarithm of real hourly wages is calculated. Finally, the real log hourly wages which are less than zero and more than four are dropped. The SS hourly wage series are constructed from the ‘ *GPAYP*’ variable which is derived from ‘*usual gross pay before all deductions for tax, national insurance and before any tax credits*’, ‘*the period covered by the gross pay*’, ‘*hours worked per week for the pay*’, ‘*usual hours of work per week*’ and ‘*usual gross hourly rate of pay*’ variables. [2] In the survey questionnaire, the workers are also asked their hourly wage rates , however the response rates are low. Therefore, the *GPAYP* variable is employed. This variable applies to all employees. In order to find the real wages, initially, the hourly wage series are deflated by the CPI(Consumer Price Index) of each corresponding periods. Secondly, the

[1] Labour Force Survey User Guide,Volume 3: Details of LFS variables 2011

[2] Skills Survey Technical Report, 1997.

natural logarithm of real hourly wages are calculated. Finally, the real log hourly wages which are less than zero are dropped and more than four are excluded.

Table A.2: Summary Statistics for All SS Sample

	1997	2001	2006	2012
Experience (Years)	18.718	18.926	20.020	20.011
	(10.732)	(10.955)	(12.175)	(12.524)
Age	38.560	38.941	40.340	40.652
	(10.635)	(10.735)	(11.748)	(11.997)
Log Hourly Wages	1.408	1.498	1.605	1.526
	(0.485)	(0.491)	(0.512)	(0.514)
90-10 Wage Gap	1.232	1.212	1.257	1.222
90-50 Wage Gap	0.654	0.683	0.736	0.706
Literacy Skills	-0.214	-0.148	0.196	0.141
	(1.093)	(1.071)	(0.869)	(0.887)
Communication-Influencing Skills	-0.214	-0.166	0.200	0.236
	(1.038)	(1.005)	(0.931)	(0.923)
Self-Planning Skills	-0.273	-0.161	0.095	0.053
	(1.165)	(1.098)	(0.899)	(0.923)
Problem Search and Solving Skills	-0.113	-0.054	0.084	-0.021
	(1.098)	(1.010)	(0.922)	(0.950)
Numeracy Skills	-0.225	-0.152	0.153	0.172
	(1.068)	(1.043)	(0.948)	(0.964)
	1997	2001	2006	2012
Sex of Respondent (%)				
Male	53.2	52.7	51.6	51.9
Female	46.8	47.3	48.4	48.1
Total	100	100	100	100
Employment (%)				
Full-Time	78.7	78.9	77.5	76.3
Part-Time	21.3	21.1	22.5	23.7
Total	100	100	100	100
Computing Skills at Work (%)				
Straightforward Comp. Skills	36.8	31.1	25.3	22.4
Moderate Comp. Skills	39.6	45.1	45.3	48.6
Complex Comp. Skills	18	17.7	21.1	20.5
Advanced Comp. Skills	5.6	6.1	8.3	8.5
Total	100	100	100	100
Routineness of Work (%)				
Routine work dummy=0	9.8	8.4	7.2	6.7
Routine work dummy=1	90.2	91.6	92.8	93.3
Total	100	100	100	100
Education Level Held (%)				
Level 4 and above	26.9	31.8	37.3	43.3
Level 3	17.9	23	23	21.7
Level 2	29	22.2	19.9	19.3
Level 1	8.2	9.8	10.3	10
No qualifications	18	13.2	9.5	5.7
Total	100	100	100	100
Holds a Degree (%)				
Degree=1	13.4	17.8	24.1	30.9
Degree=0	86.6	82.2	75.9	69.1
Total	100	100	100	100
One Digit Occupations/SOC2000 (%)				
Managers	12.9	13.6	15.5	16.2
Professionals	12.7	12.5	13.7	12.9
Associate Profes.	11.3	14.3	15.1	17.6
Administrative	15	14.6	12.9	10.8
Skilled Trades	10.9	10.8	9.2	8.3
Personal Serv.	6.1	6.9	7.4	8.3
Sales	8.7	6.9	7.1	7.7
Operatives	10.4	8.9	7.8	6.8
Elementary	12	11.4	11.4	11.5
Total	100	100	100	100
Number of Observations	2190	4000	4228	2374

Notes: SS data sample, employed male workers (excluding self-employed) aged between 20-65. The survey weights are used.

Appendix B

B.1 TIMMS and PISA Comparison

The empirical method in this study combines the TIMMS and PISA samples for Turkey. Since Turkish students did not take part in TIMMS 2003 but they participated in PISA 2003, we substitute the former for the latter. This subsection initially provides a brief comparison of the two surveys. It subsequently demonstrates that there is a high correlation between the two surveys despite the dissimilarities they possess. We then aim to explain how mathematics (mean) test scores are similar in TIMMS and PISA within the period of interest for Turkey although they may differ substantially for other countries. Eventually we verify that the two studies are comparable and hence substitutable for Turkey in 2003.

Despite sharing important common traits, PISA and TIMMS display some dissimilarities. The two main differences are worth considering. Firstly, the TIMMS student sample is chosen based on grades, in turn the PISA student sample is selected based on students' ages. Secondly, TIMMS' subject content, particularly in mathematics, has a school curricula focus whereas PISA's subject content has a priority on the functional aspect of mathematics in students' present and future life. This makes the coverage of the subject (mathematics) content areas slightly differ between the two studies. In fact,Wu (2010) demonstrates that the TIMMS item distribution by content area has more weight on algebra and measurement whereas PISA item distribution puts more emphasis on data and number. Depending on the countries' curricula topics, the differences in the content area distribution of the two studies may result in dispersion of the average test scores of the countries. She further finds that these two characteristics of the studies may give rise to variation between TIMMS and PISA mean mathematics test scores for the individual countries as well as the rankings of them internationally.

To estimate the formal relationship between the studies and the contribution of the age/years of schooling and content area differences on the predictability of one study using another, Wu (2010) fits several regression models, which are presented in Table B.1.
In the table, she examines the 2003 TIMMS and PISA average test scores for the countries which participated in both surveys in 2003. Regression model 1 reveals that there is an 84% correlation between the average test scores of the two studies. In addition, TIMMS mathematics mean scores alone explain 71% of the variation within the PISA mathematics mean scores. Model 2 in turn

shows that when TIMMS age [1] and content area distribution are included in model 1, 93% of the variation in PISA mathematics mean scores are explained and the correlation becomes 97%.

Table B.2 displays the mean TIMMS and PISA mathematics test scores for four countries, including Turkey. The two countries, Russian Federation and Sweden which took part in TIMMS and PISA 2003 and TIMMS 2007 and PISA 2006 provide a clear comparison of the mean results. The Table reveals that the mathematics mean test score achieved by Russian students is substantially higher in TIMMS than PISA for the corresponding periods whereas the mean test score in PISA is higher for the Swedish students for the given periods. On the other hand, on average Turkish students perform only slightly better in TIMMS 2007 then in PISA 2006. It is also seen that Jordan which has a mathematics mean score very close to Turkey in TIMMS throughout, has a considerably lower mean score in PISA 2006 than in TIMMS 2007.

The question now is if TIMMS 2003 and PISA 2003 are substitutable. According to Table B.1, the correlation between TIMMS 2003 and PISA 2003 for Turkey would depend on the years of schooling at the time of PISA testing and how students perform on different content areas. Since PISA assesses 15-year-old students and TIMMS examines 8th grade students (on average 14 years-old), the students who take PISA test have on average one year more schooling year than the students who take the TIMMS test. This might be an advantage for PISA results. However, the TIMMS 2007 mean test score is higher than PISA 2006 test score. It can be said that this does not affect the difference substantially.[2] Therefore the slight difference between the results might be caused by the content area differences. Since between TIMMS 1999 and TIMMS 2007 there were not any curricular changes in Turkey, it would not be expected that the TIMMS 2003 scores would have been considerably different in those years. In addition, Table B.2 shows a drop of the TIMMS scores of the other countries, in particular for Jordan from 1999 to 2003. This suggests that TIMMS 2003 mean score would have been even slightly smaller for Turkey. Consequently, it can be said that TIMMS 2003 would have had results very similar to those in PISA 2003 and therefore they are comparable. Although I acknowledge a small bias may spring from the projection.

Table B.1: Regression Models for Predicting PISA Mathematics Mean Scores

Regression Model	**To Predict (Dependent Variable)**	**Predictor(s) (Independent Variables)**	**Percentage of Variance Explained (R-squared)**	**Correlation**
1	PISA Mathematics	TIMMS Mathematics	71%	0.84
2	PISA Mathematics	TIMMS Mathematics TIMMS Age Content Advantage Index	93%	0.97
3	PISA Mathematics	PISA Reading	91%	0.95
4	PISA Mathematics	TIMMS Mathematics TIMMS Age Content advantage index PISA Reading	97%	0.99

Notes: The table is taken from Wu (2010), page 70.

[1] This is used as a proxy for years of schooling at time of PISA testing.

[2] 15-year-old students are in the first year of secondary school in Turkey. In the first year of secondary school, some of the students mainly take preparatory English classes.

Table B.2: Comparison of the mean TIMMS and PISA Results

Countries	TIMMS 1999	TIMMS 2003	PISA 2003	TIMMS 2007	PISA 2006
Turkey	**429**	-	**423**	**432**	**424**
	(4.3)		(6.7)	(4.8)	(4.9)
Jordan	**428**	**424**	**-**	**427**	**384**
	(3.6)	(4.1)		(4.1)	(3.3)
Russian Fed.	**526**	**508**	**468**	**512**	**376**
	(5.9)	(3.7)			(3.9)
Sweden	**-**	**499**	**509**	**491**	**502**
		(2.6)	(2.6)	(2.3)	(2.4)

Notes: The mean statistics are taken from 1999, 2003, 2006 and 2007 TIMMS and PISA reports.

B.2 Student and School Variables

Education in 1999,2003 and 2007 is processed to be comparable. "*How far did your mother go in school?*" and "*How far did your father go in school?*" The answer are 1 "Dropped out from primary education or did not go to school" 2 "Primary education/Lower secondary education" 3 "Secondary education" 4 "First stage of tertiary education(2 or 3 years)" 5 "Tertiary education (first degree, B.A. and second degree, M.S./M.A., PhD.)"

"*About how many books are there in your home*?" Number of books in 1999, 2003 and 2007 is processed to be comparable and then coded as 1 "0-10 books" 2 "11-25 books" 3 "26-100 books" 4 "101-200 books" 5 "more than 200 books"

Attitudes towards mathematics variables are the answers for the questions "*How much do you agree with the statement about learning mathematics?*"' The four statements for the four variables are 1 "I do well in mathematics", 3: "I enjoy learning mathematics" The answers for these type of questions are 1 "strongly disagree" 2 "disagree" 3 "agree" 4 "strongly agree"

Perceived importance of mathematics variables are the answers for the questions "*How much do you agree with the statement about learning mathematics?*"' The two statements for the two variables are 1 "I need mathematics to get a job", 2 "I need mathematics to get preferred school". The answers for this type of questions are 1 "strongly disagree" 2 "disagree" 3 "agree" 4 "strongly agree"

School characteristics variables

"*Is your school's instructional capacity affected by inadequacy of... ?*"The options are: 1 instructional materials 2 budget for supplies 3 school buildings and grounds 4 heating and lighting system 5 instructional space 6 equipment for handicapped pupils 7 computers for maths instruction 8 software for maths instruction 9 calculators for maths instruction 10 library tools for maths instruction 11 A-V resources for maths instruction. The answers for this type of questions are 1 "none" 2 "a little" 3 "some" 4 "a lot".

"*How many people live in the city, town, or area where your school is located?*" The answers are 1 "3000 people or fewer" 2 "3001 to15000 people" 3 "More than 15000 people".

Appendix C

C.1 Data Robustness

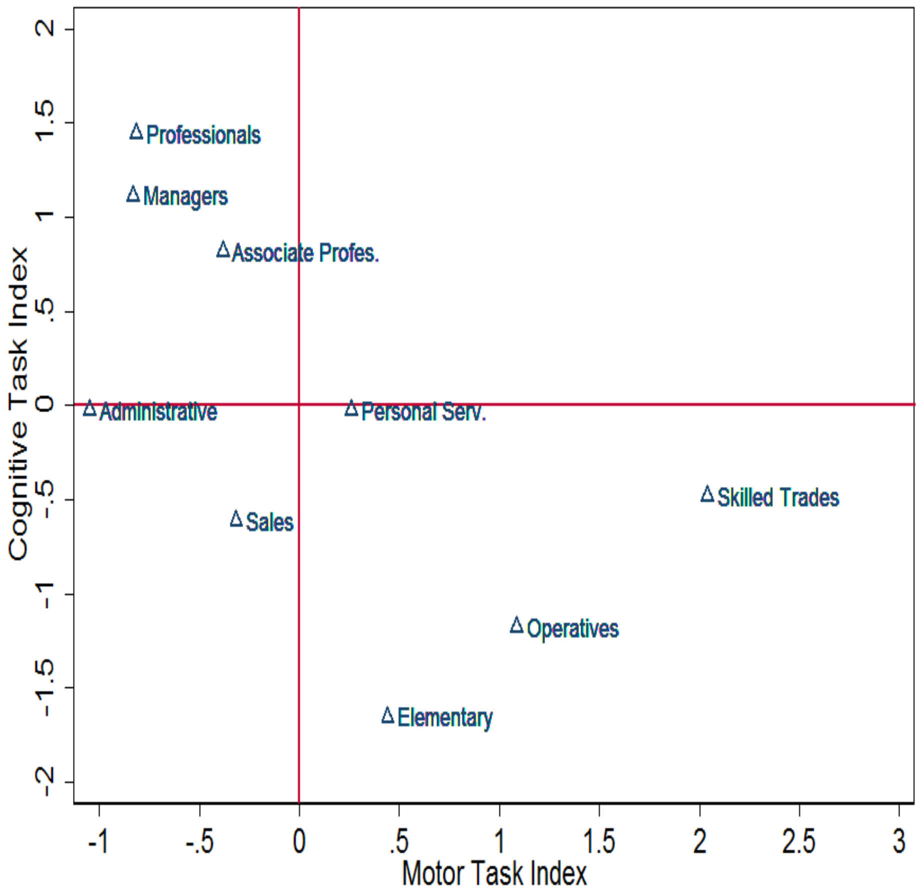
Table C.1: Correlation Coefficients of Motor Task Measures

Cognitive Task Complexity	Hands	Tools	Fault	Stamina
Hands	1.0000			
Tools	0.5987	1.0000		
Fault	0.2148	0.2703	1.0000	
Stamina	0.4578	0.3668	0.0918	1.0000

TABLE C.2: Correlation Coefficients of Cognitive Task Measures

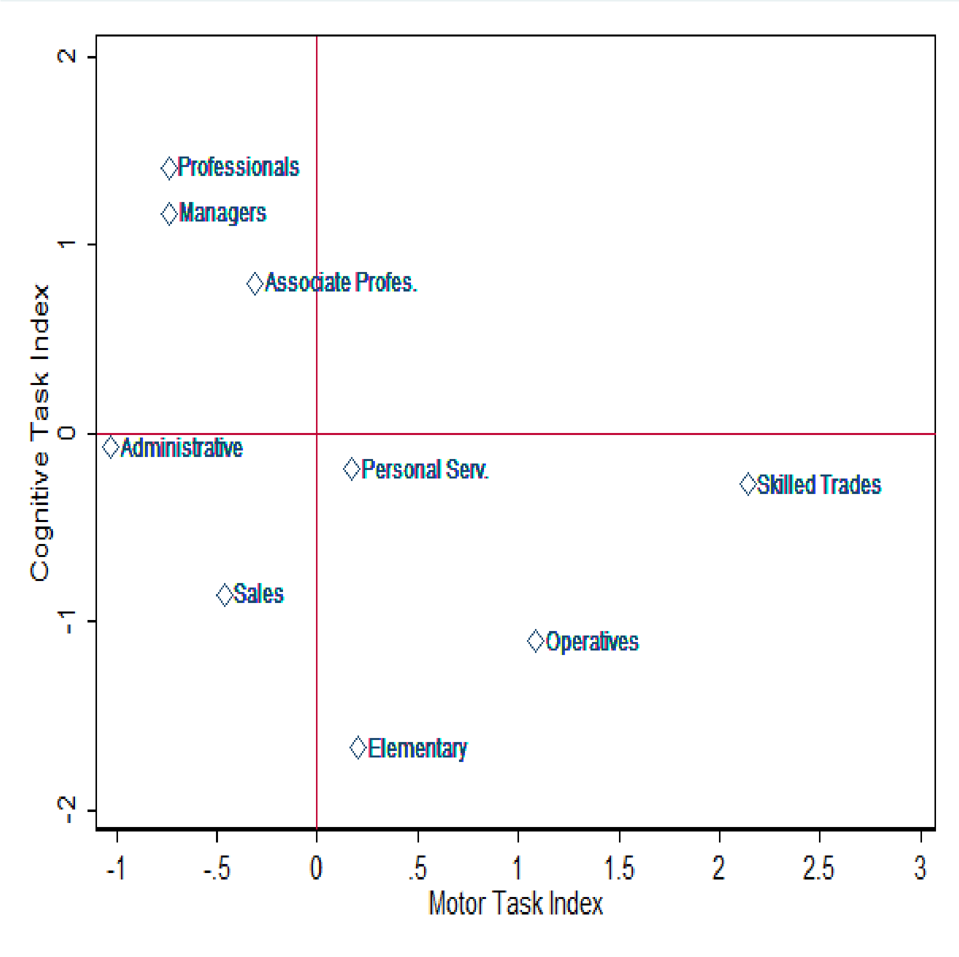
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1.Instruct	1																
2.People	0.3211	1															
3.Speech	0.4526	0.3003	1														
4.Persuade	0.4711	0.3886	0.5914	1													
5.Caring	0.3473	0.5039	0.3268	0.3872	1												
6.ProbSolve	0.3301	0.2215	0.2928	0.3835	0.2196	1											
7.Analyse	0.352	0.2281	0.4333	0.4517	0.2634	0.5971	1										
8.ReadForm	0.2643	0.2365	0.2016	0.2438	0.2534	0.3042	0.2958	1									
9.ReadShort	0.3265	0.3117	0.3556	0.3691	0.3129	0.3723	0.424	0.651	1								
10.ReadLong	0.3521	0.2803	0.44	0.4078	0.3086	0.3953	0.5277	0.5113	0.6873	1							
11.WriteForm	0.3028	0.2617	0.2948	0.2997	0.2974	0.3101	0.3341	0.5664	0.5647	0.5357	1						
12.WriteShort	0.3333	0.3244	0.4602	0.4373	0.3351	0.3851	0.4759	0.4386	0.6487	0.6288	0.6199	1					
13.WriteLong	0.3115	0.2682	0.5178	0.4279	0.2874	0.3336	0.4984	0.3333	0.5121	0.6518	0.4835	0.687	1				
14.Maths1	0.1437	0.1469	0.1575	0.1992	0.1145	0.2639	0.2572	0.2461	0.2692	0.2395	0.2535	0.2759	0.2316	1			
15.Maths2	0.1687	0.1319	0.2464	0.2542	0.1167	0.3059	0.3519	0.2174	0.2975	0.3087	0.2442	0.3369	0.3214	0.7423	1		
16.Maths3	0.1871	0.0772	0.286	0.2328	0.0871	0.2717	0.4044	0.1814	0.264	0.3405	0.2237	0.3066	0.379	0.5075	0.6616	1	
17.PlanOthers	0.5123	0.2728	0.4258	0.483	0.289	0.3537	0.3828	0.2365	0.3223	0.3613	0.2957	0.3778	0.3761	0.1908	0.2274	0.2369	1

Figure C.1: Occupations in the Task Space (SS)-Robustness 1



Notes: The raw mean scores from pooled Skills Survey in 1997, 2001, 2006 and 2012 are standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average values.

Figure C.2: Occupations in the Task Space (SS)-Robustness 2



Notes: The raw mean scores from pooled Skills Survey in 1997, 2001, 2006 and 2012 are standardised such that the mean and standard deviation are 0 and 1 respectively. The lines indicate the average values.

Standard Occupational Classification 2000; 1 Managers, e.g. All kind of managers, senior officials in national government 2 Professionals, e.g. Solicitors, chemist, civil engineers, doctors, researchers 3 Associate Professional and Technical, e.g. IT technicians, nurses, paramedics, artists, writers, sports players, air traffic controllers, musicians 4 Administrative, e.g. Civil service officers, assistants, clerks, receptionists 5 Skilled Trades, e.g. Plumbers, bakers, electricians, chefs 6 Personal Serv., e.g. Travel agents, hairdressers 7 Sales, e.g. Telephone salesperson, retail assistants 8 Operatives, e.g. Assemblers, clothing cutters, road construction operatives, van drivers 9 Elementary, e.g. Farm workers, labourers, couriers, waitress, cleaners

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