University of Kent

Doctoral Thesis

Human Capital Mismatch in the British Labour Market

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

School of Economics

Friday 29th April, 2022

UNIVERSITY OF KENT

Abstract

Division of Human and Social Sciences
School of Economics

Doctor of Philosophy

Human Capital Mismatch in the British Labour Market

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This Thesis explores Human Capital Mismatch in the British labour market. It constructs a novel measure of mismatch based on the skill and jobs distributions. Higher-skilled workers are in mismatch if they work in a lower-productivity job. Results show that mismatch distorts skill prices and its instance increases significantly after the Great Recession in the UK using data from the BHPS/UKHLS. To verify if this is theoretically supported, I use a job search model to identify mismatch capturing unmeasured parts of individual skill. The main theoretical contribution supports that mismatch comes from search frictions in the market. The ranking of workers differs between the work and skills distributions. Further, I replicate the empirical analysis for those born in 1970 using the British Cohort Study 1970. Controlling for their cognitive and non-cognitive skills does not translate in lower incidence of mismatch. Finally, the Thesis presents two case studies. First, it pays particular attention to female workers. They are more likely to be in mismatch because they face more frictions and their skills may be underutilised. Hence, this work explores the determinants of female employees mismatch. The incidence of female mismatch varies from 13% to 34% depending on the control group. Second, it intersects the female public-sector employment with mismatch. It finds that the public sector acts as a waiting room for a better job for higher-skilled female workers.

Preface

"Are we in the "right" job? Can we accept any better offers for job? Inequalities still exist. How could we break down the barriers they raise and allow people to use their skills at their full potential?" These were the questions that motivated my thinking for this Thesis when I started my PhD training. I hope this work sheds more light and offers some interesting insights.

I could not have achieved any piece of this work without the support of many people. First, I need to acknowledge the patience, support and guidance of my supervisors, Amanda Gosling and Olena Nizalova. Without them I could have been lost throughout this long journey. Second, this work has significantly improved from the feedback of our Kent community. To improve certain parts of different chapters, discussions in the MicroForum at the University of Kent have been beneficial. In particular, I would like to thank each and every participant, my fellow students and faculty. Comments from Amrit Amirapu, Bansi Malde, Anirban Mitra, Irma Clots-Figueras, Fernanda Leite Lopez de Leon and Zaki Wahhaj have been very useful. Third, during my third year of studies I participated in the GLO Virtual Young Scholar Program. I closely worked with my advisor Prof. Nick Drydakis, whose support for chapter 5 is greatly acknowledged. Fourth, some papers have been presented externally to conferences and workshops. I do recognise the feedback received from participants and discussants there. Finally, I want to thank my friends and family who have been there for me throughout this long journey. They were ready to hear my complaints, offer any piece of advice and be happy when I was happy.

The financial support from the VC Scholarship Award is greatly acknowledged. If I had not been awarded the scholarship, I could not pursue any doctoral studies.

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List of Abbreviations

BCS70	**B**ritish **C**ohort **S**tudy 1970
BHPS	**B**ritish **H**ousehold **P**anel **S**urvey
GPG	**G**ender **P**ay **G**ap
HCM	**H**uman **C**apital **M**ismatch
HCT	**H**uman **C**apital **T**heory
JA	**J**ob **A**nalysis
JCM	**J**ob **C**ompetition **M**odel
OMT	**O**ccupational **M**obility **T**heory (or Job/Career Mobility Theory)
RM	**R**ealised **M**atching
UKHLS	**UK** **H**ousehold **L**ongitudinal **S**tudy (or ’Understanding Society’)

Introduction

Wage inequality in the UK has shrunk during the last two decades across most parts of the distribution. This change is mirrored in shifts both in within- and between-group inequality. On the one hand, the changes in within-group inequality is the wage dispersion among employees with similar characteristics. On the other hand, the between-group inequality is the different returns to skills for different groups of workers (e.g. high- vs. low-skilled workers). One way to interpret these wage premia is in terms of the employment access; different groups of workers have different access to jobs given their (unobservable) characteristics.

The labour market accommodates both “good" and “bad" jobs. If one sorts them by average wage and skill requirements, a “good" job would stand at the upper part of the distribution. To this end, skill-intensive occupations have a greater fraction of better jobs. Yet, employees with similar (or identical) background are seen in both types of job. This framework motivates discussions on wage dispersion in the literature (e.g. Card et al. (2018), Mortensen (2003), and Burdett and Mortensen (1998)).

A well-paid job usually requires investing in additional education. According to Human Capital Theory, education can be seen as an investment producing knowledge which results in higher productivity. Higher productivity leads to greater earnings (Mincer, 1974; Becker, 1964). In particular, during schooling, individuals accumulate skills necessary to perform tasks. The main prediction of this model acknowledges that this accumulation results in increasing earnings. On the contrary, others have seen education as a tool to select graduates. According to Spence (1973) schooling is a filter. It allows graduates to signal their abilities to potential employers. If education has this dual role of knowledge acquisition and individual selection, why are similar workers seen in both types of job? Is it because people have different preferences and jobs present different non-wage attributes?

Even though the literature studies the role of education on wage determination in the last few decades, we still know little about individual sorting into jobs based on skills. Individuals enter the labour market with different endowments of skills. Their allocation to employers is not random. Similarly, employers remuneration standards are not homogeneous and wage dispersion persists. This may be due to dissimilarities across occupations and differences among workers. For example, differences in prior training required for a particular task, how risky a job is or production technology used may contribute to different wages for different workers. If further education guarantees a better-paying occupation, returns to education would be greater to higher-productivity jobs. To this end, higher-skilled workers would be employed in higher-productivity firms; marginal skill and productivity would be in equilibrium.

If we look at the average wage ratio between different groups of workers, e.g. high- vs. low-skilled, we may observe that returns are not always consistently higher than middle- vs. low-skilled workers. This pattern may be more accurate to lower-productivity jobs and reveals a structural inequality. For example, a PhD graduate in History (i.e. a high-skilled worker) may not be able to find a job immediately. If their parents come from the lower-end of the income distribution, they are less likely to afford spending time in unemployment. As a result, they will prefer to work in a lower-productivity job, until a "better" job arrives. This *mismatch* shows a distortion in the wages; the high-skilled worker accepts a lower wage than their adequately matched peers. In other words, part of the overall returns to education operate through an alternative channel. Varying returns to education across different occupations may be due to frictions in the labour market. These frictions may be related to the job search of heterogeneous employees for heterogeneous employers.

Contributions This Thesis explores whether workers could work in a better job. It identifies mismatch based on the skill and jobs distributions. Higher-skilled workers are identified to be in mismatch if they work in a lower-productivity job.

The Thesis overviews theories of Overeducation in Economics and their empirical methodologies of mismatch measurement. These measurement methods are subject to several limitations. Therefore, I construct a novel measure of mismatch that captures individual skills heterogeneity in more than one dimension (chapter 2). Analysis shows that human capital mismatch distorts prices of skills. This empirical wage distortion is verified theoretically using a model allowing for simultaneous heterogeneity of workers and firms. Skills are measured in a both discrete and continuous way. The model shows that search frictions generate mismatch. Individual worker's position differs between the skills and job distributions (chapter 3). Finally, this research pays particular attention to a group of workers that face more frictions and whose position may be compromised even before entering the labour market. In the UK, women are concentrated in particularly lower skills-demanding jobs than men. This contributes to them being exposed to a greater probability of mismatch. This is why, chapter 4 looks at the extent of and reasons for female mismatch. Furthermore, chapter 5 explores the mismatch in the public-sector employment. It reveals that public sector may act as a waiting room for a better job or serve as a second-best alternative.

This novel index of mismatch, proposed in this Thesis, depends on the correct estimate of the returns to education. If they are downward biased, the incidence will be underestimated. Relying on a richer definition of human capital, results show that a favoured parental background does not guarantee a matched job. This finding is robust whether we control for individual cognition and non-cognition (chapter 6). One would expect that, controlling for individual cognitive and non-cognitive skills, the instance of mismatch would decrease. Instead, results show the opposite and indicate an additional source of frictions.

Thesis Road Map

This section outlines the structure of this Thesis. The Thesis consists of six chapters. Each chapter is written to be a self-contained paper.[1] Hence, I apologise a priori for potential repetitions throughout the Thesis. Figure 1 illustrates how the chapters are connected. This section describes the contribution of each chapter and their main findings.

Chapter 1 sets the discussion framework of mismatch. It reviews the literature and summarises how scholars in Economics have studied mismatch. To this end, it reports theories and approaches ways to empirically measure mismatch.

Taking into consideration the literature review, chapter 2 constructs an alternative empirical method to measure mismatch. It is a novel multidimensional tool to measure human capital mismatch accounting for individual skills heterogeneity in more than one dimension. It identifies workers in mismatch if their skills exceed the median estimates of the more skills-demanding occupation. Hence, it considers the relative horizontal position of an individual in the skills and work distribution. As I explain this differs from the traditional horizontal overeducation measures. In the analysis, I use the BHPS and UKHLS data to study the extent of mismatch in the British labour market from 1991-2015. Findings report that the incidence of mismatch fluctuates at the beginning of the panel. In the post-Great Recession period, the magnitude sharply increases contributing to regional disparities. Finally, I exploit the panel aspect of the data and study the transitions among occupations and matching status. Workers move to different occupations because of relative skills changes (e.g. development through training or skills atrophy) in the job distribution. This may imply that skills distribution may not move as fast as the job distribution.

Is the empirical strategy consistent with the theory? To what extent estimates of the skill distribution are biased due to mismatch? Chapter 3 shows that job search frictions generate mismatch between firms and workers. Extending the Burdett and Mortensen (1998) model, heterogeneity of both workers and firms is allowed. The ranking of workers differs in work and skills distributions. This chapter further simulates the model. The simulation shows that mismatch comes from frictions in the market. It shows that women face more frictions and firms' share is only important when frictions increase. Yet, data used in earlier chapters imply that human capital

[1] This is the reason why sometimes the words *paper* and *chapter* may be used interchangeably.

or skills are not discrete. To capture for this continuity, I replicate the earlier model allowing for a continuous measure of skills. Findings show that higher-skilled workers have a lower expected wage when more friction occur. However, lower frictions move the model closer to a perfectly competitive framework, where mismatch drops.

Chapter 4 explores the extent of and reasons for female labour market mismatch. This chapter focuses on women, because they face more frictions and are concentrated in lower-skilled jobs than men. This signals an underutilisation of their potential by the market. Hence, they are more likely to be in mismatch even before entering the labour market. This paper replicates the identification strategy of chapter 2, but it changes the control group. To this end, I generate three indices which identify mismatch for women. First, in a restricted female subsample (it consists of female employees only). Second, a counterfactual case, where women are seen in the male labour market. This index eliminates potential discrimination prior to their entrance. Third, women are seen relative to median employee in the British workforce. The incidence of mismatch is estimated between 13% to 34% depending on the control group. The final part of the exercise investigates the determinants of female mismatch. Lone parenthood and number of children are positively related to mismatch. Recent entrance in the labour market, also increases the mismatch, but its effect anticipates over time. Regional unemployment instances contribute to a matching failure.

Chapter 5 looks at the female public servants and mismatch. It extends the findings of female workforce by taking into account the endogenous self-selection in jobs. The British public sector offers a few low-skilled jobs and employs high-educated, predominantly female, workers. First, the analysis reports market flows and finds greater mobility for women proportionately between sectors than men. However, greater in-/out-flows to/from private sector are observed regardless the gender of the employee. Second, to report the incidence of mismatch, I replicate in chapter 4 three indices of female HCM within the public sector. Once comparing women to the median employee, a sizeable incidence of mismatch arises due to a negative selection. Specifications using the selection model for the public sector illustrate a systematically higher magnitude of mismatch. Pooled results seem to dominate when women are observed in the male labour market or in a restricted subsample. Yet, the incidence of mismatch in the public sector may be counterintuitive and one would not expect any or very low rates. This is the reason why I explore which occupations have more workers in mismatch. The map of occupations in mismatch supports that the public sector is more attractive as a waiting room for highly-qualified graduates. In this sector, they queue less time until they find a good job. Hence, this chapter raises awareness for policy implications regarding the allocation of jobs for women.

Do individual skills *per se* matter? Chapter 6 examines the intersection of unobserved productivity and mismatch in the UK. The British Cohort Study 1970 allows using the cognitive and non-cognitive test scores throughout childhood to capture the individual heterogeneity. In this framework, human capital adopts a richer definition. HC includes the level of education

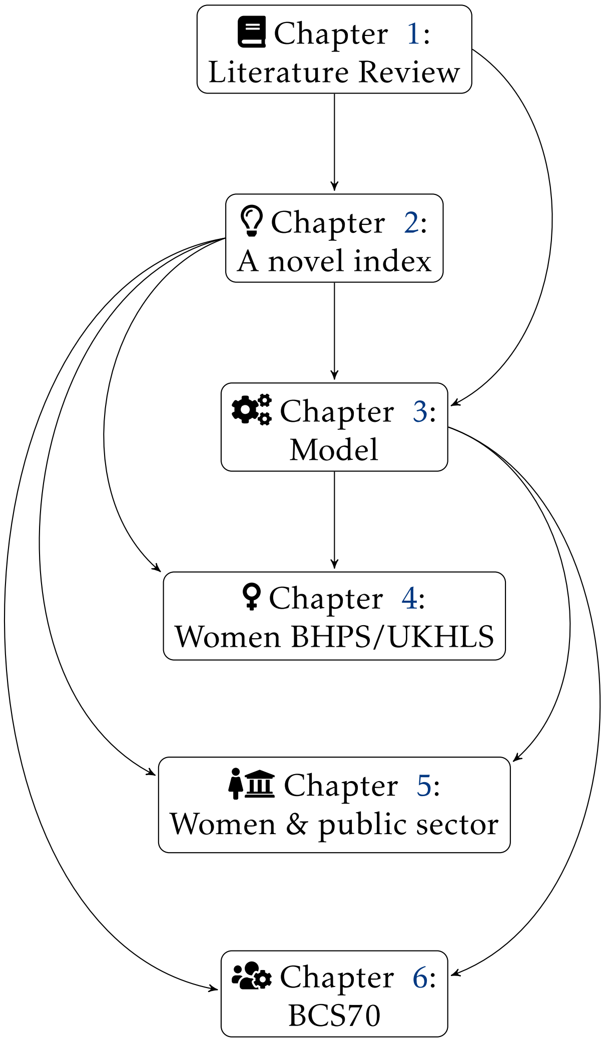


FIGURE 1: Thesis roadmap

and controls for cognition and non-cognition. The identification strategy of mismatch remains the same as before; an individual fails to match as in chapter 2. The incidence of mismatch is compared to earlier estimates based on BHPS. Results show that cohort members mismatch does not vary much over time. When controlling for cognitive and non-cognitive skills, the incidence significantly increases. Evidence suggests that unobserved productivity does not generate mismatch in the market. Data allow to connect parental background and offspring mismatch. To this end, I explore the effect of parental background on getting a graduate job using propensity score matching on average individual characteristics. Findings show that higher skilled parents increase the probability of being in match. When controlling for skills, the increasing pattern persists but the effect changes depending on the functional form. This verifies the earlier result showing an increasing magnitude of mismatch when accounting for skills.

Chapter 1

Mismatch in Economic Literature*

Abstract

This chapter reviews the literature in Economics on the topic of job-worker mismatch. It focuses on the theories of overeducation and skills mismatch. Finally, it outlines the empirical methods of measuring mismatch.

By definition, any mismatch occurs when an employee's observed qualifications/skills do not fit with the stated requirements of a specific job at a given time. In other words, the worker's individual characteristics (e.g. personal expectations and background) do not match with the job's requirements (McMillen, Seaman, and Singell, 2007; Tsang and Levin, 1985). Since the initial job requirements may differ from the job content or qualifications, *per se*, education becomes a weak identifier of the individual matching status. For instance, employees' characteristics may further include (innate) ability and (non-formal or informal) skills, cultivated through schooling or prior exposure to the labour market (Mavromaras, McGuinness, and Fok, 2009). Hence, human capital is comprised of education, ability and skills. Given its components, human capital mismatch has attracted less attention, because there is no one single measure that can capture all of its components objectively. There are four main theories that drive the potential explanation of mismatch. First, the *Human Capital Theory*, originated by Becker (1964) and Mincer (1974). Second, the *Job Competition Model*, mainly supported by Thurow (1975). Third, the *Assignment Theory* (Sattinger, 1993; Sattinger and Hartog, 2013). Finally, the *Occupational (Career/Job) Mobility* theory (Sicherman and Galor, 1990; McMillen, Seaman, and Singell, 2007), based on the Matching Theory (Jovanovic, 1979b; Pissarides, 2000) and the Signalling Theory (Spence, 1973), completes this picture. Figure 1.1[1] places theses theories on a map between worker competition and worker's ability and capital substitutability.

*This is the only chapter in the Thesis that may *not* stand as a self-contained paper.

[1]Where this Thesis fits will become more clear in the coming chapters. The final chapter discusses its exact position on figure 1.1.

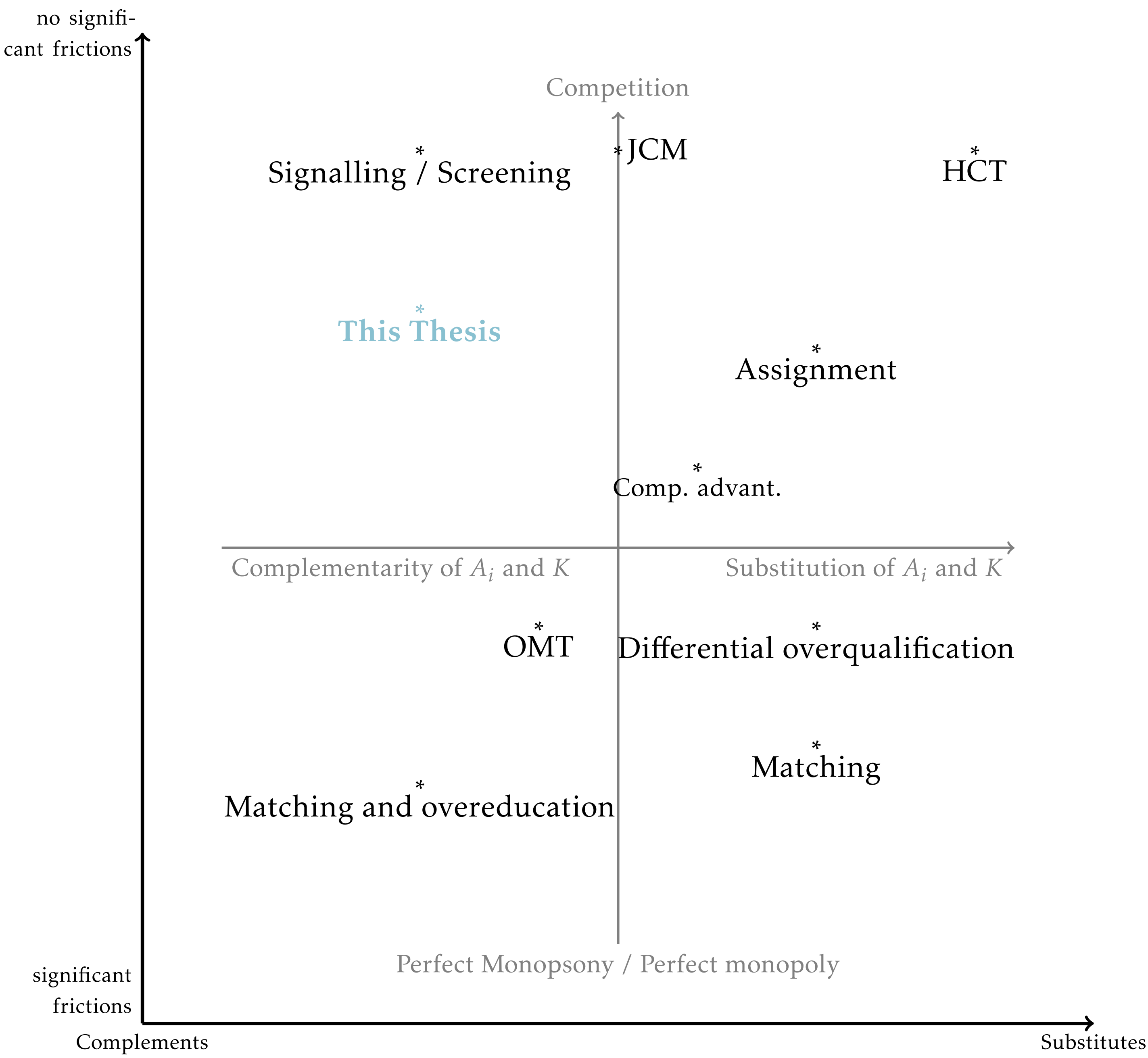


Figure 1.1: Map of labour market models
Note: A_i stands for individual ability and K for capital. Human Capital Theory (HCT) assumes perfect financial markets and the complete substitution between the employee's ability and the capital. The deviation of this position to any other place in this diagram signifies a potential existence of mismatch (e.g. overeducation). Job Competition Model (JCM) relaxes the assumption of substitutability.
Source: Own elaboration

1.1 Theories of Overeducation and Skills mismatch

A deviation from the Mincer (1974) model may capture an educational mismatch, declaring a disequilibrium between demand and supply of the labour market. The attained years of education (S_a) constitute a function of the required schooling for a job (S_r), the surplus of schooling (or overeducation, S_o) and its shortage (or undereducation, S_u).[2] This is the Over-, Required and Under-education (ORU) approach, introduced by Duncan and Hoffman (1981),[3,4] and as in Verhaest and Verhofstadt (2016) analysis, it is empirically shown as:

$$\ln[w_i] = \boldsymbol{\alpha x}_i' + \beta S_r + \gamma \underbrace{\left(S_a - S_r\right)}_{S_o} + \delta \underbrace{\left(S_r - S_a\right)}_{S_u} + \varepsilon_i \tag{1.1}$$

where $\boldsymbol{x}_i$ is a vector of variables, independent of education, but related to income; e.g. age, gender, marital status etc.

The parameter δ, in equation 1.1, is expected to be negative given the unfavourable return to undereducation (Hartog, 2000).[5] Where β is the return of the required schooling as demonstrated by job characteristics. γ captures the rate of return to overeducation. In other words, mismatched employees enjoy a wage premium on their surplus years spent in educational institutions. This surplus, though, is not sufficient enough to capture the wage differential between them and their adequately educated counterparts who are in match in the labour market. Their return to additional schooling is less than their former course-mates, or $\gamma < \beta$. Hence, this model contributes to any discussion of wage premium within a certain occupational group in which the main interest of employers lies. An alternative explanation would concern the employees themselves, demonstrating the penalty they face once employed in jobs which do not meet their educational background, $\gamma > \beta$. If the wage is determined by job requirements (or jointly by job and individual requirements), overeducated workers deal with a penalty compared to their adequately educated peers ($\gamma < 0$). In other words, workers in mismatch earn a wage premium, but they earn less than if they were adequately matched with the same level of education.

As summarised in table 1.1, various theories aim to explain and empirically estimate what happens once a deviation from the Human Capital Theory occurs and mismatch appears.

[2] If $S_a > S_r$, $S_o = S_a - S_r$; if $S_a < S_r$, $S_u = S_r - S_a$. Otherwise S_o or S_r equal to zero.

[3] Similar approach using the level of attained education, instead of years, was operated by Verdugo and Verdugo (1989). Sloane (2003) supports that this modelling encompasses Mincer (1974) and Thurow (1975) models; such an argument might hold as shown later.

[4] McGuinness (2006), Cedefop (2010), Green and Mcintosh (2007), Green and Zhu (2010), Caroleo and Pastore (2016), Capsada-Munsech (2017), and Mateos Romero, Murillo Huertas, and Salinas Jiménez (2017) criticise the ORU approach.

[5] For the shake of simplicity, as Mateos-Romero and Salinas-Jimenez (2017), the model of this essay restricts to overeducation, i.e. $\delta = 0$.

1.1.1 Overeducation

The Mincerian wage equation implies that the coefficients of educational mismatches are equal ($\beta = \gamma = -\delta$), i.e. that all years of education are equally valuable. **Human Capital Theory (HCT)** accepts human capital as a set of skills/characteristics which are developed through education (and working experience) and result in increased individual productivity,[6] and hence, individual earnings (Becker, 1964; Mincer, 1974). The phenomenon of overeducation does not persist; its insignificance comes from the usually acceptable lack of (or asymmetric) information between the demand and supply side of the labour market. Workers search individually for a job, without realising what the firms' needs are. Equilibrium is quickly restored since the employees seek for a matched job or firms adjust to their workforce skills, abilities and knowledge. The strict assumptions include homogeneity in preferences and firms and employees being profit or utility maximisers agents.

Matching theory (Jovanovic, 1979a; Jovanovic, 1979b; Pissarides, 2000), hinging on the same propositions, does not neglect the role of firms in the search-for-a-job process, equally acknowledging them for mismatches. In fact, it supports that both supply and demand present heterogeneities which create a premium (or penalty) to education, but they diverge through adjustments. Matching theory supporters claim that the surplus of education is a poor information's outcome and employees will realise it progressively by repeating the job search and, hence, achieving better matches. This is why overeducation is only a temporary phenomenon leading to shorter expected tenure. Therefore, mismatch arises due to labour market imperfections. There is a cost to find the right candidate for a vacant position. A search may lead to a successful match if a mutual agreement is made on the skills employees need to perform their job. In case of a match, the most productive worker is hired as this type of worker has the necessary skills to perform the job. If the employer is willing to offer additional on-the-job training to ensure productivity, any lack of worker skill is restored and the worker is supported to do the job well.

HCT has been extensively critised in several ways, since it seems to be more obdurate in various issues (e.g., in terms of governmental and union arrangements such as (sub)minimum wages, collective bargaining etc.). Hence, the total, or at least partial, failure of firms or labour market to comply to the current needs might lead to the dependence of worker's remuneration mainly on their job rather than, exclusively, their productivity. In this sense, **Job Competition Model (JCM)**, based on Thurow's (1975) contribution, suggests that the job characteristics, expressed through the required level of education, play an essential role in wage determination (in equation 1.1, if $\gamma = \delta = 0$, the JCM holds). JCM accepts an hierarchical classification of jobs with respect to the relative costs of training. Individuals do not compete on the wages they are willing to accept regarding their stock of HC. Instead, the skills are acquired through the on-the-job training demonstrating the labour

[6] A deviation of the perfect financial markets' assumption exposes education in front of family income and budget restrictions; and so, disparities persistence are probable. However, the wage equals the marginal product of labour.

market as the allocation tool of training opportunities to different employees.[7] So, the position one holds in the market suggests their recruitment outcome. Or, their particular place in the job queue revolves around their relative educational level. Actually, Thurow (1975) claims that an individual, under the HCT, would avoid an investment in further education, once they observe increased supply and, hence, less returns. On the contrary, under the JCM's umbrella, he strongly supports that in order to guarantee and protect their position in the job queue, education is the one-way ticket - implying an over-investment[8] resulting in a credential inflation.[9] The overeducation phenomenon seems to persist unless new high-skill (or high-educated-required) jobs are created. This is why it is a demand-side problem given that job characteristics determine the aforementioned allocation.

Between the HCT and JCM, the **Assignment Theory** could reasonably be considered as the middle path allowing both sides of the labour market to contribute to the allocation of jobs. Besides, in this framework, earnings function is not a straight-forward causal relationship, but it constitutes an equilibrium output to the solution offered by the proper assignment. Sattinger (1993) observes that the change in relative wages widens the income inequality, and hence, the neoclassical approach fails to explain the relationship among the wages, personal and job characteristics and the job's quality. Assignment models are not similar to JCM. They usually highlight an intermediate step between personal characteristics and income. Individuals choose the job (or the sector of their employment) depending on their (different) preferences and the income maximization - or in strict economic terms, they maximise their utility. Afterwards, they are allocated based on their educational background without neglecting other important individual characteristics. Hence, their allocation is not random in sectors. In Assignment Theory, the marginal product of labour depends on both the individual and the job, meaning that in equation 1.1 $\beta \neq \gamma$ and $\gamma > 0$. This is how overeducation is seen in this theory. Thus, the mismatch can be resolved if the demand or supply sides adjust.[10] In fact, no sufficient indication suggests that wage will be solely related to the acquired schooling or the individual features (as HCT supports), and none expectation relate wage determination to the job requirements (as JCM supports).

In contrast to HCT and JCM, the **Job/Career Mobility model** (or *Occupational Mobility Theory; OMT*) stands in the middle explaining the mismatch persistence of the phenomenon considering both the supply and demand

[7] People choose their job for their career progression or to acquire more working experience. However, an escape from mismatched job is not an easy process; as Meroni and Vera-Toscano (2017) claim, graduates who compete other highly educated individuals are more likely to remain displaced.

[8] The apparent implication of the Thurow model concerns the wages determination which is exclusively relied upon the required education and thus the returns to overeducation, meaning the surplus education as earlier defined, will be zero.

[9] A similarity to the signalling model emerges, but Spence (1973) limits the investment of education once benefits and costs are in balance. In JCM the limit, if any, of investment in education is not that clear.

[10] The duration of the phenomenon is not clear, since it concerns the adaptability and adjustment of both labour market's players.

sides of the labour market. By extending the HCT, Sicherman and Galor (1990, p.177) conclude that ‘individuals may choose an entry level in which the direct returns to schooling are lower than those in other feasible entry levels if the effect of schooling on the probability of promotion is higher in this entry level’. According to them, the career progression of the initially overqualified employees will be considerably quicker given the on-the-job training and the experience stock that they will have. Therefore, OMT supports the upward mobility movement of the workers which strongly relies on the job-acquiring skills from their initial voluntary mismatch. Any income penalties are compensated by future promotion potentials (Sicherman, 1991; Dekker, De Grip, and Heijke, 2002). However, empirical studies later offer questionable results regarding the OMT. In fact, Büchel and Mertenz (2004)[11] show that German overeducated employees face lower relative wage growth than their adequately educated peers. Grunau and Pecoraro (2017), employing German administrative data, find that overeducated employees have greater chances to be promoted, especially in the early years of working lifetime. This was not the case for the undereducated workers. Yet, job mobility when interrupted by unemployment does not always have a guararnteed outcome. Mavromaras, Sloane, and Wei (2015) find that unemployment generates negative future employment offers, when Veira-Ramos and Schmelzer (2018) claim that a liberal labour market, like the British one, liaise job finding. In fact, they support that graduates of tertiary and secondary education initially overeducated, after a period of unemployment, may be in match, which is not the case for more inflexible markets, like the German one.

Alternatively, one could see that this theory, accepts the **Signalling model** (Spence, 1973); employees are not able to give a signal to their potential employer that they are educated or skilled enough for a job. Hence, they remain in a mismatched position until they are ready to give a better signal. Büchel and Mertenz (2004) claim that overeducation under this perspective is nothing more than a rational choice of the market’s agents. Though, this is not necessarily true. The implied idea blames more the individuals for misleading their potential employers rather than the job characteristics, or the demands that recruiters have. Empirically, Kedir, Kyrizi, and Martinez-Mora (2012) attempt to show the relevance of the Signalling Theory, but they reject both their strong and weak hypotheses. They find that overeducation does not contribute to individual productivity. An overeducated employee’s additional schooling might imply a higher level of ability and commitment compared to their matched competitors.

The theoretical framework is completed with a view of the **differential overqualification**, suggested by Frank (1978). He examines the link between the family mobility and the gender-segmented labour markets in households where both partners are employed. Employing as main argument the limited geographical movement of the family because of the married women’s career

[11] A year later, commenting on this evidence, Rubb (2005) defends these views mainly for the underemployed population.

prospects, he attempts to explain the gender pay gap (GPG)[12] defining as 'differential overqualification' the realationship between the different-sex based overqualification potentials and the labour market size. The job life of married women is restricted due to their household responsibilities, once husband's job dominates if he is considered as the household head. The picture is not the same for the married men or the single individuals, regardless their gender. McGoldrick and Robst (1996) try to extend the test of geographical mobility constraints in the market's outcomes for any employee regardless their gender. Büchel and Battu (2003) offer unclear and mixed results when they test for commuting distances. Cooke et al. (2009) support that household migration is still associated with a significant increase in total family earnings usually led by husband's earnings prospects, despite declines in women's earnings. Finally, Castagnetti, Rosti, and Toepfer (2017) believe that overeducated women might signal their actual, albeit low, productivity level to avoid statistical discrimination. The latter occurs once average characteristics of groups indicate individual productivity, which is not the case for women given their better observed characteristics.

An interesting debate about the interpretation of the coefficients comes from Cohn and Khan (1995)[13] who claim that the earlier study of Verdugo and Verdugo (1989) misinterprets the coefficients of the overeducated. This misinterpretation, however, could be motivated when a really strong assumption is relaxed. Many studies seem to take it for granted that the unobserved heterogeneity among individuals, derived from the ability, motives, etc., is not correlated with the mismatch. Failing to hold this assumption, the issue of omitted variable bias arises. If ability is negatively (positively) correlated with overeducation (undereducation), the rate of returns are underestimated (overestimated).[14] Part of the literature in order to deal with this unobserved heterogeneity uses fixed effects models[15] (Bauer, 2002; Lindley and McIntosh, 2009; Mavromaras et al., 2013; Sloane, 2014; Iriondo and Pérez-Amaral, 2016; Meroni and Vera-Toscano, 2017; McGuinness, Pouliakas, and Redmond, 2018). However, this may not be an ideal solution given its potential biases. If OMT holds and workers change jobs,[16] an upward mobility within the same occupation via a promotion is not any more random and it

[12]Blau and Kahn (2017) discuss extensively the GPG, the impact of the gender division of labour and its implications on motherhood.

[13]Employing the same data as Verdugo and Verdugo (1989), they test both models of Duncan and Hoffman (1981) and Verdugo and Verdugo (1989) suggesting that a negative overeducation estimate does not imply undoubtedly a negative return; it can propose a wage penalty for the mismatched against their counterparts.

[14]In this Thesis, I consider from the first step that each employee goes to the labour market with a set of skills, equally composed by its level of education and its ability. Unfortunately, BHPS and UKHLS do not allow us any further specification of the worker's ability. In chapter 6, I control for cognitive and non-cognitive skills using a richer dataset of BCS70.

[15]In these models, the unobserved heterogeneity is a part of the disturbance error. They are adopted, because of their flexibility to correlate the heterogeneity with the independent variables.

[16]We do not neglect that employees might move across different occupations and find an adequately matched job, but the correlation there, if any, could be less.

may correlate with the mismatch.

1.1.2 Skills Mismatch

Acemoglu and Autor (2011) consider a task as 'a unit of work activity that produces output (goods and services)' (p.1075) and define skills in a Ricardian setting of labour market as 'a worker's endowment of capabilities for performing various tasks' (p.1118).

If the job underutilises or completely neglects individual skills, the employee faces a skills mismatch (Li, Harris, and Sloane, 2018; McGuinness, Pouliakas, and Redmond, 2018; Sloane, 2014). A way of direct measurement is only applicable to those big firms with organised HR departments. However, such indexes are not available in individual and/or household level datasets. Traditionally, scholars depend on subjective measurements derived from questions asking individuals to assess their relative position compared to the job they perform. Nevertheless, this method presents the same bias as the subjective measurement of overeducation. An additional measurement error may arise if the respondent considers skills in general terms and not exclusively the work-related ones because of the way questions are phrased (framing effect). Even though both education and skills mismatch are related to HC, the literature supports the little correlation between them (Flisi et al., 2017; Green and Mcintosh, 2007; Di Pietro and Urwin, 2006). Finally, McGuinness, Pouliakas, and Redmond (2018) acknowledge that skills mismatch measure is more accurate than the education one. Although, the questions' variation among the datasets creates difficulties in terms of estimates' comparison and research are not able to indicate the source of mismatch - e.g. labour market experience, formal training etc.

For skills mismatch, traditional datasets employed include the Survey of Adult Skills (Programme for the International Assessment of Adult Competencies; PIAAC), conducted by OECD capturing 3 basic skills: numeracy, literacy and, in certain countries, problem solving in highly-enhanced technological environments (e.g. Chłoń-Domińczak (2017), Flisi et al. (2017), McGowan and Andrews (2017b), and McGowan and Andrews (2017a)); additional questions to test the impact of the skills on earnings are used. In Europe, two main large-scale surveys contribute in the skills literature: the Flexible Professional in the Knowledge Society, briefly known as REFLEX, dataset (e.g. Sánchez-Sánchez and McGuinness (2015) and McGuinness and Sloane (2011)), sponsored by EU, and the European Skills and Jobs (ESJ) Survey (e.g. CEDEFOP (2015) and CIPD (2015)), whose questions are not similar, and ergo, comparisons are not allowed. In fact, McGowan and Andrews (2017b) find that overskilling varies from 18% to 34%, while CEDEFOP (2015) show that the equivalent percentage for EU exceeds 40%. Sánchez-Sánchez and McGuinness (2015) claim that the most overskilled employees (14%) are located in Spain, the UK and France.

TABLE 1.1: Theoretical (model-based) approaches of overeducation

Theoretical approach	Main advocate(s)	Duration of the phenomenon	Source of wage determinants	Preferences of individuals	Main feature	Predictions of returns, according to eq. 1.1
Human Capital Theory	Becker (1964); Mincer (1974)	Temporary	Supply side (Individual characteristics)	Homogeneity	The mismatch can be resolved if labour market agents adjust.	$\beta = \gamma$
Job Competition Model	Thurow (1975)	Persistent	Demand side (job queues)	Homogeneity	Allocation based on hierarchical ranking of jobs educational level and employees relative position	$\gamma = 0$
Assignment Model	Sattinger (1993); Sattinger & Hartog (2013)	Temporary or Persistent	Supply and Demand sides	Heterogeneity	Preferences and utility maximisation	$\beta > \gamma$
Matching Theory	Jovanovic (1979a, 1979b); Pissarides (2000)	Temporary	Supply and Demand sides	Homogeneity	Both firms and individuals are looking for matches	$\beta > \gamma$
Occupational Mobility Theory	Sicherman and Galor (1990)	Temporary or Persistent	Supply side (training costs paid by individual)	Not clear	Not a proper signal about the actual level of education and skills	$\beta > \gamma$
Theory of differential overqualification	Frank (1978)	Persistent	Supply side (gender and family status)	Heterogeneity	Jobs are constrained geographically and only infrequently will the best job offer for both spouses occur in the same location. Married women tend to follow their husband because of their household responsibilities.	$\beta > \gamma$

Note: Competition among employees in the labour market is captured only by the JCM.
Source: own elaboration, based on Cedefop (2010) and Capsada-Munsech (2017)

1.2 Review of empirical measurement

Despite the long history of educational mismatches, there is no (widely) accepted measure (McGuinness, 2006) due to the data-driven methodologies followed. In other words, the data availability used to demonstrate the employed method of the overeducation estimation. However, many studies test the same hypothesis utilising more than one possible definitions. Besides, the measurement method affects the incidence of overeducation reported, but not the pay penalty (Groot and Maassen Van Den Brink, 2000). The vast majority of the available studies have offered quantitative results. As shown in table 1.3, they follow two main approaches: an objective and a subjective. Under the first umbrella, one can find studies using (i) the normative or Job Analysis (JA) method and (ii) a more statistical definition or empirical method, also known as realised matching (RM). The subjective approach distinguishes between the direct and indirect self-assessment (SA) of the employee. They classify themselves as over- or undereducated (McGuinness, Pouliakas, and Redmond, 2018).

The **Job Analysis (JA)** or Evaluation method, also captured as a normative process, depends on the assessments offered by job analysts who construct occupational dictionaries having measured the education's required level and type for different occupation,[17] for example DOT[18] or O*NET in the United States or SOCS[19] in the UK (Rumberger, 1987; Elias and Purcell, 2013). This classification usually converts to years of required/requested education which are compared with the actual years an individual spent in schooling. A JA's acknowledged advantage relates to its accuracy as an output of field expertise. At the same time, this strength signals a vulnerable point, since the experts classify the requested education of each occupation upon their criteria, and therefore a subjectivity element exists. In addition, in such dictionaries all professions sharing the same title seem to ask for the same requirements, which is not necessarily true. In reality, not all same-entitled jobs require the same educational background. Hence, it might capture a minimum level of job-needed skills. Finally, potential influence of the supply forces might be neglected.

The **Realised Matching (RM)** uses the distribution of years in education for an occupation or a group of occupations. Its estimates depend on the mean or the modal level of schooling within a given occupation, classifying employees with acquired education above (below) one standard deviation as overeducated (undereducated). The strength of this method concerns its ease of calculation using various available micro-datasets enabling the cross-country comparison. However, RM faces some important sensitivities. Cohort effects may arise, especially in a rapid change of the required educational level, for a given occupation since it depends on the observed

[17] An individual's skills are separated into two dimensions: the required, job-needed, skills and the acquired ones that the employee bears due to education, some intelligence (ability), motivation etc. In the (extreme) case of perfect complementarity, the underlying production function has Leontief form.

[18] Dictionary of Occupational Titles

[19] Standard Occupational Classification System

schooling distribution. Consequently, the sensitivity expands to the level of aggregation, which is necessary to obtain the aforementioned distribution, assuming that all the jobs with the same title[20] have identical requirements. In more technical terms, when the analysis is based on the mean of the distribution, overeducation might belong to its upper tail. If overeducation is increased, the median might be quite high in the distribution generating an internal inconsistency. If the examined individual departs by more than one standard deviation of the mean, then similar results for over- and under-education are generated.

Studies employing the **subjective approach** depend on employees' self-assessment or self-report, usually in direct questions[21] in the questionnaires, declaring the level of necessary qualifications so as to get or to do a specific job. This is compared to the highest level of education acquired in reality to prove if they are properly matched, overeducated or undereducated. This methodology adjusts the measure of overeducation to the specific skills needed for a job, but the respondents may misreport the true degree of mismatch. McGuinness (2006) claims that a willingness of workers to exaggerate either their occupational status or the qualification required is not unusual. Hence, classification errors leading to measurement errors are probable; ergo, they might generate a non-random error in the incidence of over- (under-) schooling. To this extent, the skills level and the size of the organisation share an important role. For example, a low-skilled employee in a small firm might not be able to recognize the appropriate level of education that they should have so as to do the specific job due to insufficient benchmarks. Kler (2005) examines multiple approaches to measuring overeducation.

Several papers, in the 1980s and 1990s, neglect the heterogeneity among workers. They consider individuals as perfect substitutes assuming that similar education requirements would translate into similar acquisition or demand of skills. This is not necessarily correct, and from the 2000s onward, scholars have taken it seriously. A set of studies distinguishes between the *formal or apparent* and *real or genuine* overeducation. According to Cedefop (2010) (see table 1.2), the formal overeducation is observed once an individual possesses more education than their current job requires and also in which current skills and abilities are fully utilised. On the real overeducation, the skills are underutilised. The apparent overeducation[22] concerns a situation in which an individual has more education than the current job requires, but this does not adversely affect the level of job satisfaction - the job dissatisfaction comes only on so-called genuine overeducation.

[20] Sometimes sample sizes constraints limit the mode educational level to broader occupational groups than individual ones concealing the qualification variance (McGuinness, Pouliakas, and Redmond, 2018).

[21] For example, in the OECDs Survey of Adult Skills (PIAAC), individuals are asked, relative to their own education, what level of education do they think would be necessary to do their job in a satisfactory level a lower level would be sufficient; a higher level would be necessary; the same level. Similar equations exist in EU-LFS.

[22] Green and Zhu (2010) believe that the term 'apparent' seems almost to suggest the *a priori* absence of an effect.

TABLE 1.2: Typology of job-skills and job-satisfaction matching

	Skills fully utilized	Job satisfaction	Skills underutilised	Job Dissatisfaction
In graduate jobs	Matched	Matched	Educational qualifications match, but skills underutilized	Educational qualifications match, but not satisfied with job
In non-graduate jobs	Formal overeducation	Apparent overeducation	Real overeducation	Genuine overeduation

Source: Own elaboration, according to Cedefop (2010)

Table 1.3: Criticised measurement methodology

Method	Empirical definition	Summary	Pros	Cons
Normative / Job Analysis (JA)	The excess of actual years spent in schooling with comparison to years of required/requested education $S_i > S_{r_j}$	Definition of skill/education requirements for each occupation by an occupational dictionary	Objective method and accurate since it is based on field expertise.	(a) All jobs under the same title do not necessarily have the same educational requirements. (b) Potential influences of the supply forces are neglected. (c) Rare update of the classification due to high cost usually available only in national level.
Empirical/ Realised Matching	The distribution of education is calculated for each occupation: employees who depart from the mean or the mode are classified as overeducated $S_i - \left[\overline{S_r}\|j\right] > 0$ $S_i - \left[M_o(S_r\|j)\right] > 0$	Its estimates depend on the mean or the modal level of schooling within a given occupation, classifying employees with acquired education above (below) one standard deviation as overeducated (undereducated).	Given the dataset, it is always achievable to calculate	(a) Sensitive to cohort effects; it depends on the observed distribution of education especially in a rapid change in the required educational level for a given occupation. (b) Sensitive to the level of aggregation; necessary to obtain a distribution of education and it assumes that all jobs with the same title have identical skill requirements. (c) When the definition is based on the mean of the distribution: i. over-educ is defined as belonging to the upper-tail of the distribution ii. defining over-educ as depart by more than 1 s.d. from the mean, it can generate similar results for over- and the under-educated

Continued overleaf

Method	Empirical definition	Summary	Pros	Cons
Subjective	Self-defined as overeducated / mismatched	Answers to direct questions in questionnaires, declaring the level of necessary qualifications so as to get or to do a specific job. This is compared to the highest level of education acquired in reality to prove if they are properly matched, overeducated or undereducated.	The measure adjusts to the specific skills needed for each job	(a) It is affected by classification errors: researcher may not know how the employees judgment was made. (b) can lead to measurement errors which might generate a nonrandom error in the incidence of over- (under-) schooling
Income-ratio[23]	A continuous variable measured by comparing actual (y_i) and potential (y_i^*) income $$\frac{y_i^* - y_i}{y_i^*}$$	By comparing actual and potential income, overeducation is connected to underpayment, namely another labour market failure	As a result of investment in education, individuals maximise their income	As an indirect measure, it can be influenced by many other factors

Source: Own elaboration, based on table 4 of ILO (2014)

[23]This method implies a broader concept of overqualification, because it explicitly allows the substitution of education with other characteristics of individuals, firms, sectors, or regions (Jensen, Gartner, and Rässler, 2010).

Finally, a fifth way of measurement of overeducation derives from Jensen (2003) and Jensen, Gartner, and Rässler (2010). He noted that the income aspect of the overeducation is not much appreciated in these methods. This is why he introduces the '**income ratio** measure' according to which a stochastic earnings frontier estimates the individual (potential) income of an employee. Hence, the phenomenon of overeducation is treated as an income inefficiency and it is captured as the ratio between the actual and potential income. In fact, overeducation is described as a function of various determinants, while the main model tries to explain the dependence of (potential) income on determinants (e.g. human capital) of individual income (Jensen, Gartner, and Rässler, 2006).

Chapter 2

A multidimensional measure*

Abstract

This chapter constructs a multidimensional indicator of individual Human Capital Mismatch accounting for skills heterogeneities across individuals in more than one dimension. In the empirical analysis, BHPS and UKHLS data are employed to illustrate the extent of this inefficiency in the British labour market over the 1991-2015 period. To this end, employees fail any match if their skills exceed the median estimates of the more skills-demanding occupation. The analysis shows that (i) the magnitude of the mismatch increases after the Great Recession contributing to regional disparities; (ii) the changes between the matching status take place due to workers' occupational mobility and over-time skills development; (iii) employees can find better jobs or their mobility occurs earlier than the aggregate change of skills.

Introduction

Various studies,[1] from the late 1980s, pay attention to any type of mismatch explaining its effects on the labour market employing a range of different models (e.g. Freeman (1976), Tsang and Levin (1985), Hartog (2000), Chevalier and Lindley (2009), and Kalfa and Piracha (2017)). One would expect that getting higher education would be a ticket to a high-profile occupation. Additional education generates a high-skilled workforce whose earnings premia mirror differences in productivity (Mincer, 1974; Becker, 1964). This is not necessarily the case for numerous individuals who find a job requiring lower credentials or skills (Ueno and Krause, 2018). Hence, it potentially reflects an inefficiency of the labour market which fails to allocate individual talent to the different available jobs (Sattinger, 1993; Lindley, 2009). Under the neoclassical perspective of labour force competition, once the market is in equilibrium, productive efficiency is achieved. Efficiently allocated employees produce on the frontier of (their) production possibilities. Mismatch, though, is considered as an inefficiency

*Acknowledgements to participants in: (i) MicroForum (School of Economics; UKC); (ii) Department of Work and Pensions, Areas of Research Interest (ARI); External Engagement Workshop at ISER.

[1] Exemplary literature reviews conducted by McGuinness, Pouliakas, and Redmond (2018), Leuven and Oosterbeek (2011) or earlier by McGuinness (2006) can equally prove the intense interest in this subject.

because of rigidities limiting the optimal functioning of the labour market (Atukeren and Wirz, 2005).

The debate about mismatch and over-qualifications is centred around the surplus of graduates in the market given the globally increased attainment in Higher Education (HE) institutions. In the UK, since 1990, participation in HE has increased from 19% to 49.8% (figure 2.1). This 31 percentage point increase over the last 25 years has resulted from a HE's expansion policy, which aimed that the 50% of the young population pursue further education. Indeed, the non-continuation rate, despite its initial fluctuations, has declined reaching its nadir in 2011/12 when the second University fees' cap in England, was implemented. However, 2018 is the third year in a row when the drop-out rate increases steadily offering an alarming signal about how individuals interpret the inflation of credentials in the labour market (Karmel, 2015; Dockery and Miller, 2012).

In this context, the recent (financial) crisis is important since it changed significantly the British labour market map. Employees move from/to different employment statuses involving periods of increased unemployment - especially for the young graduates. The UK's real GDP has typically increased annually, despite several short-period downturns in the economy since 1980. In fact, the UK experienced 16 consecutive years of growth before the output's fall as a result of the financial crisis of 2008. In the third quarter of 2013, the output regained pre-downturn levels. Over the period 1990 to 2017, the real GDP growth has averaged at 2% per year. Throughout the last 18 years, unemployment[2] remained stable despite the Great Recession, peaking in 2011 at 8%. Forecasts predict a fair stability as far as the total unemployment rate is concerned in the coming years given the current decreasing number of people in unemployment. The youth UK unemployment rate, traditionally greater than the aggregate one, shows a gradual decline after 2012 (figure 2.2).

The literature agrees on the significance of mismatch in the labour market[3] (Green and Henseke, 2016a). As a result, various policy implications arise given the expansion of higher education and the increasing willingness of individuals to pursue further schooling. McGowan and Andrews (2017a) suggest that differences in employees' market mismatch across countries reveal the importance of Employment Protection Legislation (EPL) since it may impede the entrance in the labour market. Housing policies are, also, considered given the crucial role they play for moving decisions. Given that mismatch can be interpreted as a market inefficiency, the country does not produce at its potential. Alternatively, in macroeconomic term, a lower GDP may occur (Hanushek, 2017).

[2]The unemployment rate, as well as the number of vacancies, flourish across Europe (Arpaia, Kiss, and Turrini, 2014). Their ratio could be examined with respect to the mismatch occurrence. A link is provided in chapter 3. However, the UK does not have such a profound issue; its job vacancies rate in the third quarter of 2018 is (provisionally) 2.7% and its unemployment rate 4%, compared to 2.2% and 7%, respectively, for the EU28 (for further stats. see Eurostat).

[3]Ueno and Krause (2018) describe the consequences of overeducation for society, employers and employees.

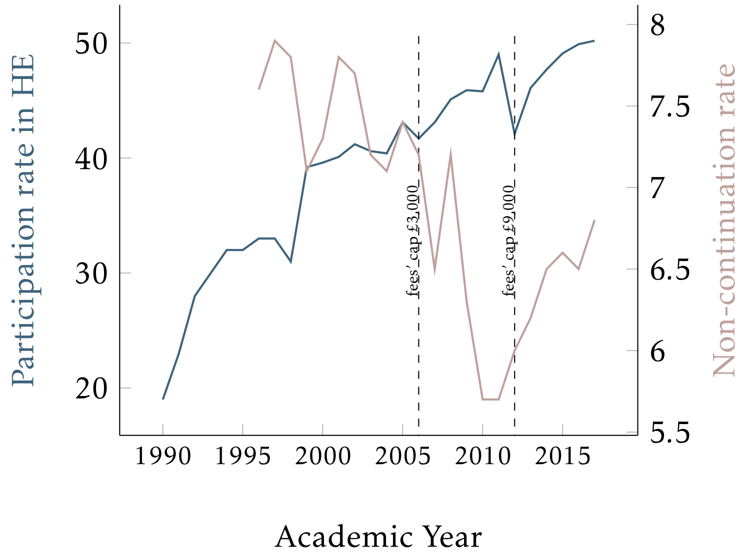


FIGURE 2.1: Participation In Higher Education and Non-Continuation Rates; total population
Note: Participation rate for 1990/91-1998/99 is measured with GB Age Participation Index (API), which was replaced by Higher Education Initial Participation Rate (HEIPR). For details see Kelly and Cook (2007).
Source: DfE and HESA

Empirical literature shows no consensus on a unique and robust way of measuring mismatch, but scholars acknowledge its multi-faceted nature. This is why, in this chapter, no single-indexed measurement will be considered. Instead, the contribution is twofold in terms of the methodology and the data used. Firstly, a multi-dimensional measure identifies workers in mismatch if their skills exceed the median estimates of the more skills-demanding occupation. Secondly, exploring the dynamic aspect of the BHPS and UKHLS datasets, we discuss the mobility among (i) different occupations and (ii) the matching status.

The paper is structured as follows: section 2.1 presents the data and the identification strategy and the methodology employed. A discussion of the results aims to explain the findings of the empirical approach (section 4), while the final section concludes.

2.1 Data and Methodology

2.1.1 Data

The empirical evidence uses the British Household Panel Survey (BHPS) data and its successor, namely the Understanding Society, the UK Household Longitudinal Study (UKHLS). A household representative longitudinal prospective survey, with retrospective elements, started in autumn of 1991 and repeated annually thereafter[4]; BHPS' last wave was in 2009, when it became

[4]In the first wave 10,000 individuals interviewed from 5,000 households covering 250 different areas of Great Britain. The same were interviewed again the subsequent years, as well as

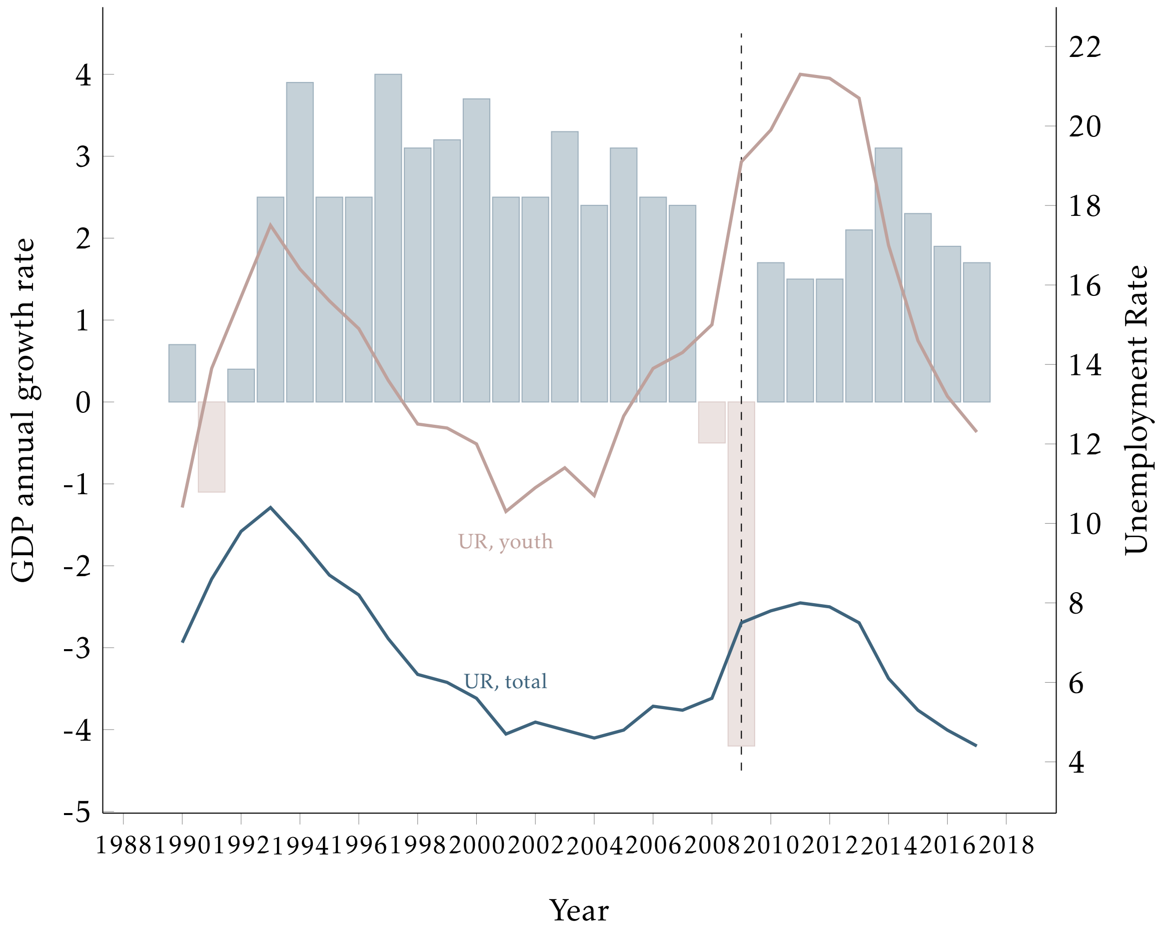


FIGURE 2.2: Annual real GDP growth and Unemployment, UK; 1990-2017
Note: The left-hand vertical axis presents the annual growth rate of GDP in percentages (bars), while the right-hand side one counts the unemployment rate in percentages (lines). The former includes negative values illustrated with red colour. The dashed line on 2009 points out the recent (financial) crisis.
Source: World Bank and ONS

part of the UKHLS which runs until today. Hence, the micro-level data used in this analysis cover a 25-year period, i.e. 1991-2016 or waves 1-18 and 2-7. The prime focus is on randomly selected individuals in a household context representing the whole UK population. The interviews conducted face-to-face or by phone containing various questions on demographics, human capital background, socio-economic and job characteristics[5] forming a wealthy source of data.

The sample in this study is confined to participants in the labour force, namely employees working full or part time and unemployed, aged 23-59 years old. The latter age restriction is related to the fact that graduates of

any new members of their household, and any new households to replace any households that left the survey.

[5]This survey offers rich information on the labour market history and as a result one can follow each individual from the time they entered the market(Zangelidis, 2008). However, we should take into consideration the significant number of missing values on the complete employment history, firstly recorded on the second wave.

higher education enter the labour market at the age of 23 and get an (early) retirement (aged 59). If someone started working younger than 23, she is captured later in the labour market. Additionally, self-employed individuals, farmers or those serving in the army and those employees who are currently enrolled in any educational level[6] have been excluded. Since a few income outliers may affect our results, the real wage has been winsorised at the first and 99th percentiles. The total sample is comprised of 152,470 observations (52% men and 48% women) and its size may vary depending on the controls of each regression.

2.1.2 Methodology

This section presents the identification strategy and the empirical approach of this paper. The first step of the exercise is to identify who is in mismatch given the skills variance among occupations. Our novel multidimensional measure captures the individual heterogeneity in more than one dimension of skill. The second, and final, part is to investigate the dynamic pattern of the occupational mobility against the miss-match in the labour market. To this end, we question how relative skills change over time.

Identification: Who is in mismatch?

In this paper, we will not consider employees' relative position *within* the same occupation accounting for the required level of education or skills. The identification strategy answers a question in a horizontal mobility[7]: does an individual hold the appropriate skills to be employed in a better job[8]? Attempting to answer this novel[9] question, we overcome any arguments - usually seen in the overeducation literature - about an oversupply of the workforce. Instead, we focus on its current composition explaining workers' status as illustrated via their earnings and the returns to education. A worker is in mismatch if their returns are above the median premium paid in a more skills-demanding occupation. To this end, I need to specify the wage equation.

Initially, I adopt the HCT's assumptions which suggest that education enhances productivity as depicted in wage differentials (Becker, 1964). For instance, I estimate the following expanded Mincerian wage function of hourly

[6]Excluding employees who are currently students is not unprecedented in the literature (like Joona, Gupta, and Wadensjö (2014)) to avoid any variation in education over time. This technique will allow the fixed effects estimator to be unbiased given the exogeneity assumption.

[7]Poor matching between employees' field of study and job requirements has been acknowledged as horizontal mismatch (see e.g. Somers et al. (2019)). In this framework, horizontal mobility is regarded in terms of ranking different occupations.

[8]The better job in this context is regarded if the individual holds the appropriate skillset to be employed in an occupational group requiring more skills than the group she is currently employed in.

[9]To the best of our knowledge, so far none theoretical or empirical work tries to explore any type of mismatch following this defining root.

wages

$$\ln[\text{wage}]_{i,t} = \alpha + \boldsymbol{\beta}_1 \boldsymbol{x}_i + \sum_{k=1}^{6} \beta_k S_{i,k,t} + \vartheta_t + u_{i,t} \tag{2.1}$$

where $\boldsymbol{x}_i$ is a vector of factors, independent to education, but (cor)related to income, personal and job-specific features; e.g. experience, age, marital status.[10] $S_{i,k,t}$ is the k^{th} attained level of education. $\ln[\text{wage}]_{i,t}$ is the logarithm of hourly wages of individual i, in constant prices of 2015 (figure 2.3). Potential concerns may refer to those unobservable characteristics which may affect earnings (usual suspect could be individual ability or non-cognitive skills). We assume that credentials acquired demonstrate a skillset composed by (innate) individual ability and personal effort to achieve a certain level of education.[11] Besides, the credential effect may bring about earnings premia supporting the idea that higher level of education does not raise directly productivity, but a better educated workforce is prone to be more productive (Patrinos, 2016).[12]

An important issue concerns the regression of wages on characteristics observed for those in employment, but not for the entire population. The former tend to enjoy higher earnings than those who do not participate in the labour force. Therefore, the results may suffer from a sample selection bias. To avoid any inconsistency, I employ a sample selection correction, which is based on the following equation:

$$\begin{aligned}\text{labour force}_{i,t} = \alpha + \boldsymbol{\delta}_1 \boldsymbol{z}_{i,t} + \sum_{n=1}^{5} \delta_n FS_{i,n,t} + \sum_{j=1}^{12} \delta_j \text{ region}_{i,j,t} + \boldsymbol{\delta}_k \textbf{HHmembers}_{i,t} \\ + \vartheta_t + v_{i,t}\end{aligned} \tag{2.2}$$

where labour force is a dummy variable, which equals to 1 if the individual

[10] Robustness checks included the number of children as additional determinant of skills; the magnitude of mismatch, though, did not differ significantly.

[11] Heckman, Stixrud, and Urzua (2006) claim that 'sociability', which is strongly related with the grades and schooling abilities affects labour market outcomes. Baum, Bill, and Mitchell (2008) claim that any individual displacements in the labour market are not unaffected by the social networks. Finally, Deming (2017a), having developed a theoretical model, explains the increasing significance of the skills in the US labour market from the early 1980s to the 2000s. However, questions regarding the social skillset of the individuals in BHPS and UKHLS are only included in certain waves and they are not frequently repeated; hence, including them would not offer any significant insight.

[12] Various specifications attempted for the HC estimation. To further convince for the applicability of this proposed methodology, we plot the returns of HC by occupation (against the percentiles). Service workers and Elementary Occupied employees enjoy greater returns comparing to other occupational groups which, by assumption, require more skills. In fact, the majority of the observations are around the top end of the distribution indicating higher wages with a potential existence of mismatch. To better specify the model, we progressively add different controls; the more controls the greater the returns of low skilled employees are.

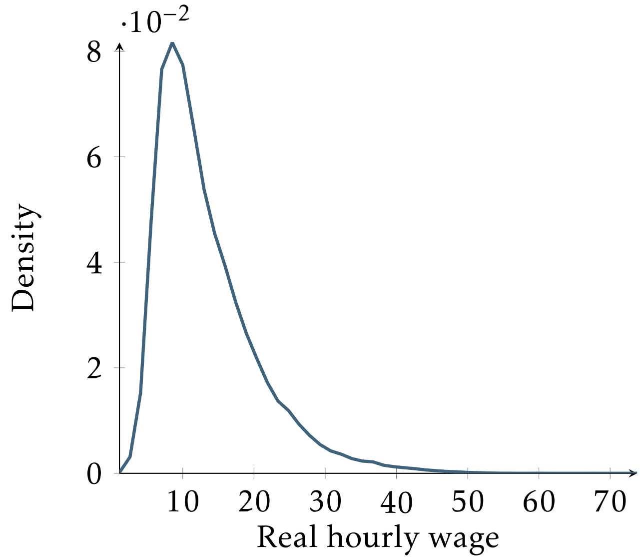


FIGURE 2.3: Distribution of wages
Note: Consistently with the literature (e.g. Bhattarai (2017)), no symmetry exists in the wage distribution, while it is right-skewed (skewness 1.5274); the median (£10.34) is below the mean (£12.16; s.d. 6.7758) probably indicating that less individuals remain productive above the average. Since the kurtosis is 6.0175, greater than 3, the distribution is leptokurtic. The graph illustrates the epanechnikov kernel density with 0.5538 bandwidth.
Source: Own elaboration

is in a paid job or unemployed and 0 otherwise.[13] $\boldsymbol{z}_i$ is a vector of individual characteristics, like age, educational level, marital status. FS_i is the financial status, while region$_{i,j}$ the j^{th} NUTS 1 statistical region of residence.[14] Finally, **HHmembers** denotes a vector counting for the number of household's members who are unemployed, retired or inactive excluding oneself. In fact, the status of the remaining members, as well as the number of children in a household, affect and co-demonstrate the disposable household income either on the revenues or the expenses side of household budget- playing an important role to the decision of accepting a job offer (Bredtmann, Otten, and Rulff, 2017; Marelli and Vakulenko, 2016; Addabbo, Rodríguez-Modroño, and Gálvez-Muñoz, 2015).

[13]The dependent variable is a dummy and not a continuous one, as usually used in Heckmans models. Greene (2012) claims that the dichotomy could affect the maximum likelihood function. In terms of the standard errors, though, we cluster on the household level, consistently with the rest of the analysis. Despite its dichotomicity, an estimation using a linear model decreases its sensitivity to distributional assumptions (Böckerman, Haapanen, and Jepsen, 2018).

[14]The last 25 years, unemployment rate across the UK had many fluctuations, suggesting a potential impact to the individual labour market outcomes. Including regional unemployment rate, though, could form a more informational model but it would collapse because of collinearity with the year dummies. However, not using it does not change the results, given that the analysis compares *ceteris paribus* the individuals. Between two different regions, the earnings gap would be captured by the regions dummy. Besides, regional unemployment generally follows the national unemployment rate. However, its deviations among the regions persist for greater periods (Lolos and Papapetrou, 2012).

The continuity of the wage variable allows an estimation with the Heckman's (1979) two-stage technique with some changes. The Heckman selection model does not require an instrument to be identified; it can be identified by a functional form alone. Here, I use the financial situation and the employment status of the remaining members of the household to determine the probability of labour market participation. Di Pietro and Cutillo (2006) related the financial responsibility with men in Italian households enhancing a disaggregated analysis on gender level. A lower household income increases the probability of individual participation in the market. If the Theory of differential overqualification holds, partner's employment will not affect the decision of a household to move unless it regards a better offer for men. I acknowledge that using the financial status of the household and the employment status of the remaining household members can affect the reservation wage in an alternative channel, too. For instance, high non-labour income (e.g. inheritance) could reduce the probability of labour market participation. However, despite how valid this concern may be, correcting the labour supply decision using the two-step Heckman approach does *not* change much the incidence of mismatch in this exercise.

Identification Algorithm Below I outline the algorithm to identify those workers who are in mismatch.

Step 1: Estimate the wage equation 2.1, corrected for the sample selection bias (eq. 5.3) for each wave.

Step 2: Calculate the linear prediction from the fitted model.

Step 3: Classify occupations in three groups based on their skills intensity required for task performing and duties or responsibilities fulfilling (table 2.1).

(a) Ranking of occupations occurs according to their median level of education and hourly earnings. I classify occupations in three groups due to the number of observations in a more finite level.

(b) The grouped occupation variable receives three values: 1 for high-skilled, 2 for middle-skilled and 3 for low-skilled.

Step 4: By occupation and wave, calculate the median predicted wage. This step implies that estimates are pooled for all occupations. It assumes that returns to covariates are the same across occupational groups.

Step 5: By wave, classify an individual in mismatch if their predicted wage in occupation j is greater than the median returns in a more skills-intensive occupation, namely in occupation $j-1$. Formally,

$$\text{mismatched}_i = \begin{cases} 1 & \text{if } \widehat{w}_i | occ_j > \left(\widetilde{\widetilde{w}} | occ_{j-1}\right) \\ 0 & \text{otherwise} \end{cases} \tag{2.3}$$

where $\widetilde{\widetilde{w}}$ is the median of the estimated wages.

TABLE 2.1: Skills, Education and Occupations

Skill Level	Educational Level	Single Indexed Occupational Groups
High	Tertiary Education (1st degree or Higher)	Managers, Legislators, Senior Officials; Professionals
Middle	Tertiary Education leading to a degree lower than the first degree (or equivalent), Secondary or post-secondary non-tertiary education	Technicians and Associate Professionals; Clerks; Service workers and Shop & Market sales workers; Craft and related trade workers;
Low	Lower Secondary; Primary Education	Agricultural and Fishery employees; Plant and Machine operators and Assemblers; Elementary Occupations

Source: Own elaboration, based on Yunus (2017). Occupations have been sorted according to their median level of education and median hourly wage. Column 2 shows the corresponding median level of education of workers in BHPS/UKHLS.

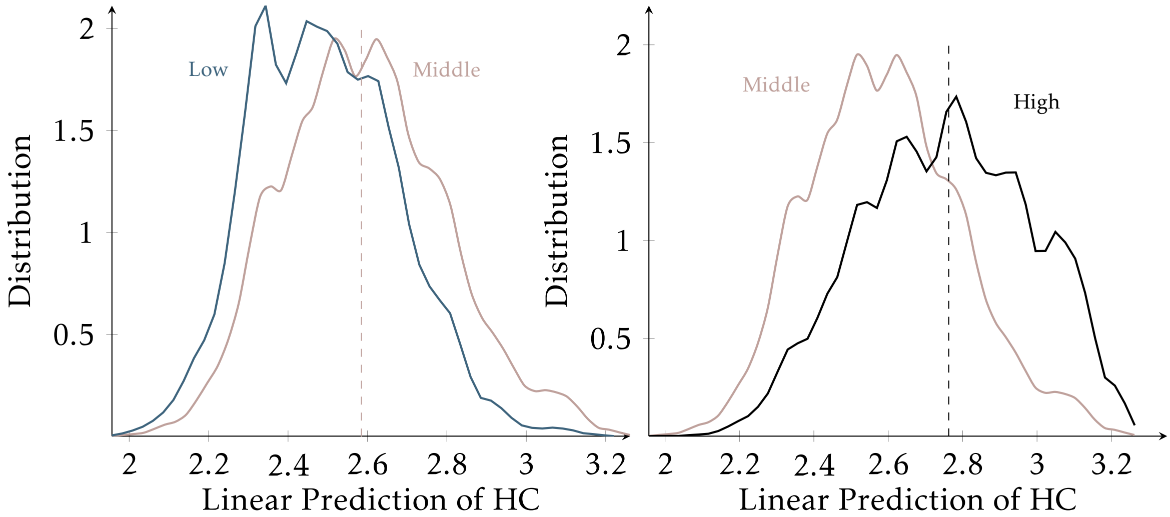
To enhance intuition, I plot the distribution of predicted wage of each group and compare the position each individual has relative to the median of the premium paid in an occupation demanding more skills. For example, consider the distributions of the middle- vs. low-skilled and high- vs. middle-skilled employees (figure 2.4).[15] By assumption, low-skilled workers (e.g.manufacturing labourers) require less skills to deliver a task comparing to the middle skilled (e.g. office clerks). To this end, let an individual be a hand packer; if her HC is above the median of the office clerk's distribution, she is considered mismatched. In other words, she holds those skills that could offer her a better position in the labour market, but instead she is currently employed as a hand packer. As a result, this multi-dimensional measure eliminates disadvantages of the earlier discussed empirical approaches and is resilient in various individual characteristics.

Mobility across skilled-grouped occupations and statuses

Martins and Pereira (2004, p.365) claim that "more skilled workers (individuals who receive higher hourly wages conditional on their characteristics) are associated with a stronger education-related earnings increment". However, skills are not necessarily coming from formal education. On-the-job training and prior working experience may equally, if not more, contribute to the construction of an individual powerful skillset. This is why I group occupations as described in Step 3 of the identification algorithm above.

What seems interesting is the dynamic aspect and whether there is a mobility from a matched to a mismatched position, and *vice versa*. The panel

[15]Changes in the bandwidth of each distribution attempted. Depending on the bandwidth, the density increases without changing who is identified as mismatched. Because of space, these attempts are not presented here.



(A) Middle vs. Low skilled
Note: Individuals after the dashed line, but on the blue line, are identified in mismatch.

(B) High vs. Middle skilled
Note: Individuals after the dashed line, but on the red line, are identified in mismatch.

FIGURE 2.4: Distribution of HC returns
Note: Dashed line indicates the median of the Human Capital (HC) distribution. Estimates illustrate the epanechnikov kernel density with common bandwidth 0.0202.
Source: Own elaborations

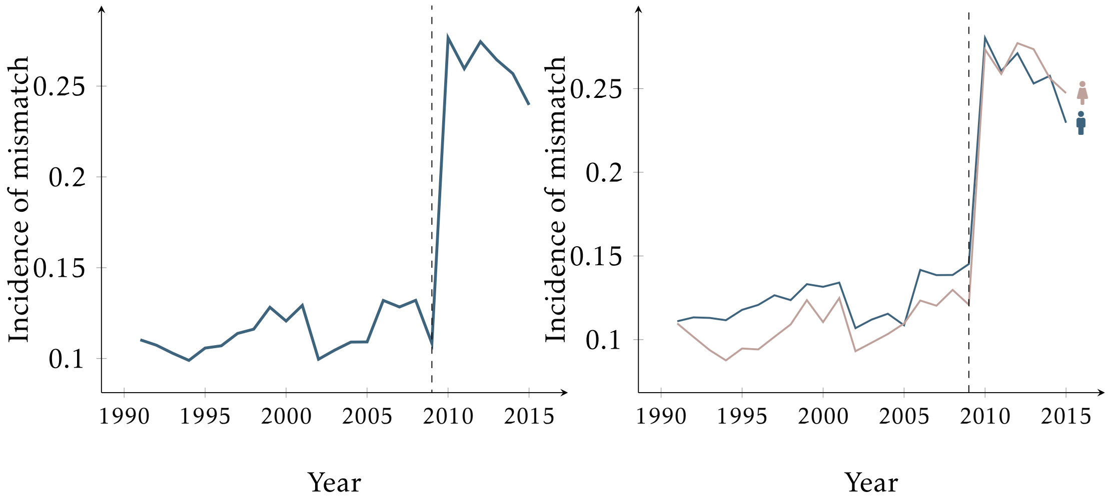
aspect contributes not only to the mobility between the matched and the mismatched status, but also to the occupational mobility. Hence, we can explain potential career changes or skills improvement over time.

2.2 Results - Discussion

2.2.1 Incidence of the mismatch

The incidence of mismatch is derived for the overall population when no gender dummy is included in the estimation of the wage equation. Initially, the mismatch rate starts below 4% following an augmenting trend reaching its peak in 2011 with a more than double ratio (8.65%; figure 2.5). The steep rise does not peak immediately after the Great Recession. The mismatch rate affected by the macroeconomic shock that the UK economy experienced follows the augmenting unemployment trend (figure 2.5a). In fact, the immediate effect was not only restricted in the labour force participation and/or the unemployment, whose changes were noticed in 2009. Interestingly, the overall rate was initially influenced by the misallocation of male employees, while during the post-recession period, women were driving its magnifying trend (figure 2.5b). Only in 2015, the percentage of mismatched workforce mirrored the pre-crisis image.[16]

[16]Preliminary results for 2016 show an increase in mismatch. This increase should be better studied if one includes the 8th wave of UKHLS where more accurate information about 2016 exists. However, the design of the survey from wave 8 and on slightly changes.



(A) Total population

(B) Pooled by gender

FIGURE 2.5: Incidence of mismatch
Note: Incidence of mismatch for workers aged 23-59. Dashed vertical lines signals the Great Recession. The same year coincides with the initial release of the BHPS successor, namely the UKHLS.
Source: Own elaboration

As the UKCES (2014) claims, despite the depth of the recession, only a moderate rise of unemployment occurred. However, the overall picture seen in the labour market did not have uniform impact to all occupations. Occupational decomposition of the employment's fall shows that some individuals suffered earlier than the crisis and disparities persisted after that shock, as well. Additionally, several structural changes have been observed in the UK labour market whose impact might drive the sharp drop of male mismatch around 2006. Regardless the various definitions employed in literature, a sectoral mobility in the market was evident especially among the high-skilled workers and/or the employees in high-paying jobs and the medium-/low-skilled ones. The after-crisis changes might come from the expansion of the private sector - more than 2 million jobs created since the early 2010 - or the shrinkage of the public one (Coulter, 2016).

An immediate comment about figure 2.5 regards the sudden increase of the incidence after 2009. Knowing the data structure, one could blame the transition from the BHPS to UKHLS which occurs at the same period. This might be true to a certain extent, given the small number of observations we have for 2009.[17] For robustness, to make sure this increase is not related to the transition from BHPS to UKHLS, I estimate the incidence of mismatch using the entire sample of UKHLS and not only those who were initially questioned in BHPS. This yields similar estimates. On the other hand, recent evidence on labour mobility and earnings support the idea of the recession's impact. Postel-Vinay and Sepahsalari (2019) harmonise these two datasets and validate its consistency with equivalent time series by other sources (e.g.

[17] 2009 was mostly covered by UKHLS. No sample coming from BHPS was interviewed additionally in UKHLS; hence, wave 1 of UKHLS is dropped following the guidelines by ISER.

the Labour Force Survey by ONS). In fact, they show that the average real weekly earnings present a parallel time profile without deviating in the level from the LFS.[18] The authors point out that this difference comes from the different sample composition.

Differences with earlier studies

Table 2.2 summarises some key findings from the late 1990s, whose data reference extends backwards to 1980s, until recently. Column 2 reports the average estimates of each study findings to enhance comparability. Earlier studies have shown that the overeducation rate in the UK was around 30% depending mostly on the employed method of calculation. Some of them, like Green et al. (1999), attempted a dynamic analysis by comparing several years proving that an increase of 3% within a decade was not a promising sign given the need for further expansion of the higher education. Another set of studies, continued on the dynamic framework but towards a mobility perspective or a persistence one, testing the OMT (Veira-Ramos and Schmelzer, 2018) or looking for a stagnation in the pool of those in mismatch (McGuinness, Pouliakas, and Redmond, 2018; Piper, 2015), respectively. More recent studies report rates around 23%, probably since the measurement methodology developed or the data offered more accurate information regarding the history of an employee. A noteworthy research by McGuinness, Pouliakas, and Redmond (2018) outlines various papers reporting their average estimates. None of these averages falls below 20%. This analysis though, does not consider the required level of education and the relative position of an individual *within* her occupation. Addressing a different question, we explore the labour market composition without neglecting the workers' heterogeneity in more than one dimension of skill.

Robustness Checks

Measurement To explore the robustness of this novel multi-dimensional index, we test how the magnitude of mismatch changes progressively by controlling for age and marital status. It is important, since no other previous work has used this way to investigate this inefficiency in the labour market. Figure 2.6 reports the incidence of mismatch annually. The dotted line illustrates the pure effect of the educational level on wages. The dashed line controls for age and its square as a proxy of experience. Finally, the solid line controls further for marital status. These estimates correct for the endogenous labour supply decision as previously described.

The trend follows the same pattern in any specification. However, when no controls are considered, the incidence does not exceed the 20% at any point. This might suggest that the mismatch is not directly coming from the differences presented through the level of education. In fact, unobserved determinants may play an additional role. Controlling for age, as proxy for experience, one can notice that the magnitude increases, especially after the

[18]Calculating the incidence of mismatch using LFS data yields similar results.

TABLE 2.2: Incidence of overeducation in the UK

Author(s)	Estimates
Sloane, Battu, and Seaman (1999)	30.63%
Groot (1996) and Groot and Maasen Van Den Brink (1997)	13-15% (males); 8-10% (females)
Green et al. (1999)	29% (1986); 27.4% (1995);32% (1997)
Green, McIntosh, and Vignoles (1999)	46% (data from University of Newcastle-upon-Tyne); 47.4% (data from NCDS)
Dolton and Vignoles (2000)	38% (first job); 30% (final job)
Chevalier (2003)	17% (objective measurement); 32.4% (subjective -job requriment) 16.2% (subjective-satisfaction)
Dolton and Siles (2003)	22%
Green and Mcintosh (2007)	37%
McGuinness and Sloane (2011) and Chevalier and Lindley (2009);	30%
Moro Egido and Budría (2007)	19.42%
Lindley (2009)	22.47% (men); 28.93% (women)
Green and Zhu (2010)	23% (women; 2001); 32% (women; 2006)
Croce and Ghignoni (2012)	31%
Ghignoni and Verashchagina (2014)	19.1% (men); 20.5% (women)
McGuinness, Bergin, and Whelan (2015)	23%
Davia, McGuinness, and O 'connell (2016) and Davia, McGuinness, and O'Connell (2017)	19.3% (men); 20.9% (women)
Boll et al. (2016)	20%
Sarkar (2017)	18.5%
McGuinness, Pouliakas, and Redmond (2018)	29% (subjective); 24.8% (empirical); 22% (job evaluation)

Source: Own elaboration

crisis. This way we can show that our measure is more resilient in cohort effects on the labour market.

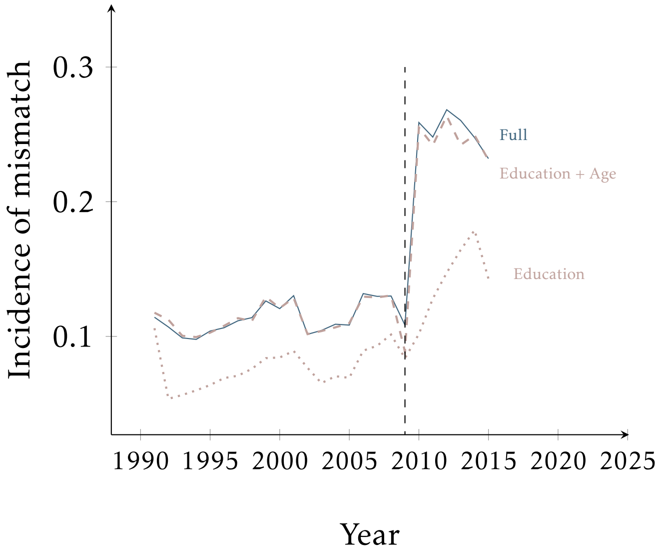


Figure 2.6: Robustness Check: Alternative Specifications
Note: This figure presents alternative specifications for the measurement of mismatch. The dashed line shows the effect of education and it reports similar incidence to overeducation measures earlier met in the literature. Having controlled for the age, as a proxy of working experience, the incidence increases (dotted line) and it is closer to what is used in this study (indexed as full on the graph). Estimates of 2016 are based on a small amount of observation due to the wave used in the study. For a better estimation for this particular year, the following UKHLS wave is required.
Source: Own elaboration, based on BHPS/UKHLS

Mismatch vs. Job satisfaction Finally, scholars declare a negative relationship between overeducation and job satisfaction (e.g. Ueno and Krause (2018), Stokes et al. (2017), Kankaraš et al. (2016), Verhaest and Verhofstadt (2016), Green and Zhu (2010), and Chevalier (2003)). They report that employees who are in mismatch are not satisfied with their job, while the contrary holds for those who perform a job fitting to their skills. Piper (2015) shows that overeducation among young people is increased, while this episode is related to lower life satisfaction. Figure 2.7 shows that the lower the incidence of mismatch the greater the job satisfaction is. As a result, this measure validates earlier evidence associated with educational mismatch.

2.2.2 Transitions and Occupational Mobility

Table 2.3 reports the percentage of people moved from a high-, middle- or low-skilled occupation in period $t-1$ to another occupation in period t. Individuals either maintain their matching status or change from the matched to non-matched, and *vice versa*. I omit the main diagonal intentionally to focus on the occupational transitions. Remaining in the same set of jobs is not part of this study. Yet, by this way, the role of over-time change of relative

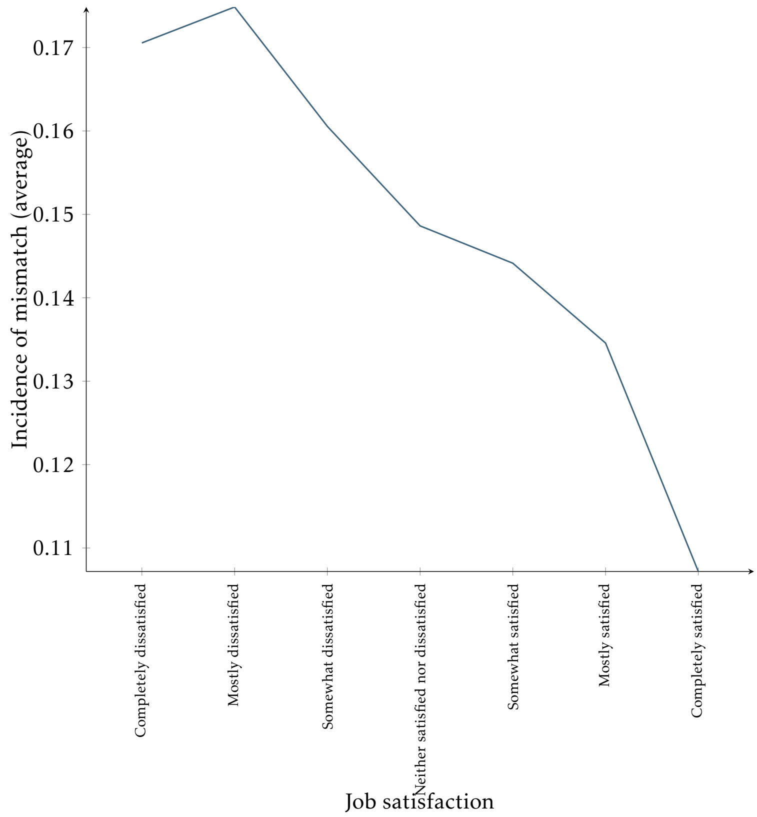


FIGURE 2.7: Mismatch vs. job satisfaction
Note: The figure plots the average level of mismatch against the self-reported job satisfaction level.
Source: Own elaboration

skills is revealed. Firstly, those who were occupied in a high-skilled occupation can, by assumption, move downwards. Around 9% of the employees preserve their matched status, even though they accept a job in a less skills-intensive occupation. The vast majority, initially, held a position for which their skills were insufficient. Hence, these displaced workers downgrade to an inferior-skilled job, consistently with Robinson's (2018) findings.

Employees in the middle-skilled occupations are able to move in either direction, i.e. upwards (to high-skilled) or downwards (to low-skilled). 72.6% become (or remain) matched, probably as a result of a promotion or accepting a better offer. 2.66% accept a subjacent job and are currently matched. Around 24% of the British employees (or roughly 400 in our sample) are in a misallocated position. The promotion case might be more obvious than accepting a subjacent job. Those who moved from the middle- to low-skilled occupation could be at the margin of the distribution in $t-1$. As time passes, their HC deteriorates and they are forced to move to another, lower to the initial, job. Alternatively, it may imply a skills atrophy or potential lost opportunities for training[19] (McGuinness, Pouliakas, and Redmond, 2018; CEDEFOP, 2018). Finally, the labour force participants in the low-skilled group can only move upwards either by one or two groups. 16.8% remain

[19] 11% of those downgraded employees entered the labour market in year t or a year before. Recent entrants might face an initial mismatch experience, but it anticipates over time.

TABLE 2.3: Occupational Mobility maintaining the previous period's status vs. relative skills' change (1991-2016)

Occ_{t-1} \ Occ_t		H	M	L
High (H)	Remained matched		8.39	0.53
	Remained mismatched		0.00	0.00
	Was matched, now mismatched		0.00	0.00
	Was mismatched, now matched		89.25	10.75
	Total (N)		3,481	359
Middle (M)	Remained matched	6.93		2.66
	Remained mismatched	0.00		1.51
	Was matched, now mismatched	0.00		23.04
	Was mismatched, now matched	65.64		0.00
	Total (N)	4,154		2,080
Low (L)	Remained matched	2.42	14.33	
	Remained mismatched	0.00	5.73	
	Was matched, now mismatched	0.00	2.51	
	Was mismatched, now matched	20.45	54.36	
	Total (N)	400	2,158	

Note: Figures as percentage of people moved to H, M or L between $t-1$ and t periods. Total (N) shows the number of observations moved. Occ stands for occupation.
Source: Own elaboration

matched in both periods given that their stock of HC exceeded the median worker in a more skilled group. However, upgrading[20] initially displaced workers reduces the inefficiency in the market by more than 70% (among 1,423 individuals). In fact, this result might be primarily driven by men (912 against 508 women) whose (temporary) mismatch is usually attributed to career-oriented reasons. Women may spend longer periods in mismatch because of family- or geographical-related reasons (Somers et al., 2019).

Most, but not all, declining incidence is related to the move across occupations (occupational mobility). As a result, a twofold reasoning can explain this change. First, employees can find jobs where their profile is a better fit to the needs. Second, the workforce mobility occurs earlier than the aggregate change of skills, or skills of the entire population, in aggregate terms, can increase faster than the individual ones. Hence, workers move to different occupations because of relative skills changes (e.g. development through training or skills atrophy) in the job distribution. This may imply that skills distribution may not move as fast as the job distribution.

[20]Whether it is a result of promotion or it constitutes an endogenous decision to accept a better job is uncertain.

2.3 Conclusions

In this paper, employees in mismatch could be employed in a better position, since they hold characteristics that exceed the median HC of the occupational group which requires more skills than the one they currently work in. The incidence of mismatch initially fluctuates and after the Great Recession seems to increase further. Significant regional variations are observed. In any case, the post-2009 magnitude of mismatch reveals an increase which is not simultaneous to the rise of unemployment. However, the return of employment to the rates prior-of-the-shock period is not accompanied by the return of the matching of employees - male mismatch persists further.

Human Capital Mismatch generates an inefficiency or, in terms of the market, a negative externality arises and the workforce produces at a suboptimum point. In other words, it distorts prices of skills or of human capital. This is the reason why the workforce allocation into different occupational groups becomes harder given that mismatch varies across individuals. However, mismatch rate variates over time for two main reasons. First, individuals are able to change jobs so that their profile fits better with the employer requirements. Second, this individual occupational mobility occurs earlier than the increase of the overall (population's) skills.

Appendix

2.A Descriptive Statistics

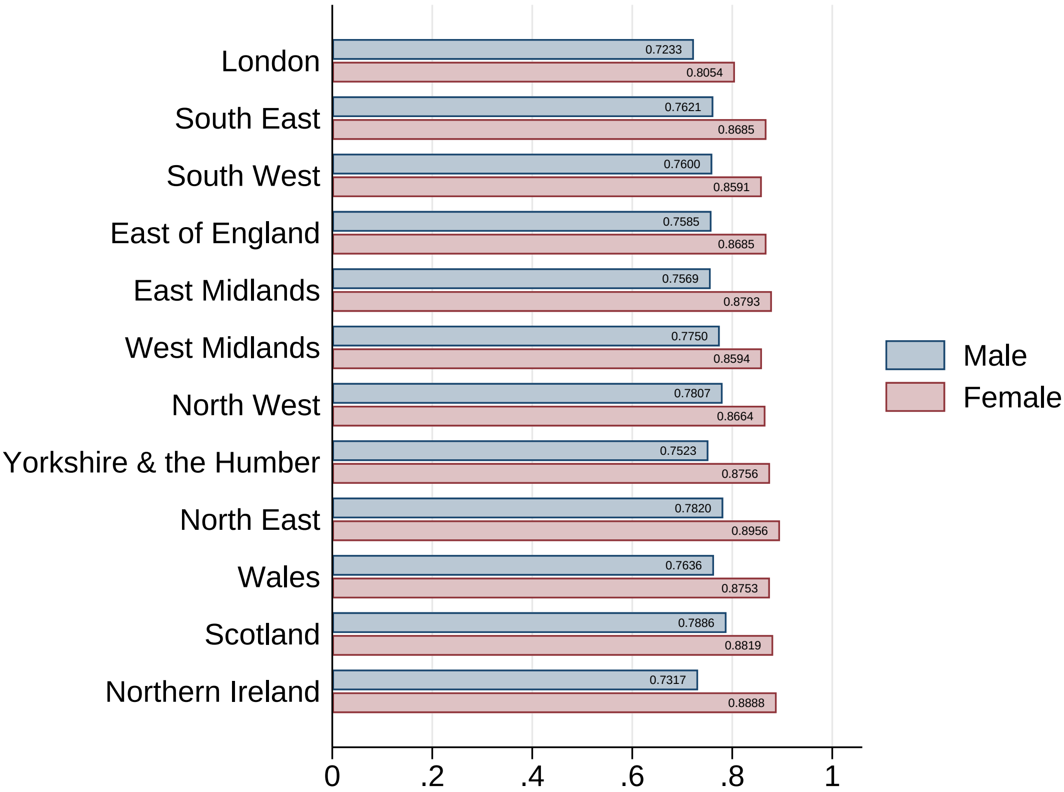


FIGURE 2.A.1: Employment rate by region and gender
Source: Own elaboration

TABLE 2.A.1: Descriptive Statistics

Variables	Men	Women	Total
Age	40.52	40.47	40.49
	(10.24)	(10.22)	(10.23)
Real (Hourly) wage	14.6424	11.3769	12.9024
	(7.1409)	(6.0604)	(6.7857)
Married	0.5396	0.5439	0.5419
	(0.4984)	(0.4981)	(0.4982)

Continued overleaf

Variables	Men	Women	Total
Number of employed members of HH	0.7968	0.8111	0.7781
	(0.7354)	(0.7085)	(1.0457)
Number of inactive members of HH	0.1237	0.0486	0.084
	(0.3402)	(0.2225)	(0.2869)
Number of retired members of HH	0.059	0.0569	0.0579
	(0.2676)	(0.2505)	(0.2587)
Unemployed	0.051	0.0324	0.042
	(.22)	(0.177)	(0.2006)
Employee	0.7198	0.6879	0.7029
	(0.4491)	(0.4634)	(0.457)
Part-time employee	0.0452	0.3557	0.1989
	(0.2078)	(0.4787)	(0.3992)
Public sector	0.2263	0.4494	0.3417
	(0.4184)	(0.4974)	(0.4743)
Education			
Higher Degree	0.0444	0.0357	0.0397
	(0.2060)	(0.1857)	(0.1952)
1st degree or equiv	0.1356	0.135	0.1347
	(0.3424)	(0.3418)	(0.3414)
Other Degree	0.1052	0.1321	0.1196
	(0.3068)	(0.3386)	(0.3244)
A-level etc	0.3139	0.2254	0.2675
	(0.4641)	(0.4178)	(0.4426)
GSCE etc	0.3939	0.3336	0.3127
	(0.4533)	(0.4715)	(0.4636)
Other qualification	0.2889	0.1381	0.126
	(0.3154)	(0.345)	(0.3318)
Occupation			
High Occ	0.3437	0.2626	0.3038
	(0.4749)	(0.44)	(.4599)
Middle occ	0.4424	0.6349	0.5373
	(0.4967)	(0.4815)	(0.4986)
Low Occ	0.2139	0.1025	0.159
	(0.41)	(0.3033)	(0.3656)
Mismatch	n/a	n/a	0.0554
			(0.2287)
Relative position	0.0393	0.0195	n/a
	(0.1944)	(0.1381)	
Relative to men's skills	n/a	0.6523	n/a
		(0.4762)	
Relative to overall skills	0.4743	0.3156	n/a
	(0.4993)	(0.4647)	
Change of occupation			
remains in high occ	0.3021	0.2265	0.265

Continued overleaf

Variables	Men	Women	Total
	(0.4592)	(0.4186)	(0.4413)
was high, now middle	0.0383	0.0329	0.0357
	(0.1919)	(0.1783)	(0.1854)
was high, now low	0.0076	0.0022	0.005
	(0.0866)	(0.0472)	(0.0705)
was middle, now high	0.0426	0.0399	0.0413
	(0.2020)	(0.1958)	(0.199)
remains middle	0.3767	0.0399	0.4796
	(0.4845)	(0.1958)	(0.4996)
was middle, now low	0.0249	0.0149	0.02
	(0.1558)	(0.1211)	(0.1399)
was low, now high	0.008	0.0024	0.0052
	(0.0889)	(0.0494)	(0.0721)
was low, now middle	0.0235	0.0165	0.0052
	(0.1516)	(0.1275)	(0.0721)
remains low	0.1763	0.0785	0.1282
	(0.3811)	(0.2689)	(0.3343)

Note: The first number corresponds to the mean; the number in parentheses is the s.d.
Source: Own elaboration

2.B Incidence of mismatch by region

2.C Skills vs. occupational mobility

How many of the entrances/exits are due to the fact that median employee - or the overall population - is becoming more skilled faster than an individual?
Figure 2.C.1 shows how the entrance to and the exit from a mismatch episode in the labour market changes by education. Employing our indicator, it seems that a downward mobility increases the probability of entrance the higher the qualifications one holds. For example, individuals most likely become mismatched once moving from a high-skilled occupation to a middle-/low-skilled one. Consistently, exiting from the mismatch occurs usually on a upward mobility

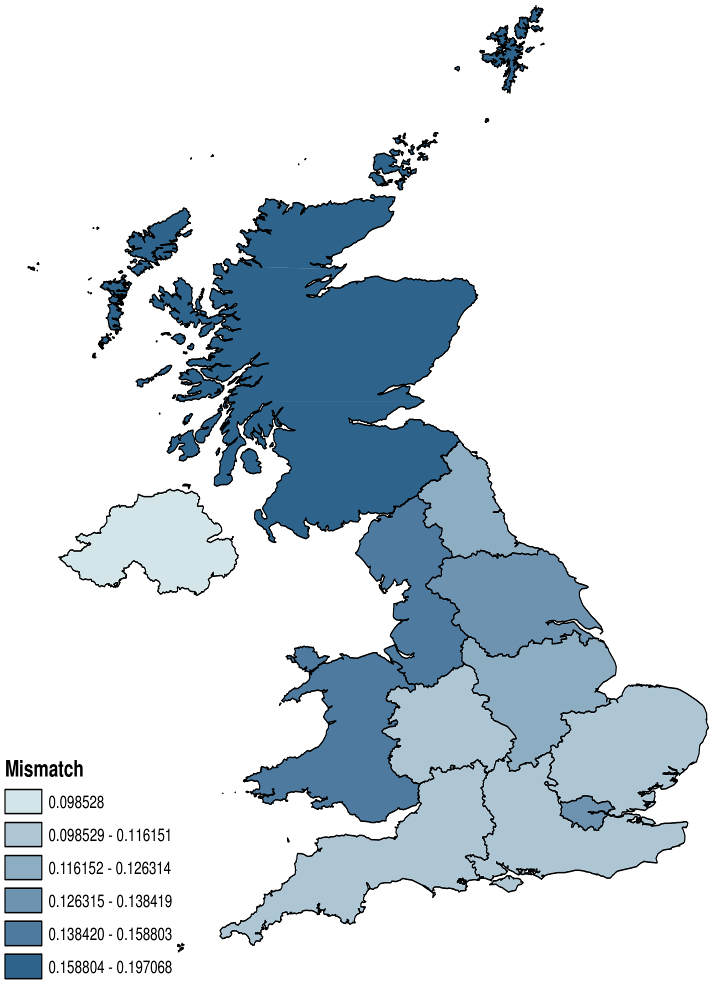


FIGURE 2.B.1: Overall mismatch; by region
Source: Own elaboration

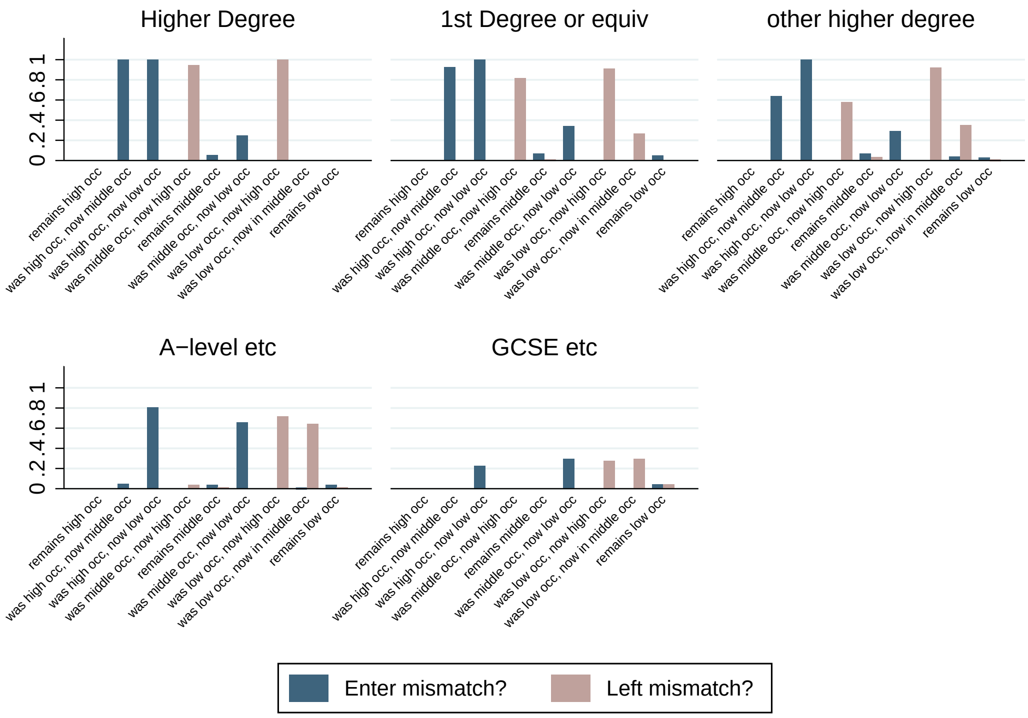


FIGURE 2.C.1: Entering and exiting Mismatch by educational group
Source: Own elaboration

Chapter 3

Are you in the "right" job? Mismatch in the Burdett-Mortensen environment

Abstract

This paper presents an extension of the Burdett and Mortensen (1998) model, allowing for heterogeneity of both workers and firms to estimate labour market mismatch. The ranking of workers is not the same in work and skills distributions. The simulation shows that job search frictions generate a mismatch between firms and workers. Women face more frictions. The firms share is only important when more frictions occur. In a continuous skills setting, higher-skilled workers, facing more frictions, have a lower expected wage. However, lower frictions bring the model closer to perfect competition, where the incidence of mismatch decreases.

3.1 Introduction

Labour market frictions affect job search to a great extent. If workers and firms are homogeneous, job search frictions have only a distributional impact. However, if the return to worker skills differs across firms, frictions have important efficiency implications. When heterogeneity[1] arises, workers are allocated into sub-optimal jobs given their characteristics (e.g. Gautier and Teulings (2015), Papageorgiou (2014), Hornstein, Krusell, and Violante (2011), and van den Berg and van Vuuren (2010)).

In a frictionless market of heterogeneous agents, the output loss due to mismatch would be negligible since all employees would be in match to their preferred job. However, workers and firms may differ in terms of their skills and productivity, respectively. Individual skills may generate (un)observable heterogeneity even within a particular job. As a result, different wages may be paid for the same job, which violates the law of one price. In the UK, firm productivity differentials are persistent over time and regions (Oguz, 2019). Burdett and Mortensen (1998) and Bontemps, Robin, and Berg (2000)

[1] Information imperfections (Banerjee and Sequeira, 2020; Conlon et al., 2018) or lack of coordination labour markets may generate further frictions. Here, I will solely address the heterogeneity issue.

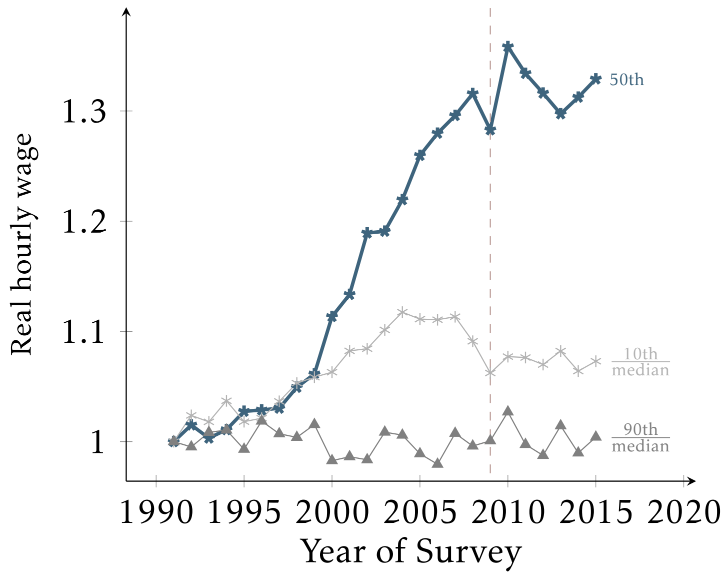


FIGURE 3.1.1: Wage Dispersion: Percentiles ratio of real hourly wage

Note: Indexed (base year = 1991) Real (CPI Index Deflator; base year 2015) hourly wage of employees aged 23-59. This graph aims to highlight the wage dispersion in Britain. Even after the Great Recession (dashed vertical line) the tendency did not change much apart from the top of the distribution.
Source: Own elaboration based on BHPS/UKHLS

argue that frictions generate wage dispersion and firm heterogeneity is reflected in wages. The literature has acknowledged the importance of these effects (Cahuc, Postel-Vinay, and Robin, 2006; Postel-Vinay and Robin, 2002; Abowd, Kramarz, and Margolis, 1999). A recent stream of studies highlight the role of high-wage firms in widening the wage gap (e.g. Barth et al. (2016) and Card, Heining, and Kline (2013)). To better illustrate the wage dispersion, figure 3.1.1 shows the top and bottom 5% percentiles ratio to the median (indexed on 1991) of real (CPI Index deflator with base year 2015) hourly wages for employees aged 23-59. Greater changes over time are observed at the lower part of the wage distribution. After the Great Recession, any temporary change restores to pre-crisis levels. Frictions arise deviating from the perfectly competitive framework[2] and allowing on-the-job search. Under the neoclassical perspective, they generate an inefficiency in the market. Due to mismatch,[3] realised wages may compress workers' productivity.[4]

In this chapter, I question to what extent is the estimation of the skill distribution biased due to the mismatch? Do frictions generate differences in the skill distribution across different groups (e.g. men vs. women)? The answers will verify the empirical strategy adopted in chapter 2 and show consistency with the theory.

[2]Wage dispersion from the Mortensen-Pissarides model is very small. Hence, not all deviations may generate significant dispersion (Hornstein, Krusell, and Violante, 2011).

[3]At least a source of heterogeneity is mandatory for job mismatch (DeLoach and Kurt, 2018; Chassamboulli, 2011).

[4]Guvenen et al. (2020) predict and support empirically that mismatch depresses both current and future wages - even if the worker switches to a matched job.

I extend the general equilibrium Burdett and Mortensen (1998) search model. Firms differ in productivity and workers in skills. The assumptions of (i) on-the-job search and (ii) endogeneity in wages distribution remain. Low-, middle- and high-productive employers[5] may coexist for two reasons. First, it is time-consuming to generate offers.[6] Second, the flow of new entrants in the non-employment (or unemployment) status is constant. Using this model, I show how the relative wage and employment of higher-skilled workers evolves in lower-productivity jobs, in equilibrium. In this setting, the labour market takes the following form. An individual chooses between work and non-employment (leisure).[7] Skills are the main sorting device[8] of joining the labour market and choosing a particular job. A low-skilled worker can only choose between Out-of-Work (OoW) and a low-productivity firm. A middle-skilled worker, has the aforementioned choices plus the job offered by the middle-productivity firm. Similarly, the high-skilled worker can choose any firm or leisure. The middle- and high-skilled worker, if lucky enough, they will be matched to a middle- or high-productivity firm, respectively. If not, they are in a job with lower skills requirements. In the latter case, they accept the job, because the present value of a less skills-intensive job is greater than that of leisure. Hence, they wait for a better job in which they will be matched (figure 3.1.2).

The arising heterogeneity from both sides may capture the mismatch in a broader way than the existent empirical over- or under-education measures. Instead, one can see that market frictions generate a mismatch in a horizontal setting[9] between employers and workers. This model argues that ranking of workers is not the same in work and skills distributions. This is the reason why workers cannot see to all potential alternative jobs. Earlier empirical work demonstrates a continuity in skills. That is why, I replicate the initial exercise for more than three types of firms and workers. By this way, I construct a more realistic measure of mismatch.

Employment can be seen as a two-player game in which the literature relates on-the-job search to the existing matching relationships. For instance, in models like Chassamboulli (2011), Dolado, Jansen, and Jimeno (2009), and

[5]To better understand low-, middle- and high-productive firms, we can look at the distribution of labour productivity, e.g. using the gross value added (GVA) per worker. Low-productivity firms could be considered those in the lowest 20th percentile, whereas high-productivity ones those in the upper 20th percentile. Those firms in-between are considered middle-productivity firms. In the UK, many firms are concentrated within the £5,000 to £20,000 output per worker range across most years. The right tail of the distribution gradually diminishes, representing the smaller number of businesses at higher levels of labour productivity (ONS, 2017).

[6]If non-employed and firms shared the same characteristics, new contract could be issued immediately.

[7]The individual may choose not to work, but also an offer may not arrive. Here for simplicity, the individual choice is work vs. no work.

[8]Bagger and Lentz (2019) quantify the sources of wage dispersion and find that sorting is its major contributor.

[9]Horizontal mismatch refers to the misfit of worker's area of study (e.g. qualification) and a particular job. This is not the same here. In this paper, the horizontal setting refers to the ranking of skills in a continuum. Skills are sorted from low to high level.

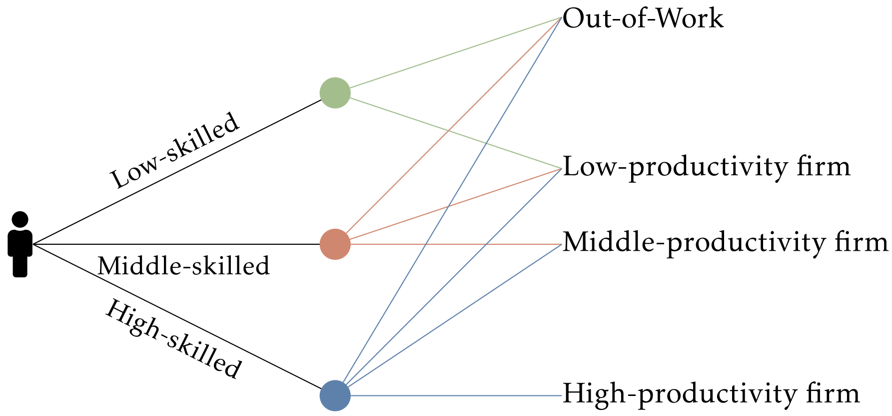


FIGURE 3.1.2: Individual decisions in the Labour Market
Note: Each individual has a set of choices depending on the skills they hold. If low-skilled, they can choose between non-employment and a low-productivity firm. If middle-skilled, they can add to the previous choices the middle-productivity firms. If high-skilled, they are further capable to be employed by high-productivity firms. In other words, low-productivity firms may offer a job to everyone; middle-productivity offer only to middle- and high-skilled workers. Finally, high-productivity firms employ solely high-skilled workers.
Source: Own elaboration

Cahuc, Postel-Vinay, and Robin (2006), two types of workers and firms are assumed. High-skilled employees are in low-productivity firms, and hence, are in mismatch. Since their wage is lower than their in-match counterparts, their search intensity is greater. Low-skilled workers face a smaller pool of jobs. As a result, they are more prone to non-employment alternative. Chassamboulli (2011) shows that mismatch occurs when a high-skilled worker is initially allocated to a low-productivity firm. This is possible during an economic downturn,[10] when high-quality workers accept low-wage, low-productivity jobs. Low-skilled workers, in this setting, are pushed to the unemployment. High-skilled workers in mismatch have a greater incentive to look for a better job than those in match. However, the data imply that we have more than two categories of workers and employees. Maintaining the duality assumption may mis-classify workers in mismatch. This is the reason why, in this model I adopt a three-dimensional aspect of the labour market, and later, I further relax the three categories for workers. By this way, I proxy the skills continuity met in the data.

The rest of the paper has the following structure. Section 2 outlines the assumptions and the steady-state equilibrium conditions of the model. Section 3 presents the simulation when skills are discrete or continuous. Section 4 concludes.

[10]The BM model has been further used to analyse dynamics of economic activity fluctuations between growth and recession; e.g. Coles and Mortensen (2016) and Moscarini and Postel-Vinay (2013).

3.2 Model

This model is akin to Burdett and Mortensen (1998) allowing for heterogeneity of both firms and workers. Labour market frictions will relate to the mismatch between job and workers' skills. This section describes the setup (assumptions, the behaviour of workers and firms) and the steady-state equilibrium conditions.

Let an economy be comprised of a continuum of firms and a continuum of workers. To simplify, both continua are assumed to be of a unitary mass.[11] Firms are heterogeneous in productivity. Initially, there are low-, middle- and high-productivity firms. p_i is type i firm's flow of revenue per employee, $i \in \{1,2,3\}$, where $p_1 < p_2 < p_3$. σ_1 and σ_2 indicate the fraction of low- and middle-productivity firms, respectively. Low-, middle- and high-skilled workers search for a job. At any moment, they choose between either to enjoy leisure and not work or to work. If they are Out-of-Work (OoW),[12] they receive a flat benefit, b, regardless of their credentials. This is the opportunity cost of employment. If they decide to work, their choices are guided by their skills and the present value of their expected wage, as described earlier. In this model, on-the-job search is allowed. Workers are able to change jobs if in work.

Firms set wages once so that they can maximise their steady-state profits. All workers under the same employer earn the same wage. At random time intervals, an individual is informed of new or alternative job positions. Let λ the arrival rate representing the parameter of a Poisson arrival process (where $0 < \lambda < \infty$); for simplicity I assume that both employed and OoW individuals obtain job offers at the same rate. Job offers are randomly drawn from the set of firms in the market or from $F(w)$, which the cumulative distribution of wage offers across firms. It is a weighted average of wage offer made by the 3 types of firms:

$$F(w) = \sigma_1 F_1(w) + \sigma_2 F_2(w) + \Big(1 - (\sigma_1 + \sigma_2)\Big) F_3(w) \tag{3.1}$$

Its respective density distribution is $f(w)$. δ is the exogenous destruction rate of the job-worker matches[13]; where $0 < \delta < \infty$.

Final important assumption regards the level of the wage. Firms are able

[11] This assumption allows a large number of employers and employees in the market. Individual firm's size, though, is not necessarily big to hold market power.

[12] Jones and Riddell (1999) support that the behaviour of inactive, with limited to none labour market attachment, and unemployed individuals is not much different. As far as the market transitions are concerned, distinction between these two states is not successful (Brandolini, Cipollone, and Viviano, 2006). Later, Jones and Riddell (2019) find that marginally-attached lie between unemployed and inactive. In fact, Krueger and Mueller (2012) highlight that unemployed spend more time to look for a job than those who already have a job or are out of the workforce.

[13] An equal number of new entrants in the market replaces those employees who leave to another firm.

to pay workers less than their productivity level. If $w = p$,[14] the model collapses to perfect competition. Though, there are certain workers willing to accept a wage lower than their marginal product if they face an alternative to exit from work. So, the wage become $b < w < p$.

The Workers' behaviour. A worker will decide to accept an offer from another employer, if their future wage is greater than their current one. If OoW, one decides to sacrifice leisure if and only if the expected wage is greater than the reservation wage (ϕ). Since jobs arrive at the same rate, individuals need to be better off now compared to non-employment. Hence, their wage needs to exceed the value of leisure to accept a job offer, or $w > b$. As a result, here, the reservation wage equals the flat benefit received when OoW, or $\phi = b$.

The firms' behaviour. The employers solve a maximisation problem. They choose a wage such that their profits are maximised, or

$$\max_{w \geq \phi} \pi_i = (p_i - w)\ell(w) \tag{3.2}$$

where $\ell(w)$ is the steady-state level of employment in a firm which pays a wage, w, drawn from the distribution of offers in the market $F(\cdot)$. A firm paying w will recruit workers from two pools: from (a) OoW if $w \geq b$; and, (b) other firms which pay less than w. In other words, the size of firms equals the ratio of number of workers in firms in the range that pay a wage not below w over the number of firms in the same range or the average employment per firm. Alternatively, $\ell(w) = \frac{g(w)}{f(w)}$. Therefore, before solving the maximisation problem, it is important to determine the level of employment.

3.2.1 Steady-State Equilibrium Conditions

1. Non-employment rate. To define the equilibrium for each type of firm $F_1, F_2, F_3, \pi_1, \pi_2, \pi_3$, in steady state, flow of workers exiting work should be equal to the flow of workers exiting OoW.

$$\delta \cdot (1 - u) = \lambda \cdot \Big(1 - F(b)\Big) \cdot u$$

where the left- and right-hand sides describe the inflow and the outflow of workers to/from non-employment, respectively. In equilibrium, employers offer wages that workers would be willing to accept and are greater than the reservation wage (which here equals b). This allows to determine the non-employment rate as

$$u = \frac{1}{1 + \kappa} \tag{3.3}$$

where $\kappa = \frac{\lambda}{\delta}$ is a market-friction parameter. κ describes the average number of offers an individual can expect before the next layoff.

2. Distribution of salaries (across workers). For this condition the flow of workers into jobs providing a wage not exceeding w should be equal to the

[14] An alternative implication stemming from the BM model considers a firm to make strictly positive profit by lowering its wage. This comes from the proposition that wants $F(w)$ without spikes, or the frictions to vary between 0 and infinity ($0 < \kappa < \infty$).

flow of workers out of jobs providing a wage no greater than w

$$\underbrace{\delta \cdot (1-u) \cdot G(w)}_{\substack{\text{Firings from jobs providing} \\ \text{a wage lower than } w}} \quad \underbrace{+\lambda \cdot \Big(1 - F(w)\Big) \cdot (1-u) \cdot G(w)}_{\substack{\text{Inflow to jobs} \\ \text{offering greater than } w}} = \lambda \cdot u \cdot \underbrace{\max\Big\{F(w) - F(b), 0\Big\}}_{\substack{\text{Firms offering a wage} \\ \text{no greater than } w \\ = F(w)}}$$

where $G(w)$ is cumulative distribution function of salaries workers; i.e. the fraction of workers paid less than w. The left- and right-hand side describe outflow and the inflow of workers from/to jobs that offer wages less than w. The left-hand side is comprised by the firings from jobs where wage is lower than w and the hirings to jobs offering a wage greater than w. Hence, the distribution of salaries is:

$$G(w) = \frac{F(w)}{1 + \kappa(1 - F(w))} \tag{3.4}$$

Inferences of the relationship of $G(w)$ and $F(w)$ are discussed later at the simulation.

3. Size of firms. The first two equilibrium conditions allow to revise the firms' profit. Assuming uniform hiring effort, the expected number of workers at a firm which pays w is

$$\ell(w) = \frac{1 + \kappa}{\Big(1 + \kappa\Big(1 - F(w)\Big)\Big)^2} \tag{3.5}$$

4. Profits. Given the above we can rewrite the profit function:

$$\pi_i = \frac{\kappa(p_i - w)}{\Big(1 + \kappa\Big(1 - F(w)\Big)\Big)^2} \tag{3.6}$$

The remaining unknown expression to characterize the equilibrium $\{F_1, F_2, F_3, \pi_1, \pi_2, \pi_3\}$ is that of $F_1(w)$, $F_2(w)$ and $F_3(w)$. To this end, note that $w_3 \geq w_2 \geq w_1$ for each w_i on $\text{supp}(F_i)$, or

$$\begin{cases} \pi_i = (p_i - w)\ell(w), & \text{on supp}(F_i) \\ \pi_i \geq (p_i - w)\ell(w), & \text{otherwise} \end{cases}$$

In equilibrium all offered wages generate the same level of profit; no other possible wages yield higher profit. For the equal profit conditions, it holds that

$$\begin{cases} (p_1 - w_1)\frac{1+\kappa}{\left(1+\kappa\left(1-F(w)\right)\right)^2} = (p_1 - b)\frac{1+\kappa}{(1+\kappa)^2}, & \text{if } w < w_1 \\ (p_2 - w_2)\frac{1+\kappa}{\left(1+\kappa\left(1-F(w)\right)\right)^2} = (p_2 - w_1)\frac{1+\kappa}{\left(1+\kappa\sigma_1\right)^2}, & \text{if } w_1 < w < w_2 \\ (p_3 - w_3)\frac{1+\kappa}{\left(1+\kappa\left(1-F(w)\right)\right)^2} = (p_3 - w_2)\frac{1+\kappa}{\left(1+\kappa(1-(\sigma_1+\sigma_2))\right)^2}, & \text{if } w > w_2 \end{cases}$$

from where we can solve for $\{F_1, F_2, F_3\}$.

3.3 Simulation

Table 3.3.1 outlines the values used to run the simulation discussed in the following sections.

Table 3.3.1: Parametrization

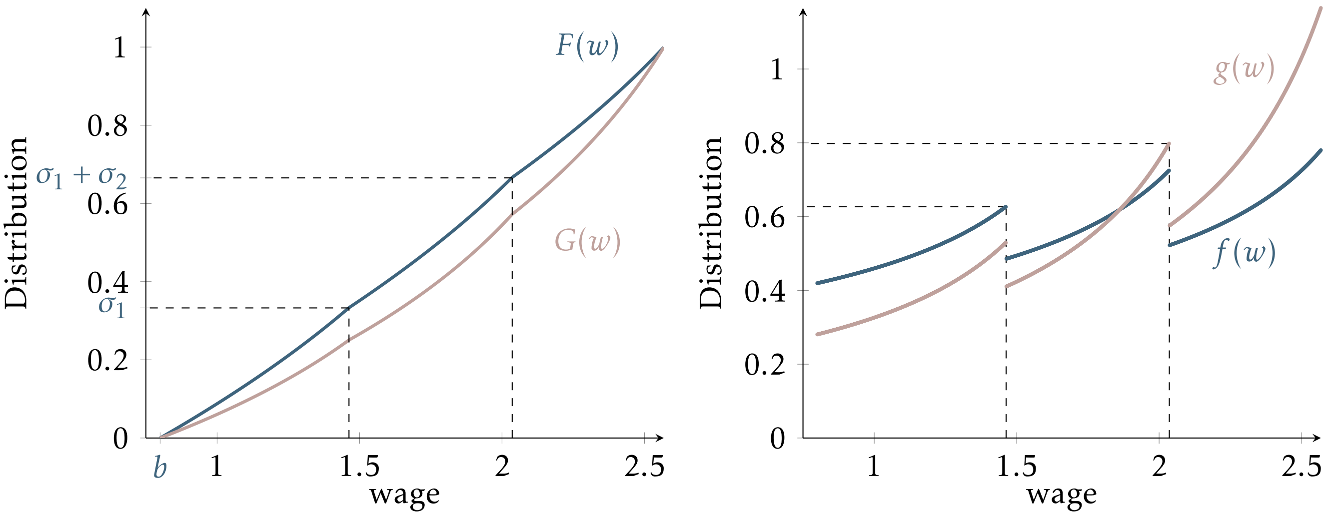
Parameter	Description	Value
b	Flat flow value to non-employment	0.8
δ	Job destruction rate	0.287
λ	Job arrival rate	0.142
p_1	Productivity of low-type firms	2
p_2	Productivity of middle-type firms	2.5
p_3	Productivity of high-type firms	3
σ_1	Share of low-productivity firms	$\frac{1}{3}$
σ_2	Share of middle-productivity firms	$\frac{1}{3}$

Note: Job destruction and arrival rates adopted by Mortensen (2003).
Source: Own elaboration

3.3.1 Discrete Skills

Based on the model described in the previous section, where three discrete types of workers and firms exist, I illustrate the Cumulative Distribution Function of the offers and salaries and their associated density probability function.

Figure 3.3.1 depicts the cumulative (panel 3.3.1a) and density (panel 3.3.1b) distribution of wage offers (blue) and salaries (pink). Panel 3.3.1a shows that $F(w)$ differs from $G(w,F)$, since the size of each type of firm varies with the wage. In fact, $F(w) > G(w,F)$ for $0 < F(w) < 1$. This means that the fraction of jobs in the equilibrium wage distribution below wage w $\left(\text{G(w,F)}\right)$ is lower than the fraction of offers below w $\left(\text{F(w)}\right)$. Workers are concentrated in the better paying jobs, implying that such firms have a higher level of employment. In other words, $F(w)$ first-order stochastically dominates $G(w,F)$.



(A) Cumulative

(B) Density

FIGURE 3.3.1: Distributions
Note: Blue lines refer to the offers made in the market and pink lines to the salaries. Panel (a) represents the distribution of wage offers $F(w)$ and the distribution of salaries $G(w)$ in this economy. Both are kinked with result into jumps for the densities of $f(w)$ and $g(w)$, in panel (b).
Source: Own elaboration

Both distributions are kinked. These kinks are related to how many different types of firms we observe. For j types of firms, $j-1$ kinks are observed on the CDF. In panel 3.3.1b, these kinks result into jumps. Here, the illustration treats wage as a continuum and does not show the wage distribution within a certain firm type to highlight that more productive firms offer greater wages. To this end, the separation of each firm type in the market occurs due to the kinks on the CDFs. Low-productivity firms separate from middle-productivity firms($\overline{w_1}) = \underline{w_2}$), while the middle- from high-productivity firms ($\overline{w_2} = \underline{w_3}$). Workers search for a job, and do not receive offers from everyone at once. Some of them wait in a firm while searching for an alternative job that pays a higher wage.[15] A reasonable question may concern the overlap of the density distributions in the middle-productivity firms. This occurs because the number of workers in middle-productivity firms exceeds the average employment per firm. Besides, this type of firms employs both middle- and high-skilled workers. Hence, the latter category of workers may wait there until they find their matched job.

The final implication regards the number of workers per firm or the firm size as depicted in figure 3.3.2. The labour force in the steady state increases with the wage; or, there is a positive relationship between the number of workers and the wage. Higher-wage firms experience greater profits, since they employ more individuals or lose less to other employers.

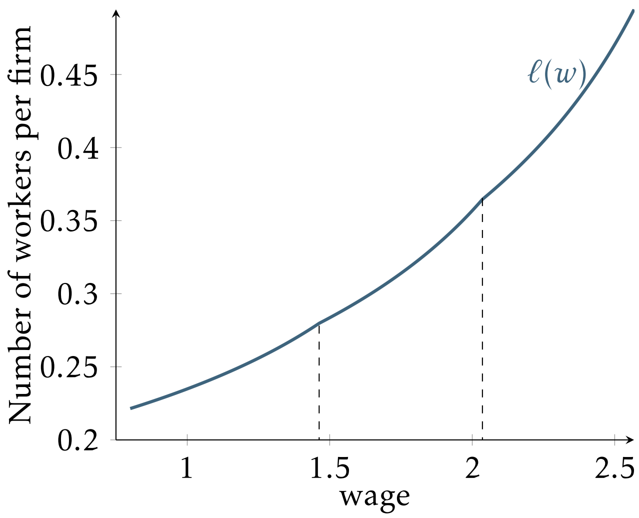


FIGURE 3.3.2: Labour Force
Note: $\ell(w)$ shows the number of workers per firm or the firm size. Dashed lines indicate the boundaries each type of firm dependent on the wage, as above.
Source: Own elaboration

TABLE 3.3.2: Proportion of each skills- and job-type distribution

		Job		
		Low (L)	Middle (M)	High (H)
Worker	L	1		
	M	$g_2(w_1)$ **0.292**	$1-g_2(w_1)$ 0.708	
	H	$g_3(w_1)$ **0.00**	$g_3(w_2)-g_3(w_1)$ **0.1851**	$1-\big(g_3(w_2)+g_3(w_1)\big)$ 0.8149

Note: Figures in bold report the incidence of mismatch. The probability of a high-skilled employed in a low-productivity job is very small (0.00001); this is why on the table is indicated as zero.
Source: Own elaboration

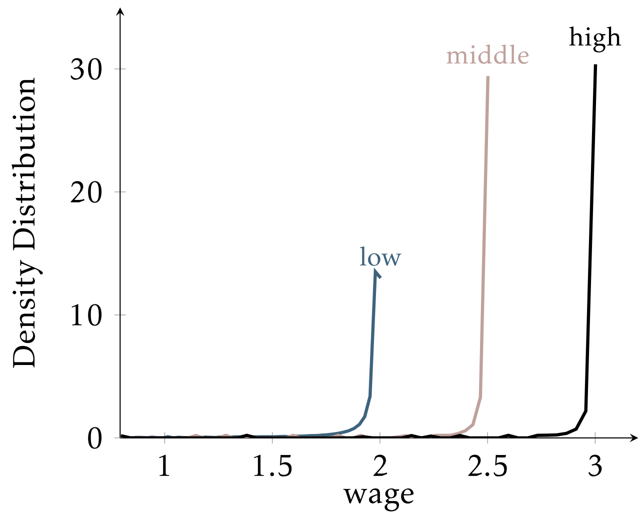


Figure 3.3.3: Identification of Mismatch
Note: This is an alternative illustration of figure 3.3.1b. The mismatch is identified on the overlap of the wage density distribution. A worker is in mismatch if she is middle-skilled, but works in a low-productivity firm ($g_2(w_1)$). A high-skilled employee is in mismatch if she works in a low- or middle-productivity firm. The first case, is not very likely to happen (0.00001; or 0 on the table 3.3.2).
Source: Own elaboration

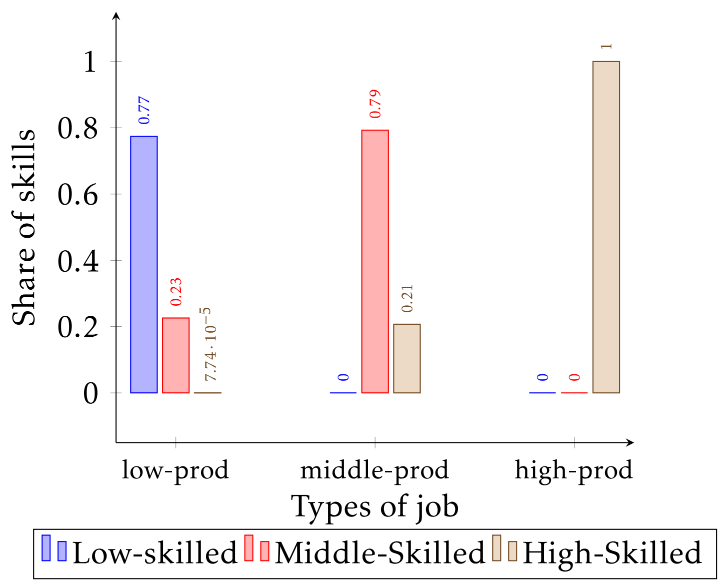


Figure 3.3.4: Workers' skills vs. types of jobs
Note: Relative share of each skill- in each job-type. For ease, I have assumed that workers are equally distributed among each skill-type; namely their share equals to $\omega_i = \frac{1}{3}$.
Source: Own elaboration

Mismatch

In this BM environment, there is not perfect sorting of employees in jobs; hence, mismatch arises due to frictions in the labour market. To better illustrate this point, figure 3.3.3 shows the Kernel density distribution of each wage *within* a certain firm-type. This graph does not distinguish the lower and upper bounds of the wage. However, it reveals that a middle- or high-skilled worker may receive an offer from a low-productivity firm. Similarly, a high-skilled worker can also receive an offer from a middle-productivity firm. In both cases, if these workers accept the offer of a lower-skills intensive job, they are in mismatch. In other words, they potentially accept a job to wait until a better opportunity arises. Their decision may be driven by their second-best alternative, e.g. unemployment.

Table 3.3.2 reports the method to calculate and the incidence of the mismatch in the BM labour market. One is not matched if she is a middle- or high-skilled worker and works in a low- or middle-skilled job, respectively. To find its extent, in a low-productivity job, we calculate how many people are middle- (g_2) and high-skilled (g_3), but they are paid with a wage corresponding in a low-productivity firm (w_1). A notable comment, here, regards the probability of a high-skilled worker in a low-productivity firm. It does exist, but it is very close to zero. This event is less likely to occur, since a high-skilled employee has greater chance to receive a better offer by a middle-productivity firm if she is not lucky enough to be matched. Figure 3.3.4 depicts the relative share of each skill-type of worker employed by each firm type. For simplicity, an assumption of equal distribution of workers among the skills categories is adopted.To calculate the share of low-skilled employees in the low-productivity firms, I follow the formula

$$\frac{\omega_1}{\omega_1 + \omega_2 g_2(w_1) + \omega_3 g_3(w_1)}$$

A similar exercise is adopted for the remaining categories.

Frictions in the Labour Market

A main result of this model regards mismatch coming from frictions in the labour market. This subsection aims to highlight how frictions affect the incidence of mismatch and whether there are gender differences. Finally, we see the role of firms' share in the market.

Figure 3.3.5 illustrates the wage profiles over the change of frictions. A greater value of the market-friction parameter, κ, reduces the job-search costs in the market. On the one hand, as κ heads to infinity, no frictions occur. Hence, the model collapses to the limiting case of perfect competition gaining its properties, where the wage equals the marginal product. On the other hand, when κ heads to zero, the model collapses to the Diamond (1971)

[15] In the UK, evidence suggests the public-sector acts as a waiting room for high-skilled employees until they find their matched job (Galanakis, 2020).

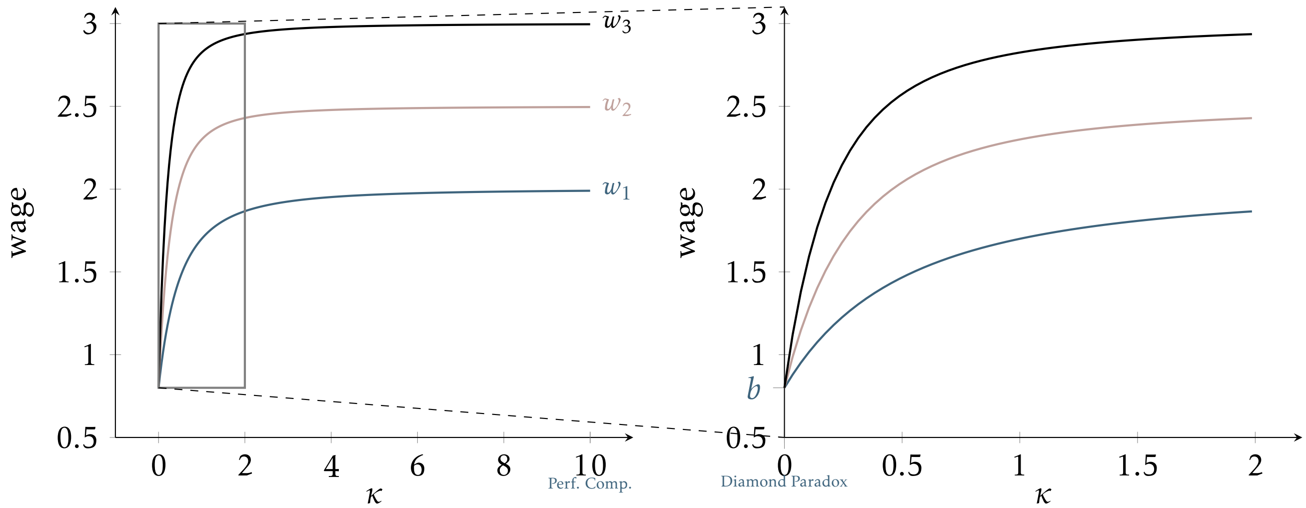


FIGURE 3.3.5: Change of κ with constant share of firms
Note: Each profile illustrates the wages in low- (w_1), middle- (w_2) and high-productivity (w_3) firms over the market-friction parameter κ. As κ increases, the model collapses to the perfect competition where employees are awarded with their marginal product. The right panel zooms to the profiles when $\kappa \leq 2$ to better illustrate the differences among wages.
Source: Own elaboration

paradox. In that case, all workers regardless of their skills receive the reservation wage. For any wage less than MPL but greater than the reservation wage, workers value less their next best alternative - i.e. non-employment or leisure - than that particular wage. The left-hand panel shows that all wage profiles start from the same point, namely the reservation wage. Lower-skilled workers profiles flatten quicker than others. In other words, as frictions decrease, high-skilled wages increase faster. To better illustrate this point, the right-hand side panel zooms in the case where $\kappa \leq 2$.

A similar picture might come from the study of the relative slopes of wages, or the returns to skills. Figure 3.3.6 illustrates them as κ changes. To highlight the gender differences, we may use the non-employment rate steady-state equilibrium condition (eq. 3.3). Galanakis (2020) finds that the mean non-employement rate for men and women is 21.7% and 34.46%, respectively. One can see that women face more labour market frictions.[16] In fact they may face several exogenous reasons why their jobs are destroyed (greater job destruction rate). For example, they may have to move because of their partner's new job opportunity, they may get pregnant, or nursery may close and they may need to provide childcare. On the contrary, they may have a lower job arrival rate because of the jobs that they are looking for. For instance, their job hunting may be restricted to a set of firms where

[16]The BM model is restrictive in the sense that workers are only mobile because of a better wage offer. However, in reality, characteristics irrelevant to the wage may be important (see, for example, Sullivan and To (2014) and Bonhomme and Jolivet (2009)). Workers may prefer firm x to y despite a greater wage offered in firm y. Amenities of firm x may attract her more than those of the competitor. Sulis (2012) finds that Italian female workers face more search frictions than their male counterparts.

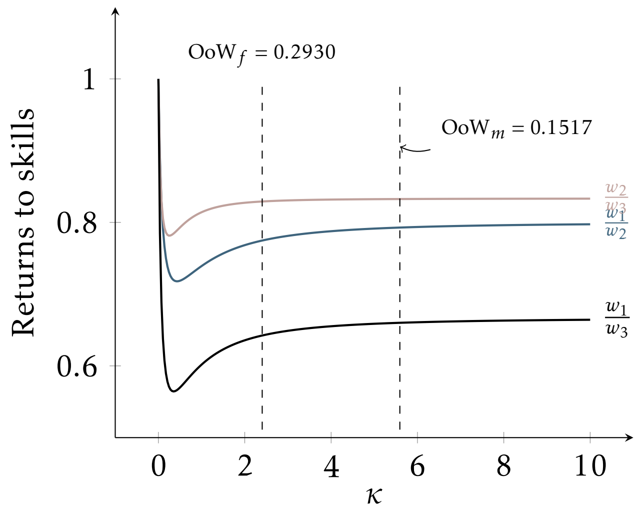


FIGURE 3.3.6: Gender differences in frictions and returns to skills

Note: This graph illustrates the relative slopes of the wages profiles over the market-frictions parameter. The vertical dashed lines refer to the level of frictions for women and men, respectively. This comes from solving eq. 1 and using the OoW rate from Galanakis (2020).

Source: Own elaboration

provision of schooling is easier or they are closer to their partner's job. Therefore, female labour supply is likely to be more dependent on their partner's employment.

Do frictions matter? The role of firms' share

Figure 3.3.7 depicts the essential role of the firms' share (σ) on market frictions, and hence, mismatch. When the market has less frictions and there is a smaller share of lower-productivity firms, the model adopts quicker the perfect competition properties. Two underlying mechanisms hold to this end. First, a lower σ determines fewer firms in the lower part of the distribution; hence, the market has more high-skilled workers who are matched in high-productivity firms. In other words, since there will be a lower demand from the lower-productivity firms, those workers at the margin will migrate to the next closest type of firm.[17] Second, σ *per se* determines the "under-reward" or mismatch penalty. A smaller firms' share moves the distribution to the right, since it decreases the upper bound of the low-skilled wages. A greater κ, or lower frictions, seems to allow no effect on the variation of the firms' share. On the contrary, more frictions in the market imply that the variation in σ does play an essential role. This becomes more clear from the differences between the solid and the dashed lines on the graph. Therefore, this suggests that a smaller share of lower-productivity firms combined with less frictions in the market decrease the incidence of mismatch.

[17] For example, if at the margin of low- and middle-productivity firms, a smaller σ will make a worker move to the middle-type. What type of worker, though, will migrate? The top-skilled workers of low-productivity firms (i.e. middle- and high-skilled ones).

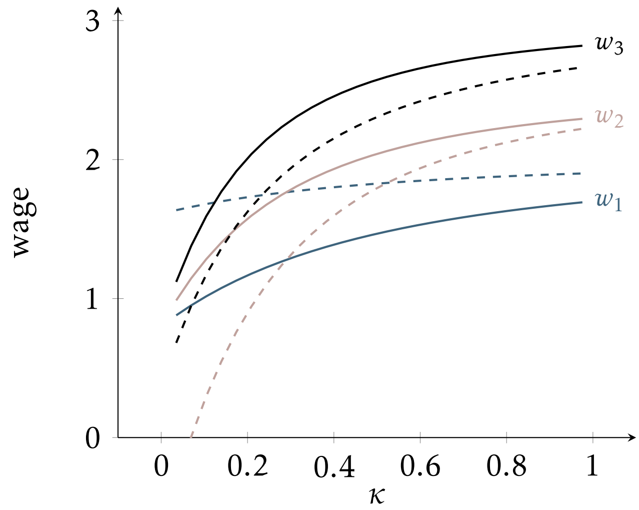


FIGURE 3.3.7: The role of firms' share (σ)
Note: Each profile illustrates the wages in low- (w_1), middle- (w_2) and high-productivity (w_3) firms over the market-friction parameter κ. As κ increases, the model collapses to the perfect competition where employees are awarded with their marginal product. Solid line: $\sigma_1 = \frac{1}{3}$; Dashed line: $\sigma_1 = 0.19$. Frictions are limited to values less or equal to 1 to better highlight the change of the profiles.
Source: Own elaboration

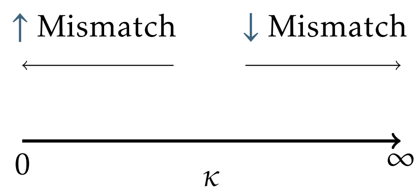


FIGURE 3.3.8: Frictions vs. Mismatch: A qualitative illustration
Note: Market frictions represented as a positive continuum. A greater value of κ reduces the incidence of mismatch, and *vice versa*.
Source: Own elaboration

3.3.2 Continuous Skills

In this setting, so far, I allow for only three types of workers. However, in the data one may see that skills present a continuity. Hence, the above-described framework may underestimate the extent of mismatch given frictions in the labour market. A qualitative illustration of frictions in a positive continuum, as in figure 3.3.8, shows that as frictions reduce (or $\kappa \to \infty$), wages determine productivity in relative terms. In other words, more frictions in the market weaken this relationship between wages and productivity distorting the skills categories. This places workers in a category *below* than the one they should be. Or, it works as an overstatement of the requirements of a particular firm type. Adopting a setting with more than 3 categories may approximate the continuity seen in the data. To this end, I repeat the exercise of the previous section by allowing 10 types of workers and firms.[18]

[18] The more types the closer we can get to continuity. However, increasing the types generates a heavier computationally problem.

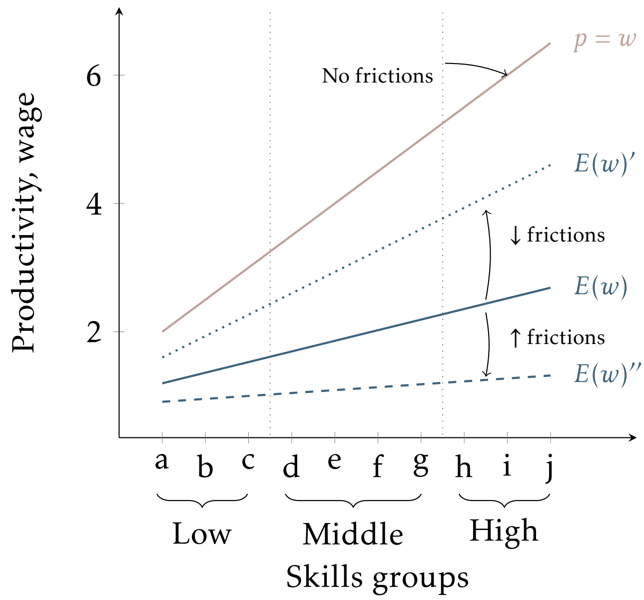


FIGURE 3.3.9: Productivity vs. Expected wages
Note: Let 10 types of firms and 10 types of workers. The steps of the earlier discrete measure's estimation repeated for each skill category. This framework allows to approximate a continuous skills measure. The market segmentation (vertical dotted lines) occurred arbitrarily to mimic the data. The pink line shows the wage in a frictionless market. The expected wage (when $\kappa = 0.492$; blue solid line) is calculated by equation 3.7. An exercise to increase ($\kappa = 0.1$; blue dashed) or decrease ($\kappa = 2$; blue dotted line) the frictions allow to see the impact on the mismatch.
Source: Own elaboration

Figure 3.3.9 includes the wage profiles of each worker given their skills-type. In a frictionless market ($\kappa \to \infty$), workers are paid with their marginal product. In this case, matching is perfect and no inefficiencies occur. When frictions arise, the expected wage will be lower. Adopting the same parametrization as before, we calculate the expected wage as:

$$E(w) = \frac{1}{1+\kappa}b + \frac{\kappa}{1+\kappa}p \tag{3.7}$$

This formula reveals a positive relationship between frictions and the gap from the frictionless model. As κ decreases, the gap rises. In fact, the difference is greater at the top of the skills distribution. This is because there are cases of higher-skilled workers in mismatch. Alternatively, productivity in that case plays a greater role - in line with the Human Capital Theory. The solid line represents the baseline estimates, when $\kappa = 0.492$. The dotted and dashed lines present an exercise of decreasing or increasing the market frictions, respectively. They assume that κ equals to 2 or 0.1, respectively. To better illustrate the gap among the models, I outline the mean productivity and expected wage for each type of worker on table 3.3.3. It may suggest that estimates depend on being able to observe productivity. However, it is usually compressed by realised wages due to the mismatch.

Following the same definitional illustration of the mismatch, figure 3.3.10 plots the Kernel densities of the linear prediction of skills (or in a broader

TABLE 3.3.3: Mean productivity and Expected wage for each type of worker

	Frictionless	Baseline Frictions		Less Frictions		More frictions	
Group	p	E(w) $\kappa = 0.495$	Diff	E(w) $\kappa = 2$	Diff	E(w) $\kappa = 0.1$	Diff
Low	2.5	1.363	-1.137	1.933	-0.567	0.955	-1.545
Middle	4.25	1.942	-2.308	3.100	-1.150	1.114	-3.136
High	6	2.521	-3.479	4.267	-1.733	1.273	-4.727

Note: Column 2 reports the average productivity within each skills group, or what it stands if no frictions occur. Columns 3-8 report the baseline friction estimates, the exercises with less and more frictions in the market. Every second column reports the difference between the particular friction estimates and the frictionless ones.
Source: Own elaboration

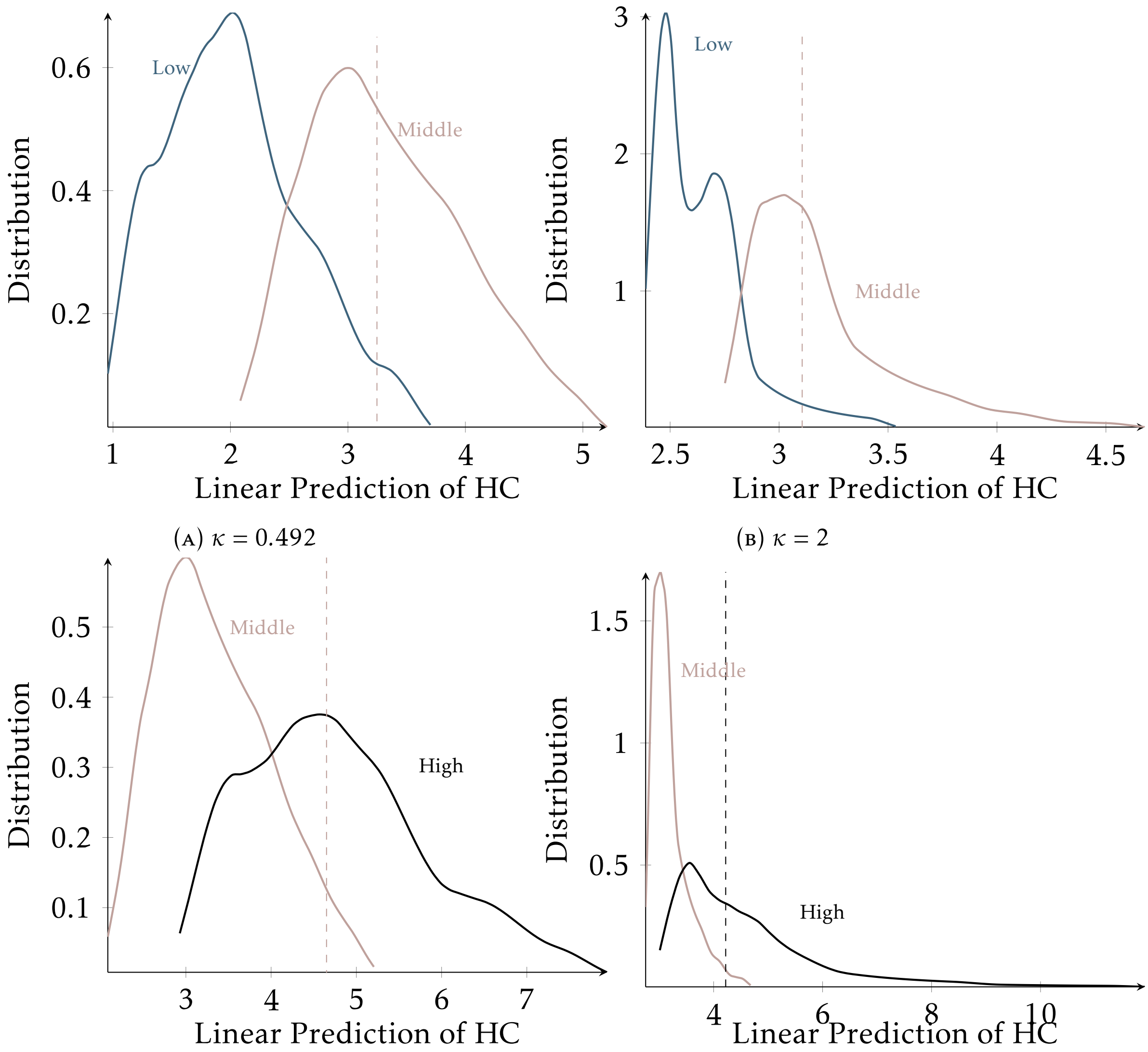
way human capital). The upper panel plots the mismatch between the low- and the middle-skilled, whereas the lower panel the one between middle- and high-skilled. The left-hand panel keeps frictions on the baseline, while the right-hand decreases the frictions. When they decrease, the distributions overlap less. Lower frictions mean that the model is closer to perfect competition, or to less inefficiencies. As a result, a lower magnitude of mismatch occurs.

3.4 Conclusion

This papers presents a structural search-and-matching model akin to Burdett and Mortensen (1998) with on-the-job search. Its extension allows an heterogeneity in worker skills and firm productivity. People search in the same labour market. If they are low-skilled, their alternatives are not to work, and hence enjoy leisure, or to work in a low-productivity firm. The middle-skilled can accept offers from either a low- or middle-productivity firms. If matched, they are in the latter type of firm. If not, they choose their alternatives (low-productivity firm or OoW) based on which has a greater present value. The same rationale applies for the high-skilled employees.

Having simulated the market (offers) and wage distributions in the economy and the labour supply curve, I estimate the incidence of mismatch. A worker is in mismatch if she works in a lower productivity firm given her characteristics. This inefficiency - under the neoclassical perspective - comes from the market search frictions. Lower frictions bring the model closer to the perfect competition and the incidence of mismatch decreases. Vice versa, more frictions limit the model to Diamond's paradox and greater incidence occurs. The firms' share plays an essential role only when there are more frictions in the market. To this end, it determines a "pay penalty" of the mismatch.

To better approximate the data, I replicate the same exercise assuming



(A) $\kappa = 0.492$

(B) $\kappa = 2$

(C) $\kappa = 0.492$

(D) $\kappa = 2$

FIGURE 3.3.10: Mismatch: Impact of frictions on E(w|skills)
After the liner predictions of human capital sorted by skills category, we plot their Kernel density. One is in mismatch if they stand above the median of the more skills-demanding job. The upper panel shows the mismatch between the low- and the middle-skilled, while the lower panel between the middle- and the higher-skilled. The left-hand side keeps friction on 0.492, whereas the right-hand side reduces frictions to 2. After an increase in κ, or a reduction in frictions, distributions overlap less, because the model lies closer to the perfect competition. Hence, a lower incidence of mismatch is expected.
Source: Own elaboration

ten types of workers and firms. In that case I segment the market appropriately to mimic a continuous measure of skills. This exercise reveals that the expected wage has a positive relationship to the productivity. In a frictionless model, the worker receives their marginal product. When mismatch occurs, the market friction reduces the expected wage. Its gap from the frictionless model increases with the productivity and frictions. In other words, additional frictions affect more the high-skilled workers' expected wage.

Appendix

3.A Continuous Firm Productivity

Bontemps, Robin, and Berg (2000) attempt an extension of the BM model. Using a two-stage non-parametric procedure, they estimate the continuous firm productivity as.

$$p = w + \frac{1 + \kappa \widehat{G(w)}}{2\kappa \widehat{g(w)}} \tag{3.8}$$

where $\widehat{G(w)}$ and $\widehat{g(w)}$ are estimated using a Kernel estimator. Workers, given $F(\cdot)$ and $G(\cdot)$, rank their current (reservation) wage and the (wage) offers they receive. Hence, this behaviour is sufficient to identify the market frictional parameters.

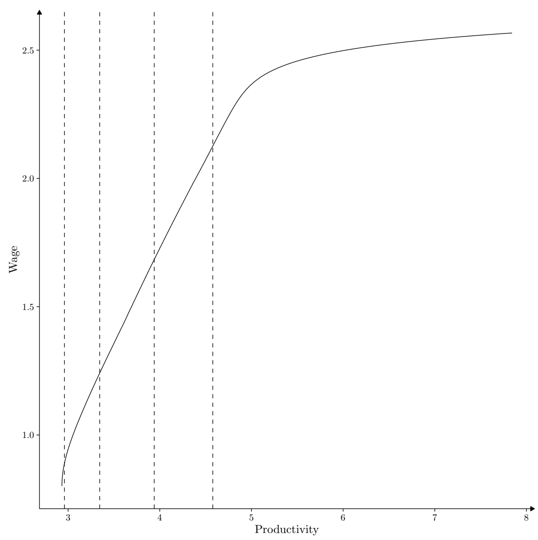


Figure 3.A.1: Quantile-Quantile plot: Wage vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity. A positive relationship between wage and productivity is revealed. Wages increase at the beginning of the productivity distribution, but smooth out beyond the 75th percentile.
Source: Own elaboration

Figure 3.A.1 illustrates a quantile-quantile plot between the wage and productivity. The vertical dashed lines represent the 5th, 25th, 50th and 75th precentiles of firm productivity, respectively. This figure reveals a positive relationship between wage and productivity. The wage increases rapidly at the beginning of the productivity distribution, i.e. mostly for low-productivity firms. The curve smooths out as we move towards the higher-productivity

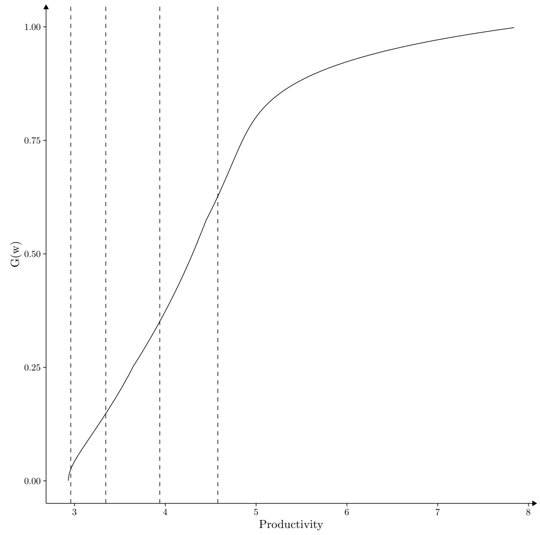


FIGURE 3.A.2: Quantile-Quantile plot: $G(w)$ vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity. Concavity smooth out beyond the 75th percentile.
Source: Own elaboration

firms. Wages increase over these percentiles but smooth out beyond the 75th percentile. Figure 3.A.2, in a similar way, plots the distribution of wages, $G(w)$, against productivity. The curve seems more concave and smoothing beyond the 75th percentile persists. Figure 3.A.3 depicts productivity against the PDF of wages as linear interpolation of the Kernel density. Further away from the 75th percentile, the slope increases and the curve becomes flatter.

Figure 3.A.4 looks at the predicted profit rate calculated as

$$\text{Profit Rate} = \frac{p - w}{p} \tag{3.9}$$

Wages strictly increase at bottom of the distribution. The profits, though, are relatively constant until the 25th percentile; thereafter, they increase more. This points out that higher-productivity firms present higher profit rates.

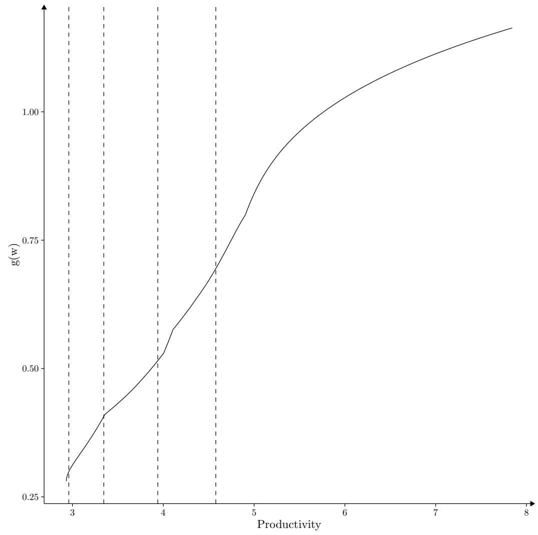


Figure 3.A.3: Quantile-Quantile plot: $g(w)$ vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity.
Source: Own elaboration

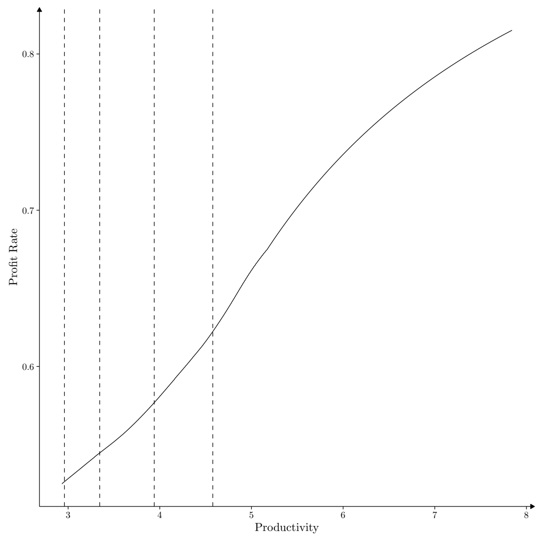


Figure 3.A.4: Quantile-Quantile plot: Profit rate vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity.
Source: Own elaboration

Chapter 4

Work in a man's shoes: Determinants of Female Human Capital mismatch in the UK*

Abstract

This paper looks at the extent of and reasons for labour market mismatch of female employees. It utilises a novel indicator of mismatch that can take account of differences across workers in more than one dimension of skill and uses data from the British Household Panel Study and its successor 'Understanding Society' covering the years 1991-2016. I estimate the incidence of mismatch varying from 13% to 34% depending on the specifications and the control group(s). Results show that individual characteristics affect the female workforce mismatch in the market. Lone motherhood and the number of children increases the probability of female mismatch. Recent entrants in the market may experience a higher likelihood of mismatch, which dissipates over time. Unemployment has a positive relationship with the incidence of mismatch.

4.1 Introduction

Human Capital Mismatch (HCM) in the labour market might occur when individuals from lower-skilled occupations have similar characteristics/profiles to those who are employed in a more-skill intensive jobs (chapter 2). Therefore, the inefficiency in the labour market distorts their wages failing to illustrate the actual changes in skills distributions (chapter 3).

Despite improvements in the position of women in the labour market, various studies do not distinguish the effect of mismatch by gender (e.g. Turmo-Garuz, Bartual-Figueras, and Sierra-Martinez (2019), Li, Harris, and Sloane (2018), Wen and Maani (2018), and Gaeta, Lubrano Lavadera, and Pastore

*Acknowledgements: I would like to thank for their comments and feedback participants of the Understanding Society Scientific Conferences 2019 (Essex, UK) and WPEG Annual Conference 2019 (Sheffield, UK).

(2018)).[1] This is crucial from a policy-making perspective, since occupational segregation persists among British employees affecting pay gaps (Lindley, 2015). This paper could stand as an initial reply to Capsada-Munsech (2017) shedding more light on the gender gap of mismatch in the British labour market.

In Western economies, over the last three decades, women have been more active (Karamessini, 2014). Women invest more in education and participate more in the labour market. First, an augmenting trend in Higher Education participation increases the gap against men - the last two years the gap increased almost by 1% (figure 4.1.1). Despite the fees' cap in England, occurred twice the last two decades, women might have reduced temporarily their presence in HE, but their dominance persists. Second, this dramatic rise of the educational attainment coincides with the steep increase in the share of women in employment, reducing the gap observed with their male counterparts (figure 4.1.2; Charles (2011)). At the end of 2018, the female labour force participation peaked at 74.8% (or 15.3 million, aged 16+), while the gap between men and women was single-digit (8.9%). Those two supply-related events potentially are not independent. By 2011, the proportion of men and women graduates did not differ much (Lindley and Machin, 2012). The counter-effect of this parity, though, might result in a credentials inflation, where employees are displaced across the labour market (Karmel, 2015; Dockery and Miller, 2012).

In the UK, women traditionally are more likely to work in a clerical, secretarial or other related administrative jobs, while they hold a strong presence - above the three quarters - in health and social work and education (Powell, 2019; Manning and Swaffield, 2008). Figure 4.1.3 illustrates the employment distribution, by occupation and gender. Occupations have been sorted by their skill-intensity, i.e. median hourly wage and average level of education, as in chapter 2. The horizontal axis counts the number of employees in each occupation.[2] Figure 4.1.3 shows women are mostly employed in middle-skilled occupations. If women are more educated than men, this may imply that the labour market does not fully utilise their skills.[3] Therefore, women

[1] On the contrary, Ueno and Krause (2018) and Mateos Romero, Murillo Huertas, and Salinas Jiménez (2017) control for gender including a dummy variable in their regression suggesting important differences against women. However, this might not be enough to illustrate the magnitude of the effect on the female workforce regardless the strong statistical evidence. For instance, Kalfa and Piracha (2018), García-Mainar and Montuenga-Gómez (2017), and McGuinness, Bergin, and Whelan (2017) and Davia, McGuinness, and O'Connell (2017) attempt to replicate their results for the restricted female subsample. The control group is essential if women are prone to experience a mismatch.

[2] Significant changes on this distribution are observed since 1991 potentially driven by technological advances (Acemoglu and Autor, 2011; Autor, Levy, and Murnane, 2003; Acemoglu, 2002; Acemoglu, 1998), employment expansion in certain jobs (Green and Henseke, 2016b), occupational upgrading in favour of the female labour force (Lindley, 2015) or the aforementioned qualifications increase. Finally, as expected, important differences are noticed when one controls for dependent children, where participation decreases especially for women.

[3] An alternative channel could regard their preferences or their optimal choices in the face of discrimination. Here, I argue that, because of the discrimination they face before entering the labour market, women are more prone to be in mismatch.

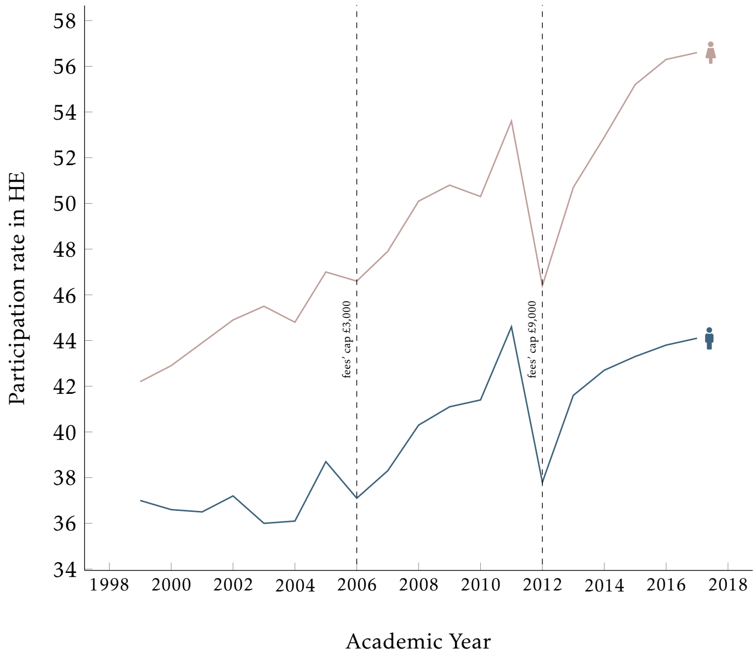


Figure 4.1.1: Participation in Higher Education, by gender
Note: For earlier rates, see figure 1 in Broecke and Hamed (2008). Earlier fees' cap on 1998 was at £1000.
Source: DfE and HESA

are more likely to be in mismatch. For example, let a woman stand in the margin of working in a higher skilled (e.g. in a professional) or a lower skilled (e.g. in an associate professional) occupation. If the argument above is valid, she works in associate professional occupation and her probability of HCM increases. If not, she works in a professional occupation. This is why one can observe a genuine greater potential of female mismatch in the labour market. Given their significantly higher qualifications, women, who suffer from a mismatch, hold more skills than their male counterparts. Or, women who are as skilled as men, receive lower wages conditional on their skills.[4] If mismatch is an outcome of oversupply or excess qualifications (credentialism) in the market, we should not expect gender differences.[5]

Focusing on female employees is further motivated by my model in chapter 3. Women face more frictions in job search than men. Why is the market-friction parameter different for women? The answer may be related to family or work events. The market-friction parameter connects the job arrival and destruction rates. On the one hand, women have lower arrival rate than men. For example, their labour supply decision is dependent on the proximity of their partner's job (e.g. is there an available job close to their partner's work?) or childcare provision (e.g. how close is a nursery or a school?). On the other

[4]Or, under the GPG lenses, controlling for exogenous human capital explains little of the gap. The gap is either driven by acquired experience or mismatch. If learning-by-doing is dependent on the quality of a match, worker's job is important. If employed in jobs with lower opportunities to acquire skills, the probability for on-the-job training is lower, and hence, more likely to be in mismatch.

[5]This argument would collapse if men and women have different preferences or they work in completely different jobs (in separate markets).

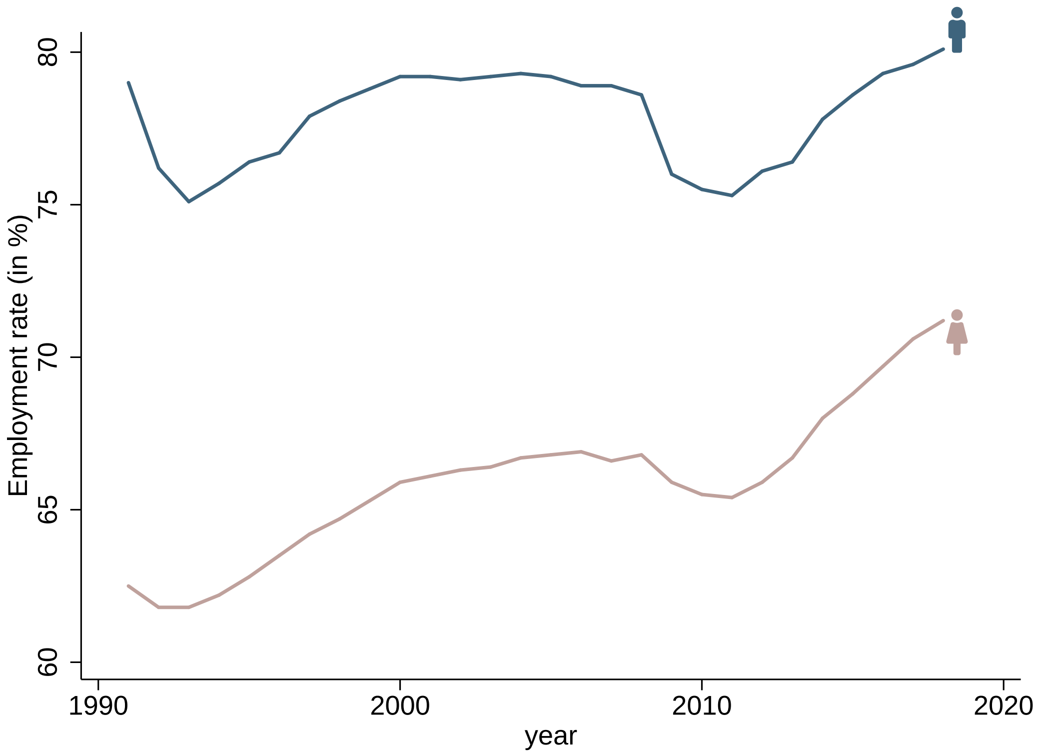


FIGURE 4.1.2: Employment by occupation: all people in employment; 1991-2016
Source: ONS UK Labour Market bulletin

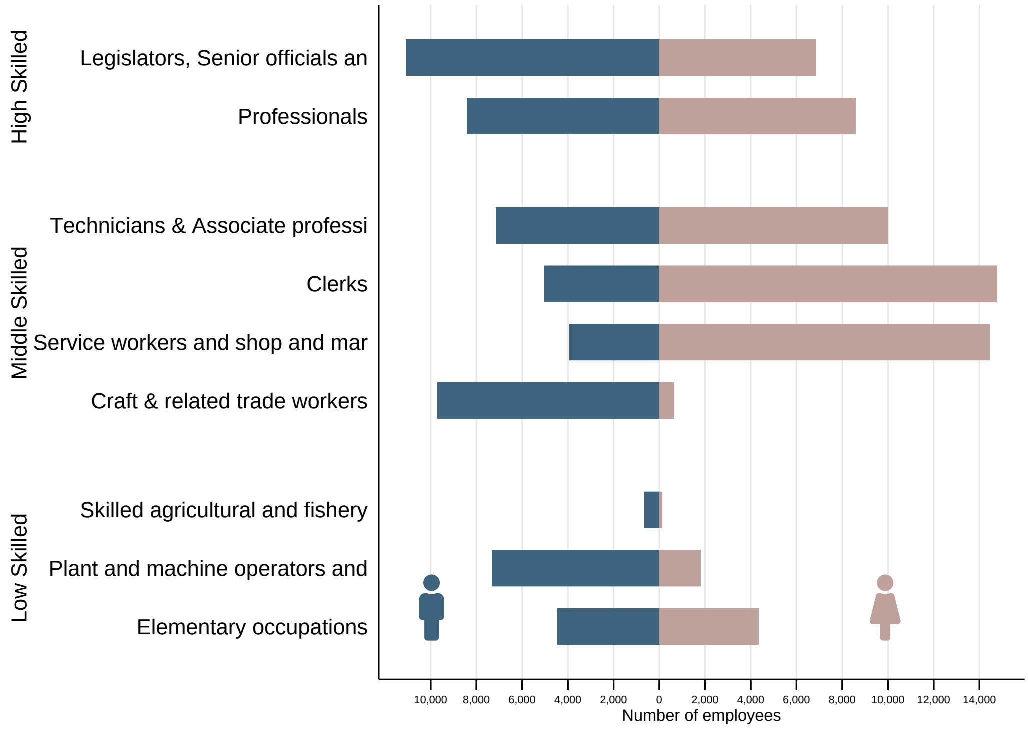


FIGURE 4.1.3: Employment by occupation and gender: all employees; 1991-2016
Note: Occupations have been sorted by their skills intensity, i.e. median hourly wage and average level of education.
Source: Own elaboration; based on BHPS & UKHLS

hand, their destruction rate is higher. They may stop working because of a pregnancy, or due to partner's new job in another area they need to quit. Both of these patterns increase frictions. Hence, women are more likely to be in mismatch.

In this paper, I utilise a novel measure of HCM taking account of differences across workers in more than one dimension of skill. To measure mismatch, I replicate the methodology of chapter 2. However, women are more likely to be in mismatch due to the additional frictions they face. Yet, they may be discriminated even before entering the market. Therefore, we need to see female mismatch in a setting that accounts for these facts. This is why I answer three identifying questions, which change the control group and create different measures of mismatch. First, does a higher-skilled female employee work in lower productivity occupation where only women are occupied? This regards a restricted (female) sample, to see the relative position of a female employee in the female labour market. Second, are higher-skilled women employed in lower-skilled jobs that men are currently occupied in? This is a counterfactual case, in which we observe women in the male labour market eliminating any in advance discrimination. Third, are higher-skilled women employed in lower-skilled jobs? This questions the female position relative to the median employee.[6] Each question changes the control group, and hence, generates a different measure of female HCM. Depending on the specification and control group(s), the incidence of mismatch varies between 13% and 34%. Different control groups generate different instance of mismatch because frictions are not homogeneous for all workers.

In the next step of the exercise, I explore the determinants of female mismatch. For all of the measures of mismatch, I run probit regressions aiming to explain the potential determinants that drive the probability of a woman to be in mismatch. Taking into account the potential selection bias problem, we further run two-stage Heckman probit regressions controlling for the endogenous labour supply decision. Findings show that individual characteristics drive the effect of female mismatch in jobs. Lone motherhood, number of children have positive effect on being in mismatch. Recent entrance in the market increases temporarily the likelihood of experiencing mismatch.

The next section discusses briefly the position of women in the British economy (section 4.2) and reports empirical findings on female overeducation (section 4.2.2). Section 5.3 describes the identification strategy, as well as the empirical methodology. Section 5.4 documents the findings on the determinants of female HC mismatch. The final section concludes.

4.2 Women in the British Labour Market

Determinants of female wages or employment outcomes may further affect job search and changes in work. These can be non-wage characteristics that contribute to frictions and are attributed to particular jobs. Hence, women face a smaller (or more limited) pool of jobs and their transitions in and out of the labour market offer them less time to find a good job. This section focuses only on this part of the problem and does not discuss the determinants of the gender pay gap in general. It treats mismatch as a potential mechanism to explain gender discrimination.

4.2.1 Brief Overview

The structure of the UK economy and the composition of its workforce have seen notable changes the last three decades. Since the early 1990s, the Gender Pay Gap (GPG) starts to decline, but it remains substantial. This downward trend is (traditionally) associated with the increased educational attainment and labour force participation of women (e.g. Olsen et al. (2018), Jones, Makepeace, and Wass (2018), and Harkness (1996)[7]), mostly concentrated in full-time employment (Powell, 2019; Roantree and Vira, 2018). There is a substantial age gradient in the GPG - it diminishes as employees get older

[6] Strong underlying idea regards a significant issue observed in the British labour market which is not just seeking and finding a job. (Career) progression, advancement or mobility from low-paid/skilled to higher-profile occupations is a matter of discussion.

[7] Harkness (1996) observes a gender earnings gap of 40% for 1973; 27% in 1983; and 22% in 1992. Jones, Makepeace, and Wass (2018) find that this long-lasting downward pattern stalls in 2010. Though, the earnings differentials is not a matter of discussion of this paper.

(Manning and Swaffield, 2008). There a a nmber of factors which may affect labour market outcomes of women, and, potentially their mismatch.

Lone parenthood. A significant responsibility on women's shoulders concerns their offspring. On the one hand, nowadays, they participate more in employment and are able to make individual choices regarding family, childbearing or intra-household issues. On the other hand, organising and providing care for children still relies mostly on women (Platt, 2011). An indirect effect of single motherhood arises from the theoretical model in chapter 3. Women face a smaller pool of available jobs due to frictions in the labour market. Moreover, their job destruction rate is higher in events like pregnancy or school/childcare availability.

In countries, like the UK, where publicly provided childcare is not guaranteed, mothers need to reduce hours spent at work. The situation gets worse once mothers attempt to find a balance between work and family, especially when they are single parents. Fertility and single parenthood increase the willingness for a paid job and decrease female flexibility in the labour market.[8] The consequent time constraints reinforce their lower bargaining power in the labour market. Hence, single mothers may sacrifice matching opportunities in exchange for job-security and flexibility (Esser and Olsen, 2018; Esser and Olsen, 2012). A new-born may create little difference to her life if a woman already has one (or more) child(ren). As a result, she adjusts to her socially-determined role and behaviours (Baxter et al., 2015). Using data from the annual UK Government survey the General Household Survey (GHS) and the Opinion Survey of ONS, Berrington (2017) reports that more lone parents work since late 1990s - even those with children younger than 5 years old (school age for the UK). Furthermore, motherhood-related career discontinuities[9] contribute to lower levels of specialisation driving women to end up in particular occupations. This is what Platt (2011) explains as *'gendering of occupations'*, related to lower pay and shorter employment periods. Blundell et al. (2016) show that single mothers, though, have been affected by in-work benefits, like the Working Families Tax Credit (WFTC)[10] in the UK. Recently, Blundell et al. (2019) consider how on-the-job training, as part of the human capital, interacts with prior education, labour supply, experience and earnings.

Occupational Segregation. Women participate disproportionately in particular occupations (Powell, 2019; Manning and Swaffield, 2008; Lindley, 2015; Platt, 2011). However, is this concentration in particular occupations a result of their choice? Or, is it because the labour market sorts women in certain jobs without their agreement? The occupational segregation could be

[8]Here, we may consider monopsonistic or imperfect competition arguments; for example, see Manning (2005). Additional domestic responsibility regards to female non-paid household contribution that remains unequally distributed between partners (Lyonette and Crompton, 2015).

[9]Even in economic terms, it would be a strong assumption to support that women predict those discontinuities and choose occupations regardless their true skills (Hakim, 1995).

[10]WFTC operated in the UK between April 1999 and March 2003. It was then replaced by Working Tax Credit (WTC). In 2010, the government announced its incorporation to the Universal Credit.

seen as a direct outcome from my model in chapter 3. Different groups of people (e.g. men vs. women) face different levels of frictions. Hence, they end up working in segregated markets.

Recently, Lindley (2015) stresses the importance of occupational upgrading for British women which increases the employment rate at the top of job quality distribution. In line with her findings, Green and Henseke (2016a) find that most of the graduate employment increase (83%) is due to female participation in graduate jobs. Noteworthy examples of fast-changing occupations regard to teaching professionals, health (associate) professional and administrative/clerical personnel. However, this may be a consequence of the employment pattern women need. Since part-time jobs are available in limited occupations, women choose accordingly (Platt, 2011). Warren and Lyonette (2015) show that female part-timers accept lower-level jobs and, mainly, crowd into same-gendered occupations. Turmo-Garuz, Bartual-Figueras, and Sierra-Martinez (2019) find that knowledge-led industries and the demand for credentials can reverse the risk of overeducation.

Economic Cycle. The labour market, as part of the economy, is strongly affected by the macroeconomic conditions and the economic cycles. Several (case) studies highlight the impact of Great Recession on employment and the mismatch (Turmo-Garuz, Bartual-Figueras, and Sierra-Martinez, 2019; López-Andreu and Rubery, 2018; Ermini, Papi, and Scaturro, 2017; Summerfield and Theodossiou, 2017). The economic recession and its forthcoming higher unemployment increases the magnitude of overeducation. In the UK, men are more exposed against the loss of their paid job than women. However, the availability of jobs to the unemployed and mainly to women is limited to low-paid, mostly part-time jobs which lack of collective bargaining (López-Andreu and Rubery, 2018). In the steady state, my model, as in Burdett and Mortensen (1998), links unemployment to mismatch through the job arrival and destruction rates, namely through frictions. In this context, I explore the effect of regional unemployment on the probability of being in mismatch.

4.2.2 Female Overeducation: Empirical Findings

Job opportunities for a less-educated workforce are limited, since employers prefer to hire higher-educated individuals whose training costs are lower. As my model shows this inefficiency of the market creates a price (namely wage) distortion, where low-skilled workers are forced to face unemployment or exit the market. The persistence of overeducation might be long (see for example McGuinness, Bergin, and Whelan (2017), McGuinness and Pouliakas (2016), and Ghignoni and Verashchagina (2014)). European evidence is mixed regarding the pattern of gender differences in terms of overeducation. Both its magnitude and its trend vary across all countries. 'Overeducation rates tend to be highest and most volatile over time in peripheral European countries, while overeducation in central European countries tends to be lower and appears to follow a somewhat cyclical pattern. Overeducation is consistently lowest and stable over time in eastern European countries.' (McGuinness, Bergin, and Whelan, 2017, p.2)[11]

As far as the UK is concerned, several studies have been conducted. Traditional measures of educational or skills mismatch demonstrate mixed evidence on the allocation of the penalty. For example, McGuinness, Bergin, and Whelan (2017), in line with earlier findings of Ghignoni and Verashchagina (2014), report that men are better off and there is none particular trend over time. On the contrary, Groot and Maasen Van Den Brink (1997) and Groot (1996) report up to 10% overeducated female employees, when their male counterparts are almost 3-5% more. Larger estimates, but common pattern, are revealed in Davia, McGuinness, and O'Connell (2017) and Davia, McGuinness, and O 'connell (2016). Lindley and McIntosh (2009) using BHPS data in 1991 reveal that women enjoy 2% less probability of overeducation, even though they do not perform a gender analysis. The recent ONS report, using data from the Annual Population Survey (APS), for 2006 to 2017, illustrates that women in the middle 2000s were in a better position. During the post-Recession period, the percentage of mismatched employees converged. However, the convergence is not because of any drop of the male overeducation. It comes from an initial fluctuation, followed by a steady increase, of female educational mismatch (Savic, Vecchi, and Lewis, 2019).

These contradicting research outcomes might be a result of different measurement methodologies.[12] Finally, it is important to highlight that the existing literature discusses the relevant position of an individual *within* a particular occupation. The contribution of this paper, though, is to apply a new multidimensional measure of HCM based on the distributions of individual skill and jobs. It considers the inter-occupational mobility where women prove to be in a better position than men potentially suffering from discrimination. Since we set a different identification question about mismatch, our results might not be directly comparable with the existent literature.

4.3 Data and Methodology

4.3.1 Data

The empirical evidence uses the British Household Panel Survey (BHPS) data and its successor, namely the Understanding Society, or the UK Household Longitudinal Study (UKHLS). A household representative longitudinal survey, with retrospective elements, started on autumn of 1991 and repeated annually thereafter; BHPS' last wave was in 2009, when it became part of

[11] McGuinness, Bergin, and Whelan (2017) claim that Skill Biased Technological Change operates in favour of men, and not of women, suggesting that skewness towards male skills enables the replacement of highly-educated women in the market. As a result, women are more likely to face overeducation. Technological changes (Acemoglu and Autor, 2011; Autor, Levy, and Murnane, 2003; Acemoglu, 2002) might urge for additional skills; ergo, workers need to respond accordingly by acquiring further qualifications and expanding their experience. However, this does not lie on the framework my model sets, and hence, the discussion I follow in this Thesis.

[12] Recall the vulnerability of each measurement tool reported in table 1.3

the UKHLS which runs until today. Hence, the micro-level data used in this analysis cover a 25-year period, i.e. 1991-2016 or waves 1-18 and 2-7. The focus is on randomly selected individuals in a household context representing the whole UK population. The interviews conducted face-to-face or by phone containing[13] various questions on demographics, human capital background, socio-economic and job characteristics forming a wealthy source of data.

The sample in this research is confined to participants in the labour market, namely employees working full or part time and unemployed. The analysis includes individuals aged 23-59 years old. An assumption that graduates of higher education enter the labour market on the age of 23 and get an early retirement (aged 59) holds. If someone started working younger than 23, she is captured later in the labour market. Additionally, self-employed individuals, farmers or those serving in the army and those employees who are currently enrolled in any educational institution[14] have been excluded. Since a few income outliers may overly affect our results, the real wage has been winsorised at the first and 99th percentiles. The total sample is comprised of 65,346 women.

4.3.2 Identification

Despite the indisputable significance of the incidence of mismatch over the entire workforce, differences between male and female participants may depend on unobservable characteristics. Blau and Kahn (2017) review evidence on gender differences resulting from cognitive and non-cognitive skills dissimilarities, statistical discrimination or issues that work by assumption and stereotypically against women. Women are more likely to be in mismatch due to the additional frictions they face. Yet, they may be discriminated even before entering the market. Therefore, we need to see female mismatch in a setting that accounts for these facts. Here, to eliminate any ex ante heterogeneity against the female workforce, three different measures are employed building further on the novel measure of HCM developed in chapter 2.

Measure I: restricted female subsample Women may face different observables than men, and hence, their returns may differ. This is why we look the relative position of each woman among same-sex employees across occupations. The classification of occupations remains the same as in chapter 2.[15] The identification question asks whether a higher skilled female employee

[13]This process slightly changes on the recent waves. Remarkable differences have been noted on the recently released wave 8, which has not been included in the current analysis.

[14]Excluding employees who are currently students is not unprecedented in the literature (like Joona, Gupta, and Wadensjö (2014)) to avoid any variation in education over time. This technique will allow the fixed effects estimator to be unbiased given the exogeneity assumption.

[15]We consider 3 distinguishable classifications for occupational groups according to their skills intensity: 1 for high-skilled occupations; 2 for middle-skilled occupations; 3 for low-skilled occupations. Occupation groups are sorted based on the median earnings and average level of education.

works in lower productivity occupation where only women are occupied? Empirically speaking, we repeat the procedure of chapter 2, restricting the estimates to women (figure 4.3.1a), or

$$\text{mismatched}_i \Big| (\text{sex=female})_I = \begin{cases} 1 & \text{if } \widehat{\text{w}}_{\text{female}} \Big| occ_j > \left[\widetilde{\widehat{\text{w}}} \Big| occ_{j-1} \text{ \& sex = female} \right] \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

where $\widetilde{\widehat{\text{w}}}$ is the median of the predicted wage.

This measure assumes that women would be paid more in a higher occupation. However, this measure probably ignores that women might be considered *a priori* lower skilled employees and, by definition, are set to the lowest occupational category. In this case, women are more likely to be in mismatch. If the incidence of mismatch differs significantly across various treatment groups, the estimate of the probability being in mismatch strongly depends on the control group. For example, if all women are in mismatch, using the female wage equation and the respective job allocation would yield zero estimates.

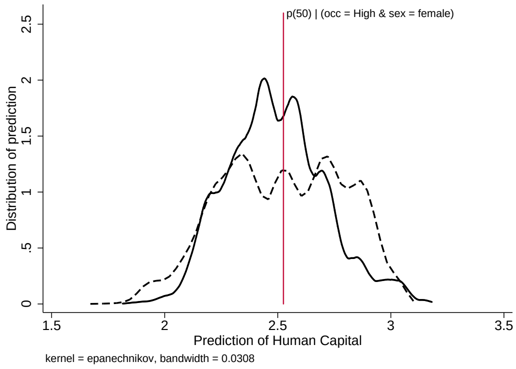
Measure II: counter-factual case Therefore, we ask if a woman in a lower skilled occupation holds a similar profile of a man in a higher skilled occupation? To shed the light whether women are in advance considered low-skilled employees and their working potentials are undermined, I estimate the predicted wage restricted to the male subsample. Then, I assign to women the male predictions. In other words, I see women in the male British labour market. A female worker in occupation j is in mismatch if, holding the male predictions (in the same occupation j), her premium is above the median premium paid in a more skills-intensive occupation, namely in occupation $j-1$. Alternatively,

$$\text{mismatched}_i \Big| (\text{sex=female})_{II} = \begin{cases} 1 & \text{if } \widehat{\text{w}_{\text{female}}} \Big| occ_j > \left[\widetilde{\widehat{\text{w}}} \Big| occ_{j-1} \text{ \& sex = male} \right] \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

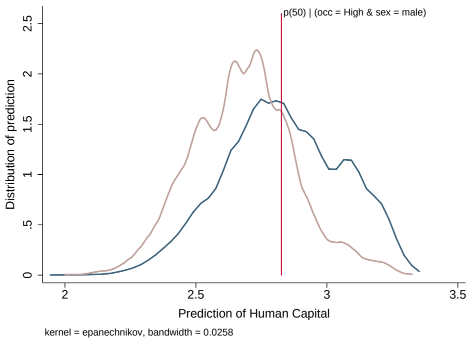
where $\widetilde{\widehat{\text{w}}}$ is the median of the predicted wage.

This measure assumes that women would be paid more in a higher occupation if they faced the same returns as men. Hence, a comparison of female position considering they hold the same skills as men is allowed, eradicating the possibility of efficiency loss because of gender barriers (figure 4.3.1b). In other words, I take into account that employers may prefer to hire a less skilled man instead of a more competent woman.

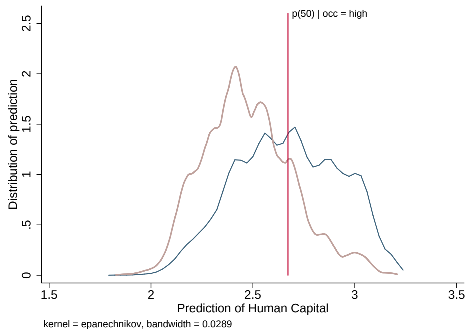
Measure III: Women relative to overall population Finally, under the same reasoning, I try to see how the female position changes if they faced the same returns as the overall population. To this extent, the identification question sees a female employee relative to the median worker of the entire population. Measure III differs, significantly, from measure I since I do not compare workers who share the same (gender) characteristics anymore. This



(A) Restricted female subsample



(B) Counterfactual Women



(C) Women relative to overall population

FIGURE 4.3.1: Illustration; Example: High- vs. Middle-Skilled Employees

Note: In panel (a), the solid black line illustrates the prediction of HC of middle-skilled women, while the dashed one illustrates the prediction of high-skilled same-gendered employees. In panel (b) the blue curve illustrates the distribution of high-skilled occupied men HC; the rose curve illustrates the middle-skilled occupied women when they hold the predicted estimates of men. In panel (c), the blue curve illustrates the distribution of the high-skilled employees HC (regardless their gender; overall), while the rose curve illustrates the middle-skilled women's HC with the prediction of the overall population. The prediction of HC is the predicted wages.
Source: Own elaboration

procedure can comment on whether gender productivity enhances skills-matching. Probably this is not the case; but, is there a correlation between gender and unobserved ability/skills? Empirically speaking, it holds

$$\text{mismatched}_i \Big| (\text{sex=female})_{III} = \begin{cases} 1 & \text{if } \widehat{w_{\text{female}}} \Big| occ_j > \widetilde{\widetilde{w}} \Big| occ_{j-1} \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

where $\widetilde{\widetilde{w}}$ is the median of the predicted wage. Figure 4.3.1c illustrates this case.

Blundell et al. (2019) explain that individual preferences might also contribute to the *ex ante* unobserved heterogeneity among employees. Preferences are highly responsible for the extent of a working day or investment decisions about additional training and might differ between men and women. Since, we aim to explain mismatch by observing the skill levels through wages, given the data limitations, we assume that measures II and III can take preferences into account.[16]

4.3.3 Methodology

The magnitude of mismatch in the British market itself is important. However, what drives people to lower skilled positions may inform policy implications, especially for women. Therefore, I will explore what factors affect the probability of female mismatch in the labour market. To do so, we will run the following probit model using the definitions of eq. 4.1 to 4.3:

$$\Pr\Big(\text{mismatched}_i \Big| (\text{sex=female})_{\text{measure}}\Big) = f\left(x_{i,t}, \text{job}_{i,t}, \text{family}_{i,t}\right), \ \forall \text{ measure} = I, II, III$$

where $x_{i,t}$ are individual-specific characteristics (e.g. entrance in the labour market last year); $\text{job}_{i,t}$ are job-related features, i.e. regional unemployment rate and, $\text{family}_{i,t}$ are all those family-specific characteristics, such as the number of (dependent) children, single motherhood.[17] Given the endogenous labour supply decision, mainly affecting the female population, we further adjust the probit model employing the same selection equation.

$$\begin{aligned}\text{labour force}_{i,t} = \alpha + \boldsymbol{\delta}_1 \boldsymbol{z}_{i,t} + \sum_{j=1}^{5} \delta_j FS_{i,j,t} + \sum_{n=1}^{12} \delta_n \text{ region}_{i,n,t} + \boldsymbol{\delta}_4 \textbf{HHmembers}_{i,t} \\ + \vartheta_t + v_{i,t} \qquad (4.4)\end{aligned}$$

where labour force is a dummy variable, which equals to 1 if the individual participates in the workforce and 0 otherwise.[18] $\boldsymbol{z}_i$ is a vector of individual characteristics, like age, educational level, marital status. FS_i is the financial status, while $\text{region}_{i,j}$ the j^{th} NUTS1 statistical region of residence. Finally, *HHmembers* denotes a vector counting for the number of household's members who are unemployed, retired or inactive excluding oneself and the number of children.

Exclusion restriction For identification purposes, the selection equation should include at least one variable that correlated with the labour force participation decision and not directly affect wages or the matching status of an employee. It is very difficult to identify such a determinant and it exposes estimates to criticism. For those out-of-work, typically, is not possible to observe their wages. This revises a usual behavioural problem in this type

[16]A richer definition of HC attempted in chapter 6. Preferences might be better captured there.

[17]For robustness checks, I include entrance in the LM two/five years ago or number of employees in the firm. Results did not change much.

[18]The dependent variable is a dummy and not a continuous one, as usually used in Heckman's models. Greene (2012) claims that the dichotomy could affect the maximum likelihood function. In terms of the standard errors, though, we cluster on the household level, consistently with the rest of the analysis. Despite its dichotomicity, an estimation using a linear model decreases its sensitivity to distributional assumptions (Böckerman, Haapanen, and Jepsen, 2018).

of models. The status of the remaining members,[19] as well as the number of children in a household affect the household disposable income either on the revenues or the expenses side of household budget- playing a primordial role to the decision of accepting a job offer (Bredtmann, Otten, and Rulff, 2017; Marelli and Vakulenko, 2016; Addabbo, Rodríguez-Modroño, and Gálvez-Muñoz, 2015). The use of these instruments may not be perfect, but they control to a great extent for the selection bias issue. Not using the Heckman probit model yields slightly higher estimates. However, they both have the same sign; hence, the marginal effect goes to the same direction. This exercise considers the potential correlation of preferences or any other sources of income that affect labour supply choice and not necessarily the matching status.

4.4 Results - Discussion

Table 4.4.1 summarises our estimates for the probability of female mismatch in the British labour market for each aforementioned index. For all of them, the first column reports the results of the probit model having controlled for the time effect. The second one adjusts the probit results accounting for the endogenous decision of labour force participation (in a variation of Heckman's two-stage method for correcting sample selection bias). The table reports the marginal (conditional on labour force participation) effects.

The first two independent variables could be considered as positively related to lower skills and additional frictions for women, but to higher skills and fewer frictions for men. In other words, single parents may face greater frictions in the labour market increasing their probability of mismatch. Evidence on the effect of being a single parent is significant, but its magnitude varies by index and across the specifications. When correcting for employment selection, single mothers holding the characteristics of the median employee are 3.6% more likely to accept a position for which their profile does not match. This result is in line with the fixed effect evidence by Lindley and McIntosh (2009) for overeducation in the UK. When women are seen in the male labour market, i.e. when we treat single motherhood as fatherhood using the estimates of men, the effect becomes stronger. Single parenthood increases the probability by more than 60%; or, the marital status or childcare commitments for lone mothers may put them in a worse position than currently occupied by a (single) father. This may be related to who is identified in this case in mismatch. The underlying assumption for this measure concerns women that would be paid more in a higher occupation if they faced the same returns as men. I use the estimates for men for whom earlier evidence has shown that the probability of overeducation for non-partnered men is significantly higher.[20]

[19] For example, partner's unemployment may increase one's willingness to work, but not necessarily their matching status. In this case, they may want to accept any kind of job to increase household income.

[20] Esser and Olsen (2018) demonstrate a penalty for single mothers; they explain that the small share of single fathers, though, limits the statistical significance.

TABLE 4.4.1: Determinants of female mismatch

	Relative to overall						Counterfactual case						Restricted subsample				
	Probit			Heckman Probit			Probit			Heckman probit			Probit			Heckman probit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Single parent	0.0641***	0.0651***	0.0574***	0.0356***	0.0357***	0.0354**	0.644***	0.644***	0.649***	0.6965***	0.6956***	0.6591***	0.12***	0.12***	0.1074***	0.087***	0.0865***
	(0.0011)	(0.0012)	(0.0013)	(0.001)	(0.0101)	(0.0693)	(0.0022)	(0.0021)	(0.0027)	(0.0021)	(0.0018)	(0.0026)	(0.0014)	(0.0014)	(0.0017)	(0.015)	(0.0015)
Number of children																	
1	0.06***	0.0616***	0.0508***	0.0336***	0.0337***	0.03432***	0.6258***	0.6264***	0.636***	0.6901***	0.6895***	0.6534***	0.1165***	0.1161***	0.0101***	0.0837***	0.0827***
	(0.0024)	(0.0024)	(0.0029)	(0.0041)	(0.01)	(0.0121)	(0.0053)	(0.0053)	(0.0067)	(0.0048)	(0.0047)	(0.0063)	(0.0031)	(0.0031)	(0.0039)	(0.0109)	(0.0025)
2	0.0689***	0.0696***	0.0578***	0.0035**	0.0035**	0.0353***	0.6227***	0.6231***	0.62***	0.6944***	0.6936***	0.6441***	0.1216***	0.1207***	0.1039***	0.0763***	0.0752***
	(0.0027)	(0.0026)	(0.0032)	(0.0021)	(0.0169)	(0.0122)	(0.0052)	(0.0052)	(0.0066)	(0.005)	(0.0048)	(0.0064)	(0.0033)	(0.0033)	(0.0042)	(0.0113)	(0.0024)
3	0.0751***	0.0759***	0.0577***	0.039**	0.0389***	0.0397**	0.6483***	0.648***	0.6676***	0.7151***	0.714***	0.6799***	0.1371***	0.135***	0.1304***	0.0935	0.0911***
	(0.0055)	(0.0054)	(0.0064)	(0.0012)	(0.0391)	(0.0207)	(0.0093)	(0.009)	(0.0119)	(0.0082)	(0.0082)	(0.0112)	(0.007)	(0.007)	(0.0094)	(0.0207)	(0.0052)
4	0.0783*	0.0639***	0.0591**	0.041*	0.0407**	0.0407***	0.6725***	0.6718***	0.6677***	0.652***	0.696**	0.6548***	0.0828***	0.0803***	0.0507***	0.0577**	0.0548***
	(0.0106)	(0.0014)	(0.0017)	(0.0078)	(0.113)	(0.0481)	(0.0214)	(0.0214)	(0.028)	(0.0199)	(0.0024)	(0.0252)	(0.0144)	(0.0141)	(0.0156)	(0.062)	(0.0109)
Single parent × Number of children																	
1	0.0533***	0.054***	0.0414***	0.0985***	0.1***	0.0965***	0.6274***	0.6265***	0.7415***	0.6913***	0.6907***	0.7092***	0.1067***	0.1063***	0.0958***	0.0833***	0.0876***
	(0.0051)	(0.005)	(0.0061)	(0.0086)	(0.2644)	(0.0712)	(0.038)	(0.0381)	(0.0465)	(0.0027)	(0.0047)	(0.0487)	(0.0068)	(0.0068)	(0.0091)	(0.1518)	(0.0055)
2	0.0461***	0.0484***	0.0376***	0.0789***	0.0798***	0.0804***	0.6723***	0.6676***	0.6457***	0.7093***	0.6932***	0.6599***	0.1032***	0.1019***	0.0769***	0.0758***	0.0833***
	(0.0059)	(0.0059)	(0.0073)	(0.0083)	(0.2639)	(0.0699)	(0.0595)	(0.0594)	(0.0727)	(0.0512)	(0.0046)	(0.0654)	(0.0084)	(0.0084)	(0.103)	(0.1523)	(0.0071)
3	0.1084***	0.1001***	0.0782***	0.1385***	0.1405**	0.1203***	0.8828***	0.8845***	0.8234***	0.6939***	0.7083**	0.849***	0.1662***	0.1630***	0.1707***	0.0906***	0.1292***
	(0.0197)	(0.018)	(0.0231)	(0.0087)	(0.0294)	(0.07)	(0.1121)	(0.1107)	(0.1565)	(0.0048)	(0.0082)	(0.1101)	(0.0229)	(0.0223)	(0.0333)	(0.1592)	(0.0166)
4	0.0324	0.031	0.033*	0.1129*	0.1147	0.1808***	0.5514***	0.5842**	0.8037***	0.7094***	0.7061*	0.7947***	0.064	0.0611	0.045	0.0559*	0.0761**
	(0.0099)	(0.0095)	(0.0131)	(0.0081)	(0.1222)	(0.0759)	(0.179)	(0.1787)	(0.1798)	(0.0083)	(0.0513)	(0.0126)	(0.0444)	(0.0426)	(0.0466)	(0.2313)	(0.0371)
Entered labour market?		0.0196***	0.024***		0.022**	0.0251**		0.0809***	0.0894***		0.0483***	0.0586***		0.022***	0.0242***		0.0219***
		(0.0039)	(0.045)		(0.0064)	(0.008)		(0.0109)	(0.0135)		(0.0096)	(0.0125)		(0.0053)	(0.0063)		(0.0037)
Regional UR			0.0098			0.0115***			0.021***			0.0019			0.0196***		
			(0.0024)			(0.0032)			(0.0052)			(0.0057)			(0.0031)		

Notes: Robust standard errors in parentheses; clustered at household level.
Estimates report marginal conditional (on selection) effects of predicted probability of mismatch.
* p<0.1, ** p<0.05, *** p<0.01

The evidence that mismatch is related to the family commitments is verified across the specifications. Although more and more mothers decide to work regardless the number of children they have or their age, we observe that the family size is significant and positively related to the probability of mismatch. As the number of (dependent) children increases, the probability of performing an inferior job increases. The latter rise is not always linear, since we observe that the marginal effect of an additional child to be more intense after the birth of the third child in all cases, *ceteris paribus*. The interaction term of the single motherhood and the number of children may capture these non-linear effects. The higher probability of single mothers to be in mismatch may be related to their job arrival rate, the pool of jobs they are exposed to and how many dependent children they have. Single mothers are more likely to look for jobs in areas where schools are or family network is closer. Women, due to their role, may be able to devote less time to the labour market. Looking in a smaller, or more limited, pool of jobs restricts their opportunities for a match. Therefore, their mismatch may be an outcome not only of their initial discrimination, but also of additional frictions in the market. To better understand the female employment in this frictional labour market, appendix 4.B outlines the share of single mothers in mismatch by 3-digit occupations.

Job-related characteristics do play an essential role as far as the matching process is concerned. Recent entrance in the labour market, i.e. entering the labour force one year ago, generates a significant negative effect. Alternatively speaking, the entering ticket to the labour market forces women to initially accept an inferior job.[21] This effect is sometimes stronger under the probit model and weakens when we control for sample selection. For example, the most significant change is observed in the counterfactual case. This suggests that men do not constitute an exception to this initial entrance mismatch penalty. If women hold male returns, they are 8% more likely to be in mismatch. This result may be sensitive to cohort effects, since they change the observed heterogeneity of individuals (Blundell et al., 2019).

Despite our control for the time effect, regional conditions of the labour market are significant. If an increase in unemployment rate reduces the available opportunities for work, higher-skilled individuals would accept a less-skilled job so that they remain actively in the market. To this end, we observe a conservative, but significant, effect of the regional unemployment rate varying by specification but not exceeding 2%. A typological analogy between a mismatch in the labour market and unemployment (Büchel and Ham, 2003) can explain the limited effect of regional unemployment rate. Ramos and Sanromá (2013), using the Spanish Household Budget Survey, found no significance between regional unemployment rate and the probability of overeducation.

[21] This result is in line with the estimates on overeducation by the ONS. In 2017, 22% of graduates earlier than 1992 were overeducated. The same year, 34% of graduates of class 2007 or later were classified as overeducated.

4.5 Conclusions

Nowadays, women are more educated and their participation in the workforce is improving constantly. A signal of potential mismatch arises, since individuals in low-skilled occupations may enjoy greater returns to HC than those in higher-skilled ones. If their role (e.g. family-driven responsibilities, discrimination from employers etc.) make women more likely to be in mismatch, those who are not displaced from the labour market are more likely to be in a higher-skilled occupation. In any case, this mis-allocation in the British labour market is sufficient to distort the wages. In this paper, using the BHPS and UKHLS datasets, for 1991-2015, I explore what determines the probability of a female employee to experience a mismatch episode in the UK. I extend our previously developed novel multi-component index which considers the heterogeneity of workers in more than one dimension of skill. I classify as mismatched those women in lower-skilled jobs who could work in a higher-skilled job.

Here, I create three indices, each of which changes the control group. The incidence changes across specifications depending on the control group. Different group faces different frictions in the market. Firstly, a comparison of women with the median employee is attempted. Secondly, a counterfactual case, where women are seen in the male labour market, is assessed to eradicate the possibility of an *a priori* discrimination. Finally, female employees are seen within their market, comparing women with their same-gendered median colleagues. What determines the likelihood of facing a mismatch event in the labour market is associated with the frictions women face. Lone motherhood and number of children are associated positively with the probability of mismatch even when controlling for the endogenous labour-supply decision. As the number of children increases, the probability of a lone motherhood leads to accept a less skill-intensive job increases. This is not a linear relationship. The probability becomes considerably higher after the third (dependent) child. Recent entrance does also increase the probability of mismatch. However, this is an effect which dissipates over time; meaning that senior employees face a lower probability of mismatch. Finally, regional unemployment's effect does not exceed 2% at any case. It may imply that an important increase of unemployment can negate the impact of other determinants.

Appendix

4.A Incidence of Female Mismatch

According to our three different indices of female mismatch the incidence varies across the specification.

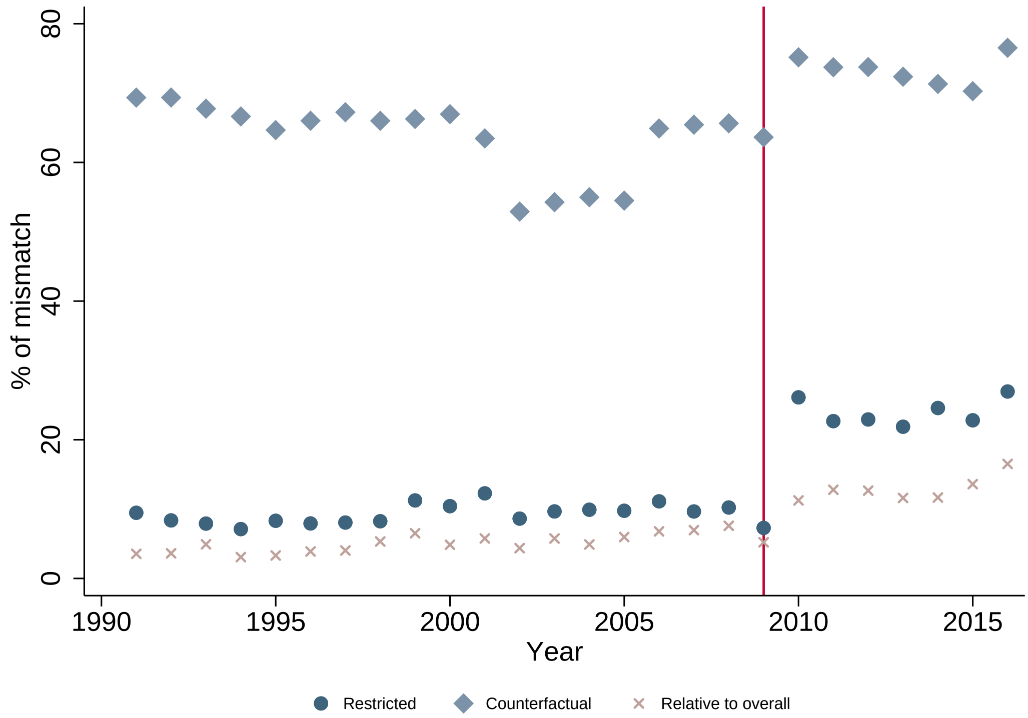


FIGURE 4.A.1: Incidence of Female mismatch
Source: Own elaboration, based on BHPS and UKHLS

4.B Single mothers in mismatch

Where do single mothers in mismatch work? This section outlines the share of single mothers with dependent children by 3-digit occupations in my sample.

TABLE 4.B.1: Share of single mothers in mismatch, by occupation (in %)

Occupation	Single parents
Physical and engineering science technicians	0.59
Life science technicians and related associate professional	4.08
Health associate professionals (except nursing)	4.12
Nursing and midwifery associate professionals	8.37
Other teaching associate professionals	4.00
Finance and sales associate professionals	1.24
Administrative associate professionals	6.77
Social work associate professionals	8.44
Secretaries and keyboard-operating clerks	1.55
Numerical clerks	2.88
Material-recording and transport clerks	6.00
Library, mail and related clerks	3.33
Other office clerks	7.95
Cashiers, tellers and related clerks	2.38
Client information clerks	3.86
Housekeeping and restaurant services workers	8.64
Personal care and related workers	8.33
Other personal services workers	17.39
Protective services workers	1.25
Shop, stall and market salespersons and demonstrators	2.76
Animal producers and related workers	7.69
Rubber- and plastic-products machine operators	11.11
Printing-, binding- and paper-products machine operators	17.65
Textile-, fur- and leather-products machine operators	16.51
Food and related products machine operators	3.45
Assemblers	1.28
Motor vehicle drivers	4.17
Street vendors and related workers	3.95
Domestic and related helpers, cleaners and launderers	7.67
Building caretakers, window and related cleaners	22.22
Messengers, porters, doorkeepers and related workers	1.08
Agricultural, fishery and related labourers	31.25
Manufacturing labourers	11.11

Source: Own elaboration based on BHPS/UKHLS

Chapter 5

Female Human Capital Mismatch: An extension for the British public sector*

Abstract

This paper looks at the extent of labour market mismatch of public-sector female employees. It contributes to earlier findings for the British labour market by taking into account the endogenous self-selection into jobs. Estimates are based on data from the British Household Panel Study and the 'Understanding Society' covering the years 1991-2016. The analysis verifies that the public sector offers a few low-skilled jobs and employs, mostly, higher-educated (female) workers. Regarding the market flows, findings show the greater mobility of the female workforce, which moves proportionately between sectors. Greater in-/out-flows to/from private sector are observed regardless the gender of the employee. Once comparing women to the median employee, a sizeable incidence of mismatch arises due to a negative selection. Specifications using the selection model for the public sector illustrate a systematically higher magnitude of mismatch. Pooled results seem to dominate when women are seen in the male labour market or in a restricted subsample. Finally, the map of occupations in mismatch supports that the public sector is more attractive as a waiting room for highly-qualified graduates. They queue less time until they find a good job. Hence, policy implications regarding the allocation of jobs for women may arise.

5.1 Introduction

Does the public sector allocate its workforce efficiently? If so, no mismatch should arise (Gomes and Kuehn, 2020; Mocetti and Orlando, 2019; McGowan and Andrews, 2017a; Gomes, 2015). The answer has important implications for gender inequality in the labour market; especially for women, for whom public sector is the major

*Acknowledgements: A project as part of the Virtual Young Scholars program (VirtYS) 2019/20 by Global Labor Organisation (GLO). Advice by Nick Drydakis has been greatly appreciated. Amanda Gosling and Olena Nizalova provided valuable comments and feedback on earlier versions of this work. Discussion with Juan J. Dolado and Linas Tarasonis were also beneficial for this project. I would like to thank participants in the MicroForum at the University of Kent; GLO VirtYS and ESPAnet2020 PhD Seminars. For updates, visit the project's webpage, here. This chapter is available as Working Paper, here.

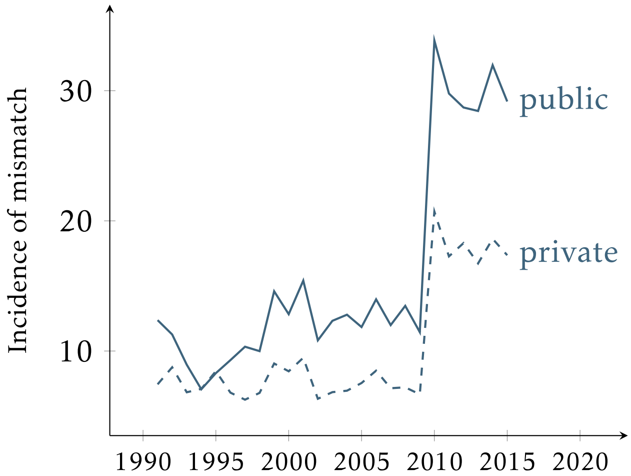


FIGURE 5.1.1: Incidence of mismatch by sector
Note: This figure pools the incidence of mismatch found in chapter 4 by sector of employment for the restricted female subsample. A woman is in mismatch if her estimated HC is greater than the median of the HC demanded by a more skills-intensive job performed by a female worker. The solid line represents the public sector, while the dashed line the private one. This graph neglects the endogeneity of jobs allocation in sectors. The difference remains significant throughout the panel.
Source: Own elaboration based on BHPS/UKHLS

employer. This is the case because women are mostly employed in healthcare and education, which are the two major industries of the public sector. In 2018, 7.4% of public sector employees were Nurses, 5.3% were Primary and nursery education teaching professionals (ONS, 2020). Implications may extend in the provision of public services and the productivity of government sector (Caponi, 2017). Garibaldi, Gomes, and Sopraseuth (2020) offer a model to compute the cost of mismatch. They find that elimination of education (or skills) mismatch, on average, raises output by 2.5 (or 3.2%); significant variation across countries, though, exists.

Human Capital Mismatch (HCM) in the labour market may occur when individuals occupied in lower-skilled occupations have similar characteristics with those employed in a more skill-demanding job (chapter 2). For instance, chapter 4 discusses the women's greater risk to be in mismatch relative to their male counterparts. It is not only that women are genuinely more exposed to the mismatch, but also gender may influence one's career even before entering into the market. However, no discussion revolved around the particular affiliated sector. For example, figure 5.1.1 shows how the incidence differs when estimates are pooled by sector. The difference remains significant throughout the panel and shows that public servants are consistently in mismatch more than their private-sector colleagues.

This paper aims to evaluate the extent of female HCM in the British public sector employing a rich dataset of individual characteristics. In neoclassical terms, if no (significant) mismatch arises, the allocation of public servants is efficient (Pissarides, 2000). Otherwise, the public-sector operates inefficiently despite its better skilled workforce.[1] Therefore, we need to consider each sector as a separate labour market. One may accept their difference, because if the public sector operated as the private one, little would it matter *where* provision comes from. Hence, there are intrinsic factors that make public-sector act differently than the private one.

Firstly, in contrast to the private sector, public sector faces a political constraint. In other words, the public-sector workforce not only produces goods and services, but it engages to activities which aim to vote maximising. Hence, its role may contribute to higher pay (Cai and Liu, 2011; Fuller, 2005; Gunderson, 1979). To this end, each sector forms a *different labour demand* and wage determinants. The public-sector demand will disproportionately benefit those workers whose skills are more useful in the production of public versus private goods (Blank, 1994). The public-sector is the major employer for specific-training jobs (e.g. nurses, teachers).[2] These specialised workers have no expectations for a better job. Their initial mismatch - if any - might result from occupational choices of younger individuals with little or no hiring by public-sector recruiters. In December 2019, 79,000 (or 1.5%) more people work in the British public sector compared to the same month a year ago. According to ONS estimates, it employs 5.44 million individuals; 0.3% more than September of the same year (Caldwell, 2020). However, the interest does not lie on the size of public sector *per se*, but on its gender composition (figure 5.1.2a). Female over-representation in the public sector persists even when we exclude industries traditionally affiliated to the public sector and in which mostly women participate in (e.g. healthcare and education; figure 5.1.2b).

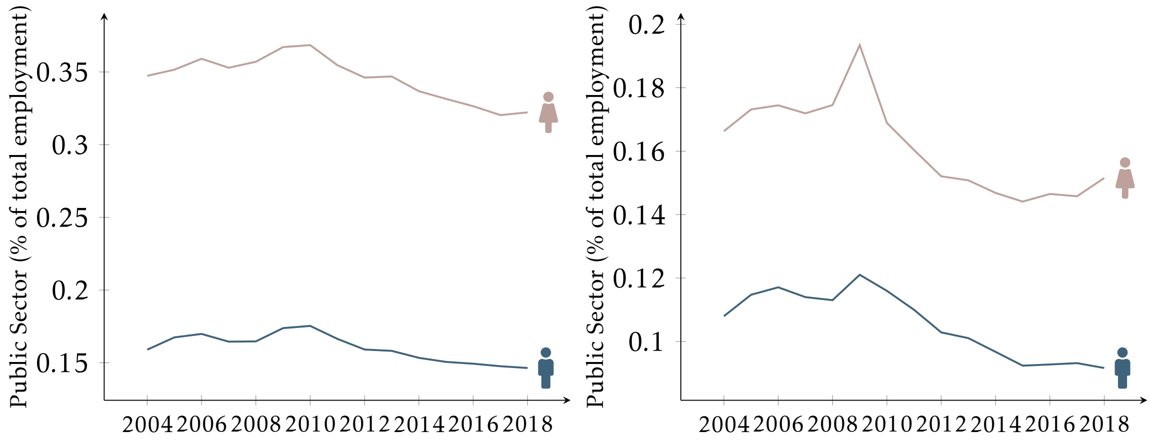
Secondly, public-sector offers only a few low-skilled (figure 5.1.3), but many high-skilled[3] and well-paid ones attracting more female candidates (figure 5.1.2; Gomes and Kuehn (2020), Anghel, De La Rica, and Dolado (2011), and Gornick and Jacobs (1998)). Due to relatively lower competition and flexibility[4] of the public sector, sizeable mismatch may arise. For instance, let us consider the marginal individual who decides whether to join

[1] Generally, the public sector attracts highly educated workers. In the recent years, public servants have become more skilled, whereas their private sector counterparts have maintained a broadly unchanged profile of jobs (ONS, 2017).

[2] Therefore, a fair expectation regards the public-sector insulation from national and international business cycle shocks because both the demand for health and education are local services, and quite independent of demand shocks (Liu, Salvanes, and Sørensen, 2016) and labour demand is rather inelastic.

[3] In the UK, public servants are mostly high-educated (43.3% and 42.28% of men and women of total workforce, respectively.) jobs. Among those highly-educated women dominate (68%).

[4] For example, in 2011 the public-sector pay freezes for all but those on annual salaries less than £21,000. Since 2013, most of those earnings rise on average by 1%. The stronger unions' bargaining, though, bring about the policy relaxation on 2017, when the private sector recovers (Cribb, 2017). ONS (2017) claims that, in real terms, public servants have been poorer because inflation was greater than the pay growth since 2011. As a result, the public sector is restricted to remunerate its workforce. This restrictive potential is, additionally, indicative in terms of the full use of labour force's abilities.



(A) All industries

(B) Exclude industries of “Education" and “Health & social work"

FIGURE 5.1.2: Public Sector employment, by gender; 2004-2018
Note: Public Sector employment rate as percentage of total employment, by gender. A persistent over time unadjusted gender bias in favour of women participation is observed. Panel (b) excludes the industries of Education and Health in which women disproportionately participate.
Source: Annual Population Survey, ONS

the public service.[5] If she is highly-qualified but her competition is too high,[6] she may *initially* be allocated in a position demanding less skills. Otherwise, she would be immediately matched; e.g. nurses or teachers who queue less for a matched job. If jobseekers disproportionately search for jobs in sectors where productivity is relatively low, hires are concentrated in the wrong sectors (Patterson et al., 2016). In other words, if public-sector wages are not high, a few unemployed would be willing to look for a job and public-sector may face recruitment difficulties. Transitions from public to private sector, though, may lead to a better-educated and more productive private labour force (Cribb, Disney, and Sibieta, 2014). Though, these transitions are not very frequent (see unconditional transitions; figure 5.4.3).

Finally, the public sector aims to alleviate widespread disparities met in its competitive counterpart. In fact, in most of the countries, as in the UK, female public servants outweigh their male counterparts. For instance, intrinsic preferences make women choose the public sector; hence, occupational segregation is an expected outcome. Greater job security and satisfaction and better conciliation of work-family life push to the same direction. Therefore, we would not blame the public sector for any mismatch. First, horizontal match is more successful in the public rather than private sector

[5]One enters into the public sector if her utility exceeds the one coming from private-sector employment or unemployment. Hence, a fair argument may claim that the public-sector reservation wage should exceed the competitive-sector one and the unemployment benefits. Further assuming that one dislikes inactivity is convenient for this analysis.

[6]In other words, high competition implies an inflation of graduates with similar characteristics, whose supply cannont meet the demand (number of jobs available).

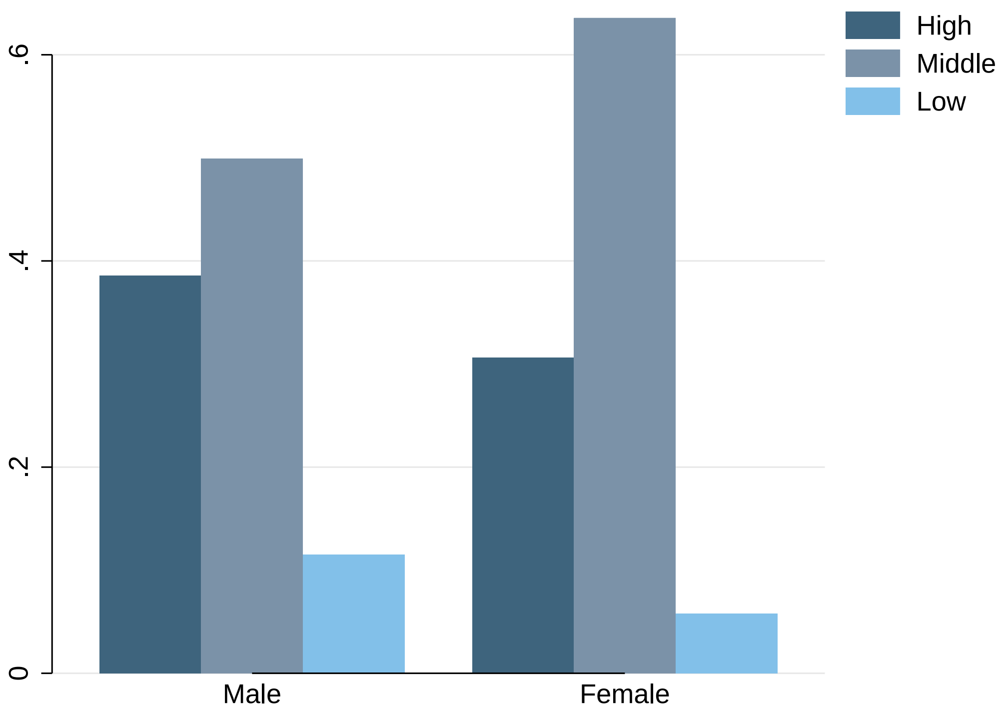


FIGURE 5.1.3: Size of the public sector, by type of occupation; 1991-2016
Note: 1-digit occupations defined using the International Standard Classification of Occupations: ISCO 88. They have been sorted by the median level of education and hourly earnings; classified as high-, middle- and low-skilled. The former category includes "Legislators, Senior officials and managers" and "Professionals", while the latter includes "Skilled agricultural and fishery workers", "Plant and machine operators and assemblers" and "Elementary Occupations". The middle-skilled jobs include the remaining occupations. For details, see Galanakis (2019a).
Source: Own elaboration, based on BHPS/UKHLS

(Wolbers, 2003).[7] Second, public-sector better matching achieves efficient allocation (Gomes, 2015). However, if allocation is not random, the public-sector labour market is segmented and probability of mismatch increases.

This paper has a twofold contribution in terms of evidence and methodology. First, I document the extent of HCM in the public sector given its gender-participation bias. Yet, I provide insights on why women are willing to join and wait in the public sector until they find their matched job. Gomes (2015), assuming labour market segmentation and unemployment search according to governmental hirings, shows that public-sector wages play an essential role in efficient allocation. Any premium arisen there reflects the differences in frictions across sectors with two inefficiencies[8] occurring simultaneously. Later, he extends his model in a more realistic set of assumptions and shows the essential role of the endogeneity on the number and type of candidate

[7] Somers et al. (2019) attribute this assumption to healthcare and education; two sectors which mostly employ graduates in the public sector.

[8] (a) Persistent queues and significant unemployment for low-skilled and (b) recruitment problems for high-skilled.

employees in the public sector (Gomes, 2018). Though, what Gomes does not discuss regards the flows of those employees in mismatch and different sectors dynamically - why would they accept a less skills-demanding job initially? If hires in the government sector are from a private-sector pool, the cost of mismatch should be lower.[9] Santos and Cavalcanti (2015) show that a premium generates (mis)allocation effects and significant productivity losses using a model calibrated for Brazil. Literature connecting the public-sector employment with the mismatch is not rich and has not reached to any consensus. Empirically, Dolton and Vignoles (2000)[10] reject the HC interpretation that wage losses of overeducated are due to the public-sector rigidities.

Second, I account for the endogenous decision of sectoral affiliation. Pooling estimates may be a potential way to examine the magnitude of mismatch in the public-sector, but it neglects the unobserved worker heterogeneity (Nickell and Quintini, 2002) resulting from the self-selection into jobs. OLS estimates, which do not account for selection into the public sector, might be biased.[11] If allocation into sectors is not random, then estimates might overstate the existent gap. Some studies addressing this issue, either employ a selectivity correction or instrumental variables (e.g. Afonso and Gomes (2014) and Maczulskij (2013)).[12] Some scholars have taken advantage of the privatisations and use them as a 'natural experiments' (e.g. Danzer (2019) and Disney and Gosling (2003)).[13] Clark and Senik (2006) use individual fixed effects. Estimates, which are less sensitive to errors, may come from double selection models, like in Heitmueller (2006). However, this implies that we can identify what affects the labour-supply decision and not the public-sector choice. This exercise might be puzzling given the timing of individual decisions and the data availability. To this end, I restrict the sample to those in paid employment and control for the endogenous decision to contribute as public servants.

My model does not establish any causal impact of the public sector affiliation to the mismatch. It is hard to pin down the public sector's effect on mismatch from different selectivity. Instead, it implies the existence of different skills distribution in the two sectors. The selectivity may arise due to the different job arrival rates between the public and private sectors. This means that each sector will have different levels of productivity, and hence, different (matching) thresholds for different occupations.

[9] The idea of the cost here stands only for motivating purposes. No discussion on the penalty of mismatch is evolved in this paper.

[10] Scholars usually employ a dummy variable in their analysis aiming to explore the effect of overeducation in the public sector. This is not necessarily correct as the (strong) working assumption considers that the rest of covariates are equally distributed across sectors. Instead, analysis should be separate for each sector trying to control for the endogenous sectoral decision.

[11] In fact, these estimates suffer from a double selection, especially important for women. Initially, individuals decide if they will work (labour supply decision). Upon participation, they choose the sector of employment.

[12] Inconclusive findings of empirical studies signal the difficulty of identifying instruments for the public-sector.

[13] This method may neglect dynamic effects of those enjoying the public-sector pay premium.

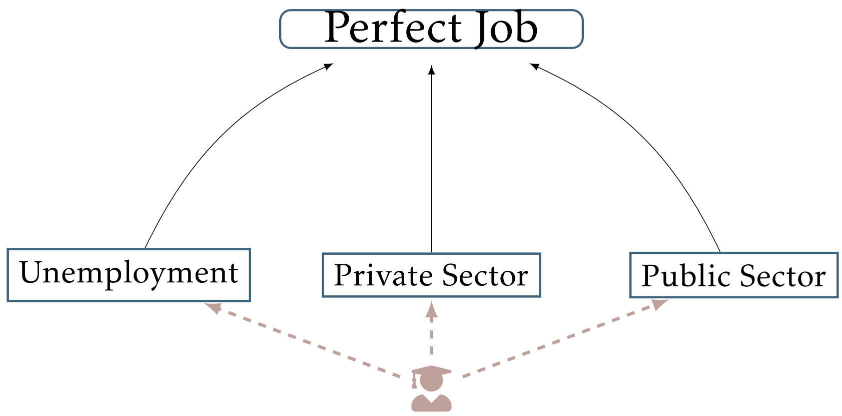


FIGURE 5.1.4: Alternative mechanism of the public sector: Example of Ph.D. in Philosophy graduate

The alternative mechanism this paper examines looks the public sector as *waiting room* for high-skilled workers of particular (scarce) jobs. Figure 5.1.4 illustrates an example of a recent Ph.D. graduate in Philosophy. Their best choice would be a job in the Academia. However, the academic market in Philosophy is not big enough to match immediately all graduates. Hence, there are three alternatives for these graduates. First, they can spend some time in unemployment until they find a better job. However, since they are high-skilled, this may not be very likely. Second, they can accept any private-sector job offer, e.g. in a retail store. Third, they can choose an administrative occupation in the public-sector. Between the two latter alternatives, and because of the non-pecuniary benefits of the public sector, they may choose the public-sector. In that case, the public-sector becomes the waiting room to a better job.

Using data coming from the UK for 25 years (1991-2016), I find evidence of negative selection for the public sector employees, which contributes to the incidence of mismatch for women. Changing the control group creates differences in the incidence. When comparing women with the median employee, one may notice a sizeable magnitude of mismatch reaching, on average, 37.8%. This may be explained if we see which occupations suffer the most. They usually include entry-level jobs which may act as a waiting room. Highly-qualified individuals seem to prefer waiting in a public-sector position being in mismatch rather than a private-sector matched one. In the former case, the likelihood finding better jobs is greater. What this measure likely picking up is the individual lower relative labour market experience. Since they end up in a matched position later than their well-allocated colleagues, they have accumulated less relevant experience. To this end, the policy perspective of this paper regards the allocation of talent in the public sector and its impact on the sectoral competitiveness and quality of goods and services offered. In other words, in this paper I stress the relative scarcity of the high-skilled jobs in the public sector. The negative selection implies the lower return to skills in the public sector coming from the unobserved individual productivity.

The rest of the paper is structured as follows. Section 5.2 describes the British public sector. Section 5.3 reports the methodology followed in this paper. Section 5.4 discusses the results, while section 5.5 concludes.

5.2 The British Public Sector

In the mid 2019, ONS estimated that 5.4 million employees (or 16% of labour force)[14] work in the public sector in the UK (Bodey and Haughton, 2019). This may include cleaners and drivers to technicians and nurses. Prior to any attempt of analysis regarding public-sector workforce mismatch, it is essential to describe its composition. Whether jobs belong to public sector depends on the organisation's degree of governmental regulation. In other words, who funds, controls and owns a company indicate the sector of a certain job.

To this end, some individuals are clearly public servants, like workers in civil service or the central government. To the opposite extreme, others are, undoubtedly, private-sector employees, e.g. developers in a tech start-up company. Considering the above jobs allocation as a continuum (figure 5.2.1), where on the one side we have strictly public-sector jobs and on the other side solely private-sector ones. The in-between area constitutes a grey area without clear boundaries. For example, Higher Education Lecturers are employed by non-profit (at least in principle) institutions. They are independent to the government despite their subsidy or control on EU-students' fees. Finally, School Academies or Foundation Hospitals may belong to charitable institutions and enjoy a certain degree of freedom in terms of hiring staff. Their funding and regulation, though, lie on the central government (Fontaine et al., 2020; Cribb, Disney, and Sibieta, 2014).

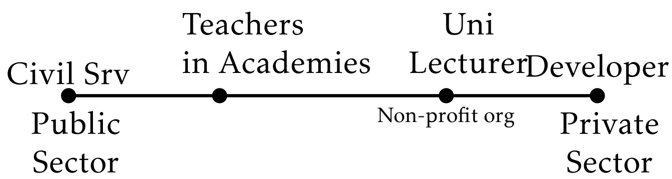


FIGURE 5.2.1: Allocation of jobs in sectors: Examples
Note: This figure illustrates a continuum of the jobs allocation between the two sectors. Above the continuum, one finds examples of jobs in each sector.
Source: Own elaboration

The distinctive feature of the public sector regards the provision of a good (or service) to the population financed by the taxation. If an organisation does not belong in this sector, *by definition*, is part of the private one.[15] As in the official statistics, in my data, the distinction between the sectors comes

[14]In their analysis, demographics depend on the Annual Population Survey estimates. This estimate is based on the public sector employment (PSE) which lacks in the individual characteristics of British workers.

[15]Therefore, private sector consists of both for-profit firms and non-profit organisation uncontrolled by central government.

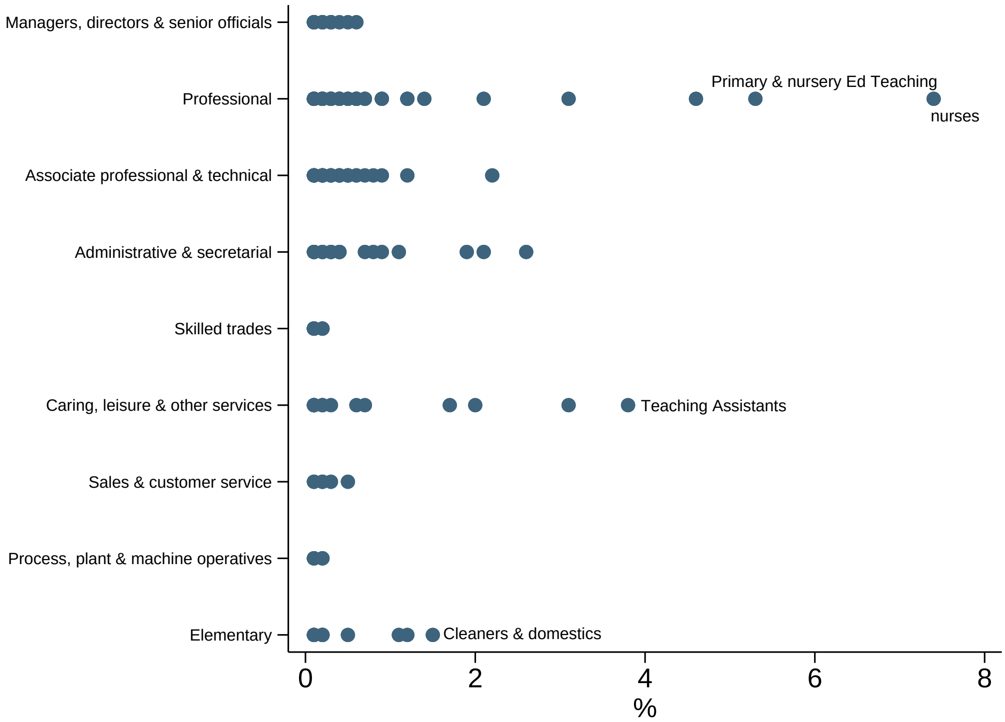


FIGURE 5.2.2: Distribution of occupations in the British public sector

Note: Percentage of UK public-sector employees in individual occupations, Jan-Dec 2018. Public sector demands more than 300 various occupations. *Nurses*, *Primary & Nursery education teaching professionals* and *Teaching Assistants* constitute the 7.4%, 5.3% and 3.8% of the public servants, respectively.
Source: APS; Data retrieved from ONS on 14.01.2020

from a self-reported variable[16,17] For this paper, I adopt the definition from Fontaine et al. (2020), excluding (i) every private organisation; (ii) public companies; (iii) Nationalised industry or state corporation; (iv) Charity, voluntary organisation or trust; (iv) other organisation.[18]

Figure 5.2.2 illustrates the distribution of more than 300 various occupations demanded by the British public sector in 1-digit classification. Following this classification and sorting occupations by the median level of education and hourly earnings, 3 occupational groups (high-, middle- and low-skilled) are generated, as in Galanakis (2019a).

[16]The question asked "What kind of non-private organisation do you work for?".

[17]Self-reporting raises concerns about misclassification of the sector or the kind of organisation one is employed for. To a certain extent, the measurement error might overstate the (unconditional) transitions between the sectors. Though, less problem is generated once looking the overall sector and its human capital composition. Greater issue might lie on the bottom of the occupation distribution, where only a few jobs in the public-sector exist.

[18]For robustness check of the mismatch magnitude, I have generated a variable equal to 1 if individuals are employed by NHS or work in Education industries, and 0 otherwise. The mismatch does not seem to come from these industries, since the incidence has minor changes. This may further motivate the analysis operated on the last section.

Regarding the size of public sector, one can observe slight changes annually in aggregate terms. The proportion of each industry within the public sector illustrate these changes. Official statistics verify that NHS and Education dominate other industries (figure 5.2.3). At the same time, it is interesting to see how the public-sector participation dropped since 1992 and its size shrank significantly by 2018. Structurally, austerity's result contributed to a significant flow of workforce from the public to private sector. The recession's aftermath brought about a cap on nominal wages increases on 2010 by the UK government aiming to cut the budget deficit. Seven years later, when participation was less than 17% of the total employment and a noticeable private sector recovery occurred,[19] this policy was relaxed (Cribb, 2017).

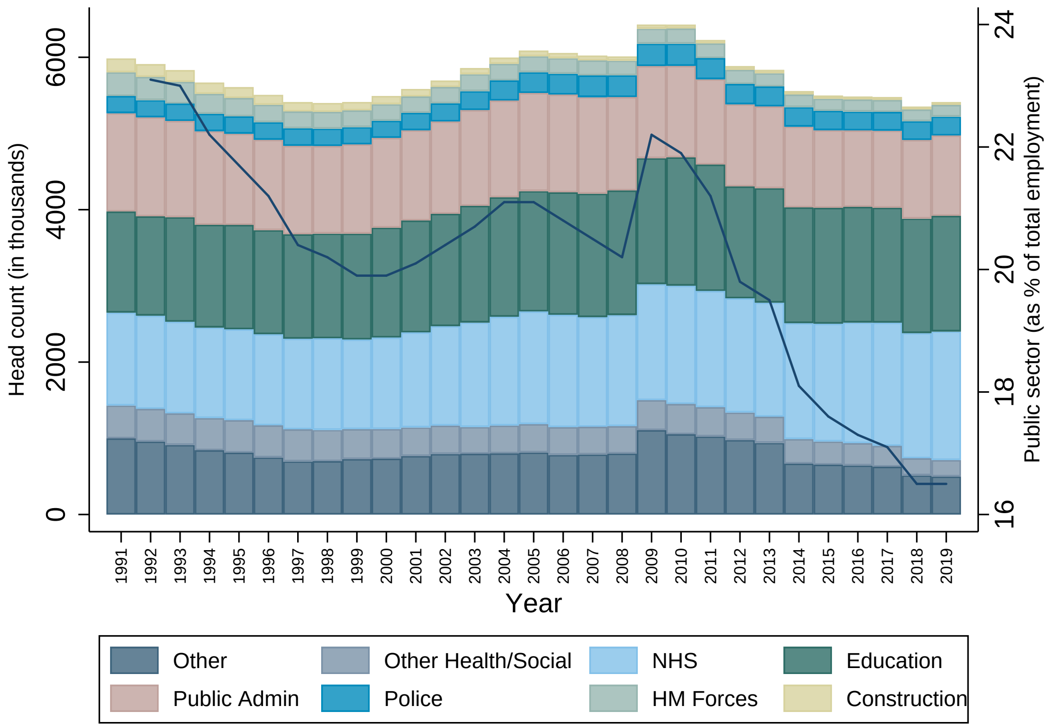
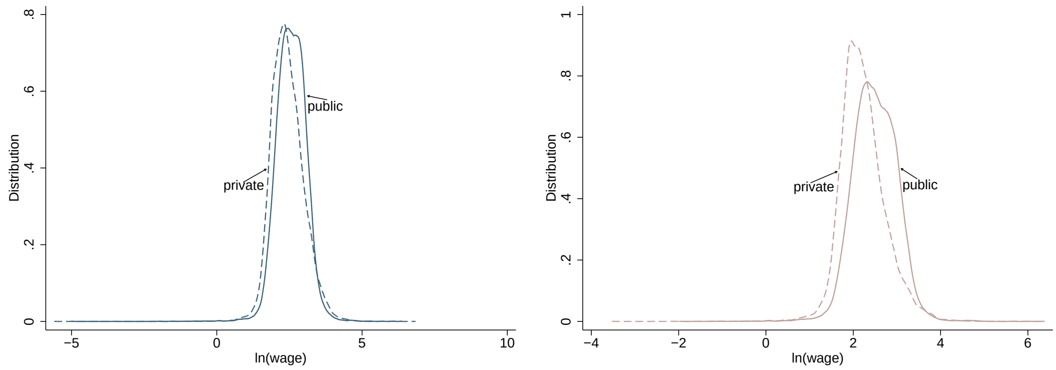


FIGURE 5.2.3: Size of Public Sector, by industry; 1991-2019
Source: ONS; Dataset ID: PSE; Released 11 June 2019

5.2.1 Wage differentials

The literature very often visits the wage differentials between the public and private sectors. It acknowledges a public-sector double-premium, mostly evident for (low-skilled) women, but not for men. This twofold premium relates to the higher quality jobs and better pay, which contribute to greater

[19]During the period of Great Recession, private sector shrank by 0.8 million from its before-crisis peak. Since 2010, private sector jobs increase by around 2 million (Coulter, 2016).



(A) Total population; age 23-59 (B) Women; age 23-59

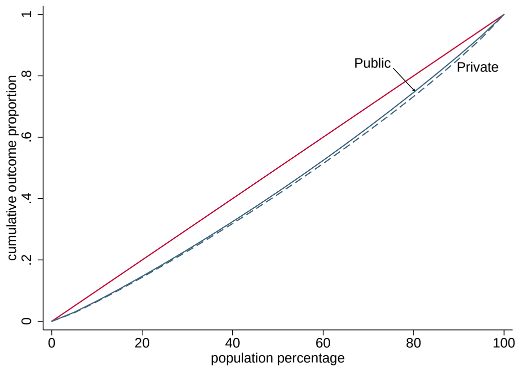
FIGURE 5.2.4: Average unadjusted wage gap, by sector; 1991-2016

Note: Panel (a) illustrates the distribution for the total employees in the labour market. The difference of the average ln(wage) between the sectors is -0.1337 (se 0.0035), significant at 1%. Panel (b) focuses on women whose difference is -0.2777 (se 0.0043), significant at 1%. Source: Own elaboration, based on BHPS/UKHLS

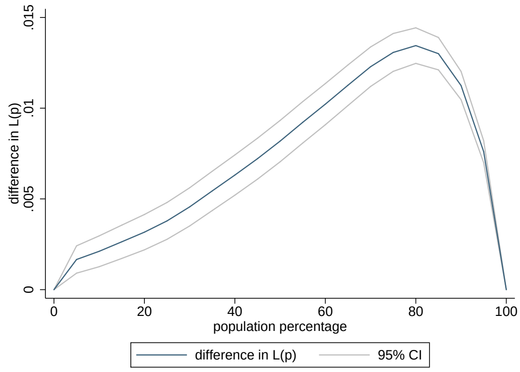
job satisfaction[20] (for a relevant discussion see Blackaby et al. (2015)). Traditional arguments include the better long-standing formation of the public sector (Davies, 2012), its highly unionised institutional environment (Hoque and Bacon, 2014). Cribb (2017) and Disney and Gosling (1998) support that an important (fringe) benefit attached to the public sector, particularly among women, regards the occupational (or workplace) pensions; their value remains higher than in private sector.

Figure 5.2.4 illustrates the wage distribution by sector highlighting their unadjusted gap. Each curve represents the average of 25-years data for the total population and for women. In both cases, the earnings distribution of the public servants stands on the right of private-sector workers. In raw terms, hourly pay is higher in the public sector, partly reflecting that workforce is high-skilled or more educated (Cribb, Emmerson, and Sibieta, 2014). A simple exercise, here, tests for Lorenz dominance, for the female subsample, to elaborate on inequalities and preferences in favour of the public sector. The lorenz curve of ln($wage$) of female public workers lies above the Lorenz curve of private sector women (figure 5.2.5b). This suggests that the private-sector wage distribution is more unequal, revealing public-sector as a fair employer. Whether the latter is preferable, from a welfare point of view, Generalised Lorenz (GL) dominance is essential. Again, a dominance of the public-sector distribution is verified signalling a slight preference in favour the public sector, in average terms (figure 5.2.5c). Figure 5.2.5d shows that not only less equality arises for women in the private sector, but also they strongly prefer the public one from a welfare perspective (Jann, 2016).

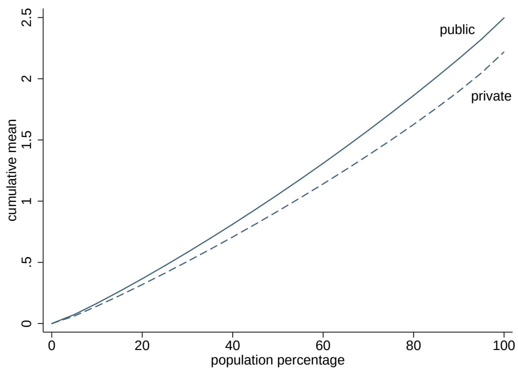
[20]As a result, the public sector, seen as an employer, enhances the work-life balance (WLB). Lewis et al. (2017) question senior professionals employed by the British public sector in Human Resources positions. They find that WLB is not only a personal concern for employees, but it also has a structural role during the times of financial pressure. However, austerity shrinks WLB concerns.



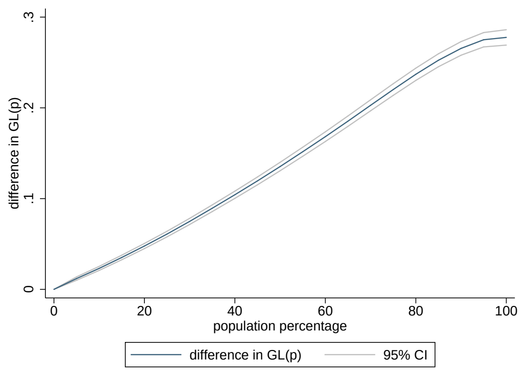
(A) Overlayed Lorenz curves, by sector
Note: Blue solid and dash lines represent the public and private sectors, respectively



(B) Difference in Lorenz curves, by sector



(C) Generalised Lorenz curves, by sector



(D) Difference in Generalised Lorenz curves, by sector

FIGURE 5.2.5: Lorenz curves for female employees, by sector
Note: For this set of graphs Stata command lorenz has been employed. Clustered on HH level s.e.
Source: Own elaboration, based on BHPS/UKHLS

A large part of the literature does not neglect the adjusted public/private wage gap employing several controls, such as job tenure, size of enterprise, managerial responsibilities etc. Attempts for cross-country comparisons are not always successful, even among EU countries. The main reason of failure of such comparisons regards the different public-sector structure in different countries. The country-specific studies decomposing the pay hiatus are more frequent aiming to relate differentials to regional frictions.[21]

In the UK context, recent evidence declares a larger differential for women. In fact, Blackaby et al. (2018) find that additional controls make the differential for men negative and significant. However, their results are sensitive to the measurement of hourly earnings. To this end, earlier evidence has shown that the gap narrows the higher one stands on the income distribution (e.g. Blackaby et al. (2015), Cribb, Emmerson, and Sibieta (2014), Lucifora and Meurs (2006), and Disney and Gosling (1998)). The same stream of literature points out that public premium favours mostly those low-paid, low-skilled women and younger employees (Giordano et al., 2015; Depalo, Giordano, and Papapetrou, 2015). This evidence arisen by the individual heterogeneity, additionally, points out that more educated workers enjoy a lower premium (Postel-Vinay and Turon, 2007). Hence, the public sector aims to alleviate inequalities. However, whether it allocates its employees efficiently remains a concern. This paper aims to highlight whether efficiency arises, controlling for the individual self-selection into jobs.

5.3 Data and Methodology

5.3.1 Data

This study utilises an unbalanced panel covering the period 1991-2016. It comes from the British Household Panel Survey (BHPS; waves 1-18), and its successor, United Kingdom Household Longitudinal Survey (UKHLS; also known as "Understanding Society"; waves 2-7).[22] I employ survey data for their informative power in terms of household dimensions and individual status.

The sample is restricted to women aged 23 to 59, employed in either sectors. The analysis does not look at self-employed, those working in the army or farmers. Hence, these categories have been excluded. The main analysis of this paper does require information regarding the individual wages. Income outliers, though, may affect the estimates. Therefore, the top and bottom 1% of the distribution have been dropped ending up with a sample size of 64,690 observations.

[21] Elliott, Mavromaras, and Meurs (2007) make a comparison of 5 European countries, including the UK. They find that the British differential is not the same as in Mediterranean public sectors, while high-earnings areas - like London - deal with issues of common public services provision.

[22] For a more thorough description of the dataset and the cleaning process, see Galanakis (2019a) and Galanakis (2019b).

5.3.2 Methodology

Earlier work supports that female employees face a greater probability to be in mismatch in the labour market (Galanakis, 2019b). Here, I offer new and better informed estimates for the British public sector controlling for the endogenous decision related to the sector of work. To do so, as in Galanakis (2019a), an individual i is in mismatch if her predicted HC in the public-sector occupation j is greater than the median returns in a more skills-demanding public-sector occupation, namely in occupation $j-1$. In this identification strategy, I keep ranking occupations according to their median level of education and hourly earnings. Occupation here takes three values; 1 for high-skilled, 2 for middle-skilled and 3 for low-skilled. Alternatively speaking, the magnitude of mismatch replies the question: "How many women employed in the public sector in $j-1$ occupation hold similar expected wage to their colleagues in j one?". Or,

$$\text{mismatched}_{i,t} = \begin{cases} 1 & \text{if } \widehat{w}^{\text{pub}}_{i,t} | occ_{j,t} > \left(\widetilde{\widehat{w}}^{\text{pub}}_{t} | occ_{j-1,t} \right) \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

where $\widetilde{\widehat{w}}$ is the median of the estimated wage.

To calculate the $\widehat{w}$, a Mincerian wage equation is necessary. As before, due to data restrictions HC is formed through the level of education.[23] Here, I estimate the following:

$$\ln[\text{wage}]_{i,t} = \alpha + \boldsymbol{\beta}_1 \boldsymbol{x}_i + \sum_{k=2}^{7} \beta_k S_{k,i,t} + \vartheta_t + u_{i,t} \tag{5.2}$$

where $\boldsymbol{x}_i$ includes controls of age (and its square) and marital status. $S_{k,i,t}$ regards the k level of education. Estimates will have year fixed-effects (ϑ_t) and standard errors are clustered in household level.

The Ordinary Least Squares (OLS) estimates of equation 5.2 may be inconsistent. In fact, they are exposed to two types of selection bias: the first one comes from the endogenous labour supply decision, whereas the second one from the choice to work in the public sector. If individuals systematically decide to be in paid employment, the assumption of random sample selection is violated (Heckman, 1979). This is usually addressed in the literature; the application of 2-step Heckman approach is usually adopted. Given their participation in the market, individuals choose the sector of their employment. If the sectoral allocation is not random, OLS estimates would be downward biased (Maddala, 1983). The underlying idea comes from the fact that each sector faces different wage equations due to their different demand of skills or unequal skills distribution. Hence, we need to control our estimates for a dual-selection bias, which arises from the simultaneous or sequential decision a woman makes (Tunali, 1986).

[23] A richer definition of HC is offered when using cohort studies where tests of (non-)cognitive skills are offered. See details in Galanakis (2019a).

The self-selection problem into jobs and sectors of employment is not thoroughly visited in the literature and no consensus on how to treat this enodgeneity exists. Considering decomposition exercises for pay differentials, one can find several examples where the endogeneity is not treated at all (e.g. Jones, Makepeace, and Wass (2018), Mahuteau et al. (2017), Ramos, Sanroma, and Simon (2014), and Cai and Liu (2011)), or a dummy variable for the public sector aims to capture the effect (e.g. Dolton and Vignoles (2000)). Heitmueller (2006) attempts a double-selection model, but his findings are not on a dynamic framework. Long, Appleton, and Song (2017), Christopoulou and Monastiriotis (2016), Christopoulou and Monastiriotis (2014), Luechinger, Stutzer, and Winkelmann (2010), and Dustmann and Van Soest (1998) proceed with a endogenous switching regressions aiming to alleviate the dual selection bias. Their identification power, though, rests on very strong functional assumptions; a collapse of the exclusion restriction generates inconsistent estimates (Danzer, 2019).

To proceed with this dual-selection model, data need to provide enough information so that we can identify sufficient instruments. This approach would require a variable to affect only the decision of employment and not the wages or public-sector affiliation. Similarly, another variable should only affect the decision of employment sector and be independent to the labour supply decision and the wages. However, as literature acknowledges, it is very hard to identify this variable that respects the exclusion restrictions credibly and correct for the selection bias (Araujo, 2020; Van Ophem, 1993). To overcome this identification problem, I restrict the sample to employees and correct for the potential sector selection. The final step of the exercise revisits three indices for mismatch, as in Galanakis (2019b). Changing the control group is crucial,[24] since it generates different estimates on the magnitude of mismatch. Hence, I look the (a) position of a female worker relative to the median employee; (b) counterfactual case - where I consider estimates of the male labour market; and, (c) the position of a female worker relative to their colleagues (in the female labour market).

To control for the endogenous self-selection into sectors, a two-step Heckman model will be applied. The decision to work in the public sector will be instrumented using the hours of paid overtime, a public-sector time lag. Furthermore, a set of dummies will be employed to signal an older worker or a highly educated employee.[25,26] Hence, the public-sector participation could have this form:

$$\text{public}_i = \delta \boldsymbol{z}_i + v_i \tag{5.3}$$

where public_i is the dependent variable. $\boldsymbol{z}_i$ is a vector of the independent variables as described above. For each wave, linear predictions are sorted by

[24]For example, recall the assumption that women are more likely in mismatch. It signals that when women seen in the male labour market, alleviating any *a priori* discrimination, their probability of mismatch may change.

[25]It receives the value of 1 if a worker is older than 35 years old or has a level of education greater than A-levels, respectively.

[26]A battery of robustness checks controls for the number of children and the single parenthood. None change the incidence of mismatch.

occupation to calculate the median of high- and middle-skilled ones. The final step of the exercise applies eq. 5.1 to identify those in mismatch.

Exclusion restriction To control for the endogeneity arisen from the self-selection into jobs, we need at least one instrument that is not related to the wages and mismatch. This instrument needs to be related to the probability one chooses the public sector. I could not identify one single, strong instrument in the data regarding the public sector affiliation. This is why I choose instruments based on the public servants' features. First, hours of paid overtime and a public-sector lag are related to the public-private sector pay gap (Depalo, Giordano, and Papapetrou, 2015; Giordano et al., 2015). The public sector as a fairer employer would pay the hours worked overtime increasing the willingness to join the government sector. A prior employment in the public sector increases the probability to stay with the same employer given the better compensation and the job satisfaction it offers. Second, the public sector concentrates older workers (see figures 5.C.1 and 5.C.2) who are higher skilled (Bodey and Haughton, 2019). This is why I use a dummy variable if public servants are older than 35 years old, and one for their level of education (above A levels).

5.4 Results - Discussion

5.4.1 Female over-representation in the public-sector

Descriptive results may motivate further the mismatch estimates in the British labour market. Table 5.4.1 employs several measures to validate the female dominance in the public sector. In fact, it seems that 46.21% and 23.95% female and male, respectively, are employed in the public sector as percentage of the total employment. A closer look on the female workforce indicates that the monopolistic sector is the main employer for them (41.69% against 39.84% in the competitive sector). Panel B presents two accounting definition exercises, as in Gomes and Kuehn (2020). The first one shows the ratio of public employment shares. It is defined as share of women relative to share of men's employment. Over the examined period, both ratios increase (figure 5.4.1). This may be related to the augmenting female labour supply decision. Around the Great Recession, a drop is noticed most likely driven by the significant changes in the private sector and/or the shrinkage of the public one.

One may wonder about the public servants' age. Indeed, this data verifies that older worker prefer to be occupied in the public sector. Figure 5.C.1 illustrates the normalised age-public-sector-employment profiles pooled for men and women. At the beginning until early 30s, individuals share same prospects of employment. Noticeable differences arise after the age of 32 when women seem to dominate.[27] This dominance may be related to their

[27] Consistent result arise the ratios of public and women's employment shares by age (figures 5.4.2 and 5.C.2). The slope becomes significantly steeper the older a worker is. Greater jump noticed after the 40 years of age.

TABLE 5.4.1: Different measures for the female over-representation in public employment; employment shares

Panel A.i (as % of total employment)		
	Men	Women
Public-sector	23.95	46.21
Panel A.ii (as % of female workforce)		
	Public	Private
Women's empl share	41.69	39.84
Panel B: Accounting Definition Exercises		
Ratio of public empl shares	1.9897	
	(0.1438)	
Ratio of women's empl shares	0.8627	
	(0.1392)	

Note: Panel A presents a descriptive analysis regarding the public sector. *A.i* shows the employment shares in the public sector by gender. *A.ii* shows the female employment share by sector over the female workforce. Panel B reports the accounting definition exercise (as in Gomes and Kuehn (2020)). s.d. in parenthesis. Figures reported for individuals aged between 23 and 59.
Source: Own elaboration, based on BHPS/UKHLS

intrinsic preferences or the family-related decisions which occur around that age. Childbearing and household production may urge women towards the public sector.

5.4.2 Transitions

Given the panel aspect of the data, we can discuss labour mobility across the sectors or out of employment. Here, out-of-work status is broadly defined including both unemployment and inactivity. To elaborate on the different decisions between men and women, descriptive statistics on the labour market stocks and flows (table 5.4.2) are crucial. Stocks are calculated as a fraction of the entire working-age population.[28] This is why figures in tables 5.4.1 and 5.4.2 differ. Flows are expressed for the sample applying any age restriction. Gender differences in flows and transitions are statistically significant at 1% level.

Still, on average 7.3% more women are employed in the public sector, but 4.3% more men are occupied in the private one. Public servants face a lower probability to exit from employment.[29] A probable explanation for this pattern might arise by the different demand of skills for the public sector and the preferences of women. Regardless the sector of prior affiliation, women are more prone to exit from work mirroring their lower participation rate

[28] The definition of the working-age population adopted by the BHPS. It includes individuals aged 16-65 and 16-59 for men and women, respectively.

[29] The trend is not persistent, though, when looking at the unemployment or retirement separately. Though, this is not a case of analysis in this paper.

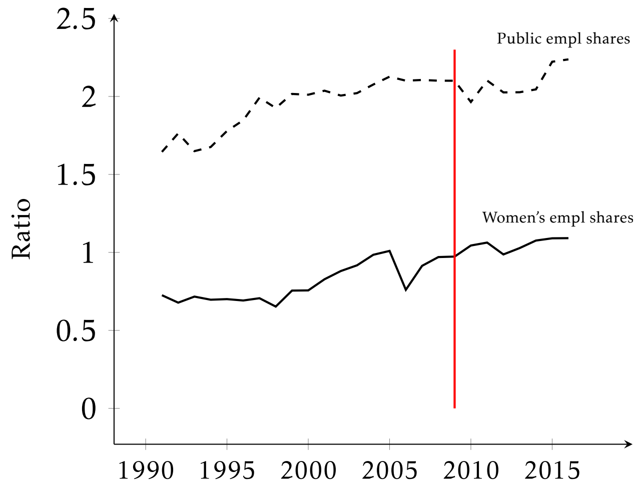


FIGURE 5.4.1: Ratio of public employment shares and ratio of women's employment shares

Note: Dashed line illustrates the ratio of public employment shares by year. This measure is defined by the share of women over the share of men employed in the public sector. The solid line illustrates the ratio of women's employment shares. It is defined as the share of women in the public relative to the private sectors. A vertical red line for 2009 is added to signal potential differences after the Great Recession.
Source: Own elaboration, based on BHPS/UKHLS

in the market. Figure 5.4.3 adds some further quantitative results. Women are more mobile than men in general. The female state-sector inflow dominates the male equivalent one. Once in the public sector, women are less willing to leave within a year. Potentially due to greater job security, the outflow from work is greater in the private sector. Additionally, this works vice versa, because of the quicker job creation (Lavery, 2015). Finally, flows between sectors are similar for women, but not for men; the majority of the latter are willing to join the private sector probably due to lower risk aversion (Borghans et al., 2009). These unconditional worker flows are consistent with recent evidence on the UK; interstate flows are significant, but smaller than to/from out-of-employment (Chassamboulli, Fontaine, and Gomes, 2020).

Gender differences between the sectors may come from composition effects or sampling variation. To account for this concern, I estimate the conditional transition probabilities to observable characteristics (see 5.B). Marginal effects are illustrated on figure 5.B.1. Conditional probabilities to OoW coming from public employment is equal to zero for men and close to zero women. Transitions from the private sector differ, though. Men are less likely to lose their job, while women are more prone to exit verifying the lower employment attachment they have.

5.4.3 Incidence of Mismatch

The main purpose of this paper is to highlight the extent of HC mismatch female employees face in the public sector. To do so, the endogenous decision related to the sector of employment is considered. To see whether the selection model is of any need, I compare the estimates with earlier findings from

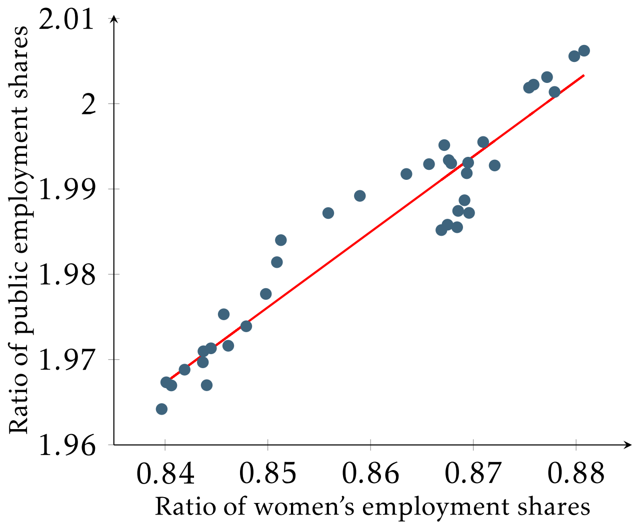


FIGURE 5.4.2: Correlation of ratios of employment shares, by age
Source: Own elaboration based on BHPS/UKHLS

chapter 4 pooled for public sector. If the estimates using selection model differ, it is essential to control for this source of endogeneity.

Relative to median employee Firstly, the position of a female employee relative to the median employee is observed. I estimate the returns to HC for the entire population. Then, I assign them to women and see their position compared to the median employee. Figure 5.4.4a outlines the main result of this index. Specifications, restricted to the employees, with the selection for the public sector model denote a sizeable incidence of HCM. It is not only the magnitude reaching (or exceeding) 40%, but it is the difference with the pooled results. The pooled estimates declare a more moderate picture. Before the crisis, the selectivity model looks to be systematically above the pooled one. Right after the Great Recession, a v-shape increase of the selectivity model occurs; the incidence later meets the results from the pooled estimates. Hence, this questions *why* the selection model shows an important level of mismatch? Technically speaking, each specification of the two-step Heckman selection model is statistically significant. The average gap is 12.64% (s.e. 0.0035; significant at 1% level) against the pooled results denoting an underestimation if one neglects selection for the sector of employment.

Restricted female subsample Secondly, I test the position of a female employee relative to her colleague in a more skills-intensive job. For example, the comparison takes place between a Teaching Associate and a Teacher, both women. Here, we still observe a difference between the selection specification and the pooled estimates. Though, the average gap is smaller than before (figure 5.4.4b); 3.62% (s.e. 0.0035; significant at 1% level). The trend is similar at the most of the time with effect increasing after the Great Recession.

Counterfactual female subsample Finally, to alleviate any discrimination women may face even before they enter the labour market, I see their

TABLE 5.4.2: Stocks, flows and transitions of the British Labour Market, by gender

	Men	Women	
Panel A: Stocks			
Public Empl	0.0689	0.1419	
	(0.0098)	(0.0234)	
Private Empl	0.2413	0.198	
	(0.0351)	(0.0267)	
Out-of-work	0.2170	0.3446	
	(0.0122)	(0.0087)	
Panel B: Flows			
Out-of-work	0.1517	0.2938	***
	(0.3587)	0.4555	
Panel C: Transitions (in %)			
Pri2OoW	3.97	5.47	***
Pub2OoW	1.14	2.95	***

Note: *Panel A* figures are as fraction of the total working-age population, regardless whether they are (in)active. All panels are expressed for this study's sample (aged 23-59). Out-of-Work (OoW) includes states of unemployment and inactivity. The unconditional transition probabilities report the probability of an employed worker to exit from employment. Figures are averages over the total period of 1991-2016. The rightmost column (***) declares that differences are significant at 1% level.
Source: Own elaboration based on BHPS/UKHLS

position in the male market. To do so, I assign the estimates of the male subsample to women and see their relative position. By this way, I consider that they have the same observables as men questioning how this changes their position. The average gap is -0.91% (s.e. 0.0059; significant at 10% level). Figure 5.4.4c depicts that the trend is not always the same; opposite direction revolves after the period of the financial crisis. The selection model specification matches the pooled estimates in 2009/10. Right after the crisis, the former shows a quicker adjustment to the pre-crisis levels.

A persistent common pattern across the three measures - despite the control group change - regards the point of the big rise in the mismatch magnitude. When the British economy suffers from the financial crisis and the Great Recession, the incidence seems quite high both in the selection model and in the pooled results. Lazear, Shaw, and Stanton (2016) claim that hires during recessions are better matched in the public sector than those in booms. However, this does not seem to be the case here. Instant response of the market, is an initial misallocation which aims to be restored several years after.

Selection Inference One may reasonably question why the estimates coming from the selection model specifications are greater. The necessity of correcting for the endogenous self-selection into jobs regards the non-random allocation of workers. If they were randomly assigned between sectors, estimates of HCM would be accurate; not controlling generates a smaller magnitude of this inefficiency. Table 5.4.3 reports the average difference on the

Table 5.4.3: Average difference of the HCM incidence between selection models and pooled estimates; 1991-2016

Model	Mean (s.e.)	
Panel I: Relative to overall		
Selection	0.3782	
	(0.0023)	
Pooled	0.2519	
	(0.0023)	
Difference	-0.1264	***
	(0.0035)	
Panel II: Restricted Female subsample		
Selection model	0.1133	
	(0.0025)	
Pooled Estimates	0.1496	
	(0.0023)	
Difference	0.0362	***
	(0.0035)	
Panel III: Counterfactual female		
Selection model	0.5969	
	(0.0035)	
Pooled Estimates	0.5878	
	(0.0047)	
Difference	-0.0091	*
	(0.0059)	

Note: The first number of each model declares the mean. Standard errors are reported in parenthesis. Each panel contains one measure with the 2 different models, the specification with selection of the employment sector and the pooled estimates, as in figure 5.4.4. The ultimate row reports their average difference and s.e.. The ultimate column declares the statistical significance.

Significance level: * 10%; ** 5%; *** 1%

Source: Own elaboration based on BHPS/UKHLS

incidence of HCM between the selection model and the pooled estimates for public sector affiliation. Panels I and III show, on average terms, that the selection model dominates the pooled estimates. The opposite holds for panel II. In fact, in most of the cases,[30] the correlation of error terms (between the wage equation [eq. 5.2] and the public sector one [eq. 5.3]; ρ_{uv}) is negative. This signals a negative selection for the public servants; the allocation into jobs between the two sectors depends on additional determinants than the individual observed skills (selection on unobservable productivity). The matching of workers across sectors decreases, since the gap between pooled estimates and Heckman specifications increases. This sorting tool drives women with great demands of work-life balance or specific intrinsic preferences[31] into the public sector. This means that, before they enter into the market, women are already endowed with unobservable characteristics[32] in favour of the state-employer and its accompanying work-life balance which increase their wage. For example, if a high-skilled woman is likely to join the public sector given her preferences, she is not well-suited for the private sector (e.g. she might be more risk averse; Guiso and Paiella (2008) and Bonin et al. (2007)). This could mean that her counterfactual private-sector wage is lower than her counterpart who actually works in private sector (due to negative selection). At the same time, this implies a lower return to skill in the public sector, as in Hanushek et al. (2017) and Hanushek et al. (2015).

Alternatively, not selecting for the sector of employment underestimates the extent of HCM (figure 5.4.5). Since the incidence increases after correcting for the self-selection problem into jobs, pooled estimates are downward biased understating the real HCM. Greater mismatch is caused by a correlation between individual inherent skills and public-sector affiliation (Danzer, 2019). In other words, the returns of the high- and middle-skilled workers are closer in the selectivity model, while in the pooled one they are further apart. Or, people who do not enter immediately in a public-sector job, but hold features and preferences in favour of good job there, accept a "pay cut". They wait at the back of the waiting queue for this good state-sector job, while being underpaid. This elaborates empirically why the incidence increases when controlling for the sector affiliation.

[30] There is a small variation regarding the sing of the Inverse Mills Ratio (IMR) over the specifications. On 2009 and 2016, lambda becomes not significant. Losing the significance, though, may not necessarily imply an absence of the sample selection bias. A small sample (as in these cases), Heckman model are not likely to produce significant lambdas (Certo et al., 2016). Non-significance may, additionally, occur if exclusion restrictions are weak.

[31] Gomes and Kuehn (2020) find that female preferences for state-sector activities explain 95% of the gender bias participation in the UK. According to them, women count more work-life balance, while men job security. They relate this evidence to the higher female opportunity cost of labour supply by accepting lower wages.

[32] These features may include intrinsic preferences to work in the public sector; preferences for particular state-provided jobs (recall the different demand) or they are more risk averse.

Waiting Room for university graduates

A reasonable argument may revolve around the primary results. According to an alternative interpretation, the public sector does not cause the mismatch and it has a better matching process; so, *why* do we observe this great magnitude of mismatch? A twofold reasoning declares the importance of the measure which accounts the position of women relative to the median employee. First, it presents the greatest gap between the selection model and the pooled estimates. Second, its magnitude is around (and sometimes exceeds) 40%.

Aiming to explore the mechanism driving this result, we need to see which occupations bear the greatest impact of mismatch. Recall figure 5.1.3, according to which only a few low-skilled jobs exist in the public sector. Hence, the incidence noticed (figure 5.4.4a) should mostly come from those employed in middle-skilled jobs holding enough HC to be in a high-skilled one. Table 5.4.4 reports the average percentage of those in mismatch in each 3-digit-classified occupation. Consistently as before, the incidence changes when the control group is different. One occupation may be in mismatch when women seen relative to overall population, but not in the restricted subsample, and *vice versa*.

Table 5.4.4: Map of occupations in Mismatch; 1991-2016 (in %)

Occupation		Restricted Female Subsample		Relative to overall	
Code	Title	Matched	Mismatched	Matched	Mismatched
311	Physical and Engineering Science Technicians	33.33	66.67	35.56	64.44
312	Computer Associate Professionals	100	0	100	0
313	Optical and electronic equipment operators	91.67	8.33	91.49	8.51
321	Life science technicians and related associate professional	33.33	66.67	37.5	62.5
322	Health associate professionals (except nursing)	54.19	45.81	63.92	36.08
323	Nursing and midwifery associate professionals	51.22	48.78	53.67	46.33
334	Other Teaching Associate Professionals	50	50	44.44	55.56
341	Finance and sales associate professionals	46.77	53.23	62.96	37.04
342	Business services agents and trade brokers	60	40	70	30
343	Artistic, Cultural and Culinary Associate Professionals	70.53	29.47	67.02	32.98
344	Customs, tax and related government associate professionals	68.42	31.58	68.52	31.48
345	Police inspectors and detectives	100	0	100	0
346	Social work associate professionals	64.91	35.09	71.03	28.97
347	Artistic, entertainment and sports associate professionals	56.25	43.75	54.55	45.45
411	Secretaries and keyboard-operating clerks	86.55	13.45	88.83	11.17
412	Numerical Clerks	70	30	76.19	23.81
414	Library, mail and related clerks	86	14	90.12	9.88
419	Other Office clerks	82.57	17.43	85.25	14.75
421	Cashiers, tellers and related clerks	90.48	9.52	92.86	7.14
422	Client information clerks	92.17	7.83	93.24	6.76
512	Housekeeping and restaurant services workers	98.41	1.59	99.15	0.85
513	Personal care and related workers	86.39	13.61	89.8	10.2
516	Protective services workers	79.72	20.28	82.48	17.52
522	Shop, stall and market salespersons and demonstrators	84.21	15.79	87.5	12.5
612	Animal producers and related workers	20	80	30	70
731	Precision workers in metal and related materials	66.67	33.33	66.67	33.33
832	Car, Van and Motorcycle Drivers	33.33	66.67	80	20
913	Domestic and related helpers, cleaners and launderers	77.96	22.04	95.54	4.46
915	Messengers, porters, doorkeepers and related workers	58.14	41.86	70.27	29.73

Note: In this paper, mismatch is initially defined on 1-digit level. ISCO88 codes including only matched employees have been omitted. Codes with less than 10 observations have been eliminated.

Source: Own elaboration based on BHPS/UKHLS

These occupations concentrating workers in mismatch are mostly those entry-level jobs which individuals may choose until they find a better opportunity. In other words, these occupations may act as a waiting area for a matched position. This would be the case mostly for high-educated workers who have more options than their low-educated peers. The former type of workers can either find a matched position immediately after graduation or be unemployed. Alternatives include to be employed in the public or private sectors. In any sector, they may find a job and be in match or mismatch. Hence, university graduates have six options after graduation. Assuming a similar arrival rate would not be irrational. Hence, the question is where do they prefer to wait for the "perfect" job?

For instance, a nurse, a teacher or a psychologist can go quicker or directly to a matched job.[33] On the other hand, a Ph.D. in Philosophy graduate[34] may need to further wait for a lectureship outside of the traditional academic sector due to job scarcity (Canal Domínguez and Muñiz Pérez, 2012). In the meantime, a low-skilled job in a retail store or as a waiter[35] would not look appealing (due to frustrations, e.g. a lower job satisfaction). Instead, accepting a public-sector job in mismatch may look significantly more attractive given her preferences. Yet, this type of workers benefits the public sector since they are more productive, under the HCT. Figure 5.4.6 illustrates these choices and their unconditional transition rates reaching the perfect job within two periods. The least likely waiting area occurs in unemployment. It concerns highly-educated workers whose skills are important for any market; they rather be employed than unused. On the other hand, workers previously in the public sector seem to find their matched position sooner. Estimates imply that almost 1 in 6 female public servants (18%) are more likely to end in a matched job sooner, while almost 1 to 8 (or 12%) for those in the private sector (difference statistically significant at 1% level). The aforementioned matched position is highly likely to be in the public sector (table 5.4.5). This evidence argues, further, in favour of accounting for the endogenous decision of the affiliated sector. Individuals may choose the public one due to its attractiveness, fringe benefits and opportunities.

Job satisfaction and sector of employment

To validate the argument above, I further test whether these choices are consistent with the self-declared job satisfaction of employees. If highly-educated workers prefer to be in mismatch and work in the public sector,

[33]The focus centres around those educated workers, because they are qualified to be employed in either sector. They are probably not going to get a graduate public-sector job, because they do not hold the job-specific skills or they face a great competition (excess labour supply). Otherwise, if they did, as for example nurses, they would already have the graduate public-sector job.

[34]De Paola and Gioia (2012) find that higher risk aversion should induce students to enrol in humanities. If Human Capital Theory holds, these students make an investment in education, which will pay off in the long-term.

[35]There is a direct relationship between the mismatch and firm productivity across different working environments (Mahy et al., 2015).

TABLE 5.4.5: Where is the perfect job?

	Period t			
	Private		Public	
Period $t-1$	N	%	N	%
Public	7	7.29	89	92.71
Private	61	93.85	4	6.15
Unemployment	2	40	3	60

Note: In period $t-1$ a high skilled individual is in mismatch and the consecutive period, i.e. in period t, she finds the perfect (matched) job. The measure of mismatch employed here regards the restricted female subsample.
Source: Own elaboration based on BHPS/UKHLS

they should report greater job satisfaction than their colleagues who are in the private sector (and in match), *ceteris paribus*.

To this end, I run an ordered probit regression of job-satisfaction on the offers one may have controlling for the level of education, the age (and its square, as a proxy for experience), marital status, number of children and the danger of retirement for any female employee and for high-educated type one. Regional fixed effects included. Figure 5.4.7 reports the marginal outcomes of offers on the jobs satisfaction. Results suggest that more satisfied with their job women accept a less skills-intensive job in the public sector. Alternatively, female employees prefer to wait in the public sector in mismatch rather than the private one in match. This is robust with the earlier result and consistent for both highly-educated and any type of female employee. To make it more clear, for the highly-educated women, I group the 7 self-reported answers into 3; dissatisfied, neither satisfied not dissatisfied and satisfied. This step is more interpretable and strengthens the same argument. The greater job satisfaction in the public sector is not unprecedented in the literature (Blackaby et al., 2015), even in non-UK context (e.g. Danzer (2019)).

5.5 Conclusions

This paper looks at the extent of female public-sector employees in mismatch. It contributes to earlier evidence accounting for the endogenous self-selection into jobs. To this end, I examine the position of a woman relative to the median employee, her peers or in the male labour market. Working assumption treats each sector as a separate, potentially segregated, labour market which has a different demand for skills. This is why each sector offers different wages.

Initially, I verify the existent gender bias in favour of women regarding public-sector participation. The government sector employs more women and older workers (whose age exceeds the 33 years). Concerning their educational profile, public servants are mostly highly educated. Besides, this sector does not offer many low-skilled jobs.

The incidence of mismatch differs when the control group changes. Once women are seen relative to the overall population, the magnitude may reach, or in some cases exceed, 40%. The mechanism aiming to explain this sizeable magnitude of mismatch is not frequently visited by the empirical literature. Occupations, which mostly suffer from this inefficiency, include more entry-level jobs. Individuals may not find their matched job immediately due to job scarcity and great competition. These junior positions endow the employees with job-specific skills for their future career. Workers may find later their 'perfect' job most likely in the same sector they wait. Otherwise, if employees enter into the labour market highly-educated holding specialised skills, they will probably end up in the matched position without waiting or queuing for any better job. Therefore, what this mismatch measure counts is the lower relevant labour market experience these individuals have relative to their initially matched counterparts.

This analysis is consistent with the self-reported overall job satisfaction of employees. If the aforementioned mechanism holds, i.e. individuals prefer to wait in the public sector in mismatch, they should gain greater job satisfaction from their job. Indeed, other things being equal, public servants in mismatch report greater satisfaction than their counterparts in high-skilled private-sector jobs.

Limitations First limitation of this paper regards the dataset used. BHPS and 'Understanding Society' are survey data with small number of observations; their informative power, though, is strong. Second limitation concerns no control for the participation decision, since the working sample is only comprised of those in paid employment. This choice was driven by the data limitation to respect the exclusion restriction. To the best of my knowledge, there was no variable to contribute exclusively in favour of the labour supply. A potential claim of not directly comparable estimates between the selection model and the pooled one is recognised. An additional source of data may help to identify a double-selection model, as in Tunali (1986).

Policy Implications The importance of this evidence sets the framework on efficient allocation in the public sector. This paper does not aim to answer *how* the public sector should allocate its workforce. It stands a step behind and highlights the extent of mismatch. Men and women are not symmetrically affected by employment and wage policies. This discussion should welcome great attention, since women, who are prone to be in mismatch, are overrepresented in the public sector. Clear implications, standing in line with earlier research (Mocetti and Orlando, 2019), may regard the effectiveness of governmental investments and the quality of services provided. Misallocated human capital endowments may result in lower competitiveness. Finally, evidence on the negative selection in the public sector implies that what increases the probability of becoming a public servant acts as a 'pay cut' for those selected. In other words, the return to skill is lower in the public sector. Given that the analysis provided concerns women, this has direct implications on their working life and can address motherhood policies.

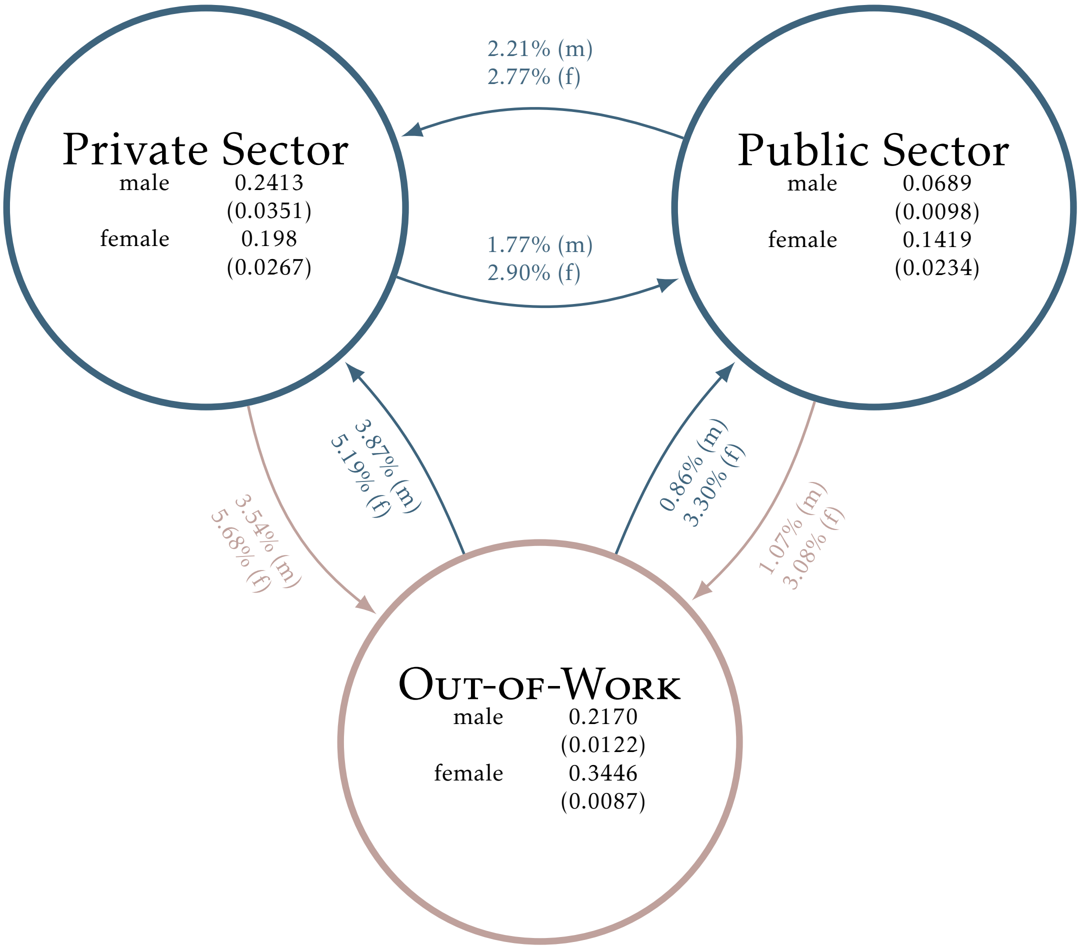
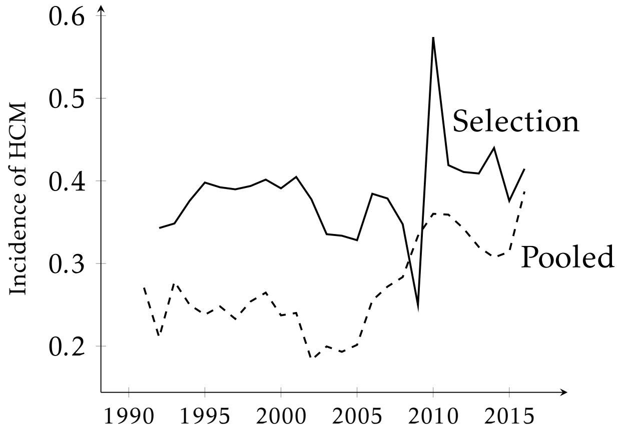
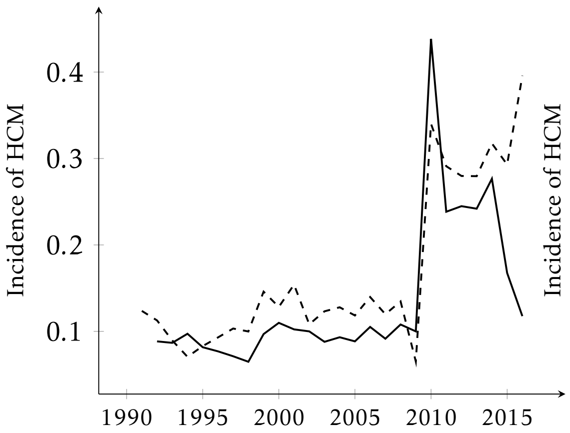


Figure 5.4.3: Average unconditional worker transitions, 1991-2016

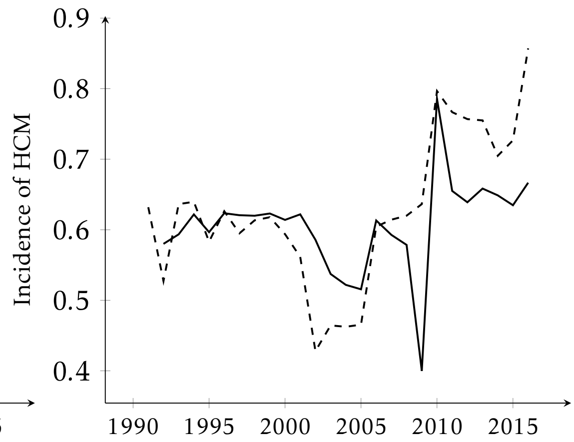
Note: The *circles* illustrate the average employment (blue) and Out-of-Work (pink) stock rates over the period of 1991-2016. The blue circles show that a worker can be either employed in the private or public sector. Within a circle, the first value shows the average stock rate; the s.d. is in parenthesis. Worker stocks are expressed as a fraction of the total working-age population (definition followed by BHPS including individuals aged 16-65 and 16-59 for men and women, respectively). The *arrows* illustrate the unconditional transition from the one status to the other within two periods, e.g. between $t-1$ and t. The values above each arrow show average probability to move from the one status to the other. *(m)* and *(f)* represent the values for men and women, respectively.
Source: Own elaboration, based on BHPS/UKHLS



(A) Women relative to median employee
Note: I assign the overall population estimates to women and I compare their relative position to the overall distribution of the more skill-demanding occupation.

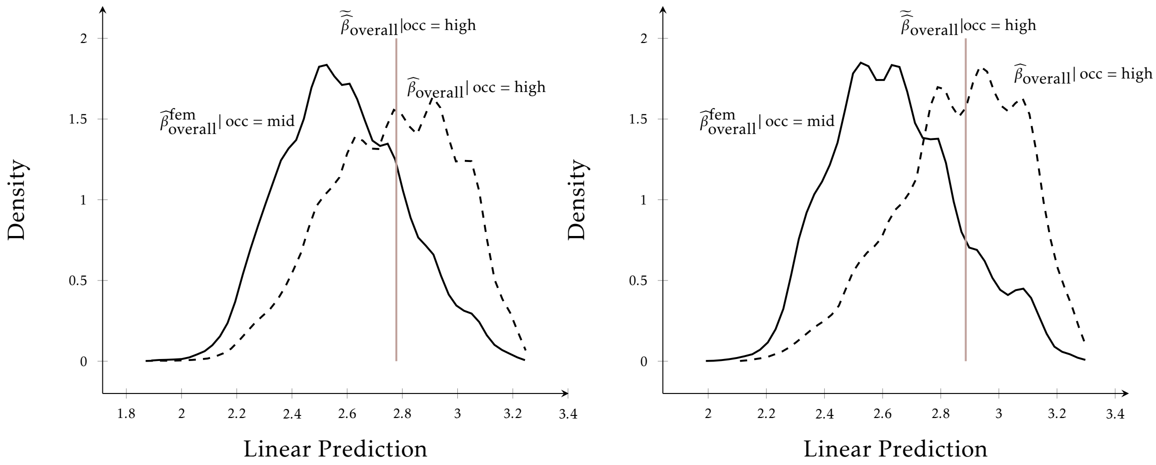


(B) Restricted female subsample



(C) Counterfactual Female
Note: I assign the estimates of men to women. I repeat the previous exercise. By this way, I alleviate any *a priori* discrimination against women. Alternatively, this method treats women as being in the male labour market.

FIGURE 5.4.4: Incidence of Human Capital Mismatch: three indices
Note: Solid lines show the estimates from specifications using the selection model for the public-sector employment. Dashed lines show the estimates from pooled results for those in the public sector. In terms of the economic context the period when peaks observed: In 2010, the government in the UK implements a nominal wage cap across the public sector but for salaries below £21,000. Since 2013, most annual pay rises have not exceeded an average of 1% annually. This policy has been relaxed in 2017 given the recovery of private-sector real wage growth (Cribb, 2017; ONS, 2017).
Source: Own elaboration based on BHPS/UKHLS



(A) Selection Model (B) Pooled Estimates

FIGURE 5.4.5: Importance of the selection model: negative selection; relative to median employee

Note: Solid line regards female employees in middle-skilled occupations with the overall population estimates in the public sector. Dashed line regards the overall population estimates employed in high-skilled occupations in public sector. The vertical solid line shows the median of the dashed line. Whoever stands on the right-hand side of the median and on the solid line is in mismatch.
Source: Own elaboration based on BHPS/UKHLS

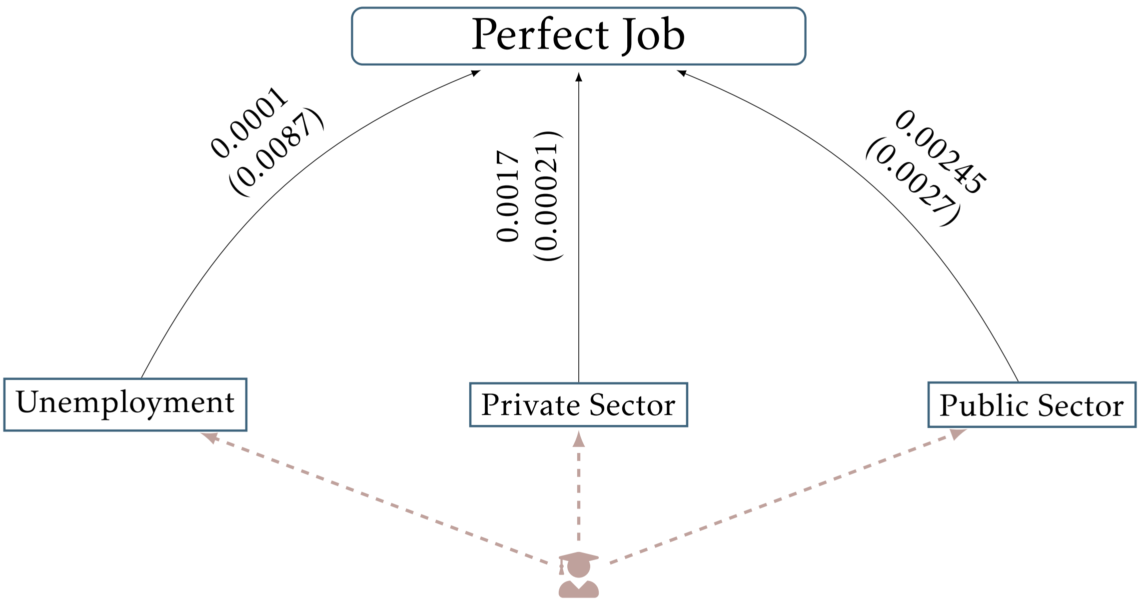
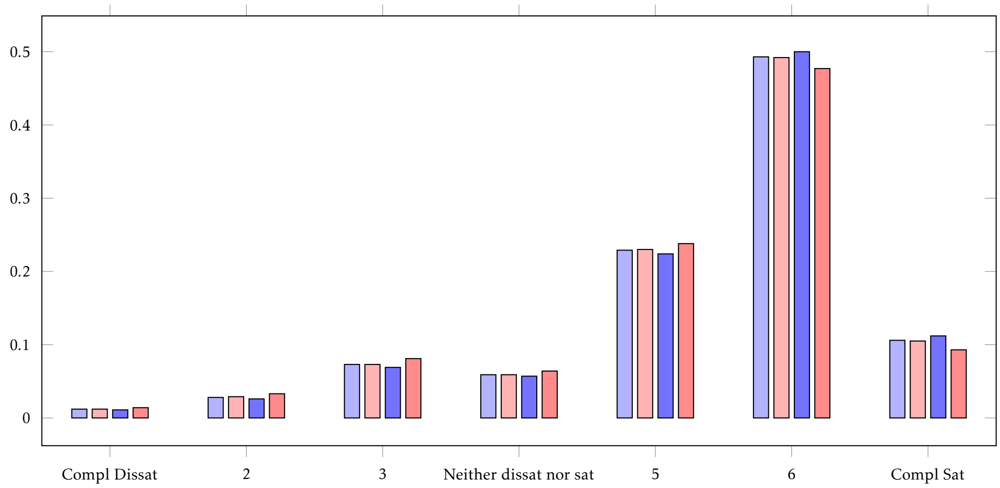
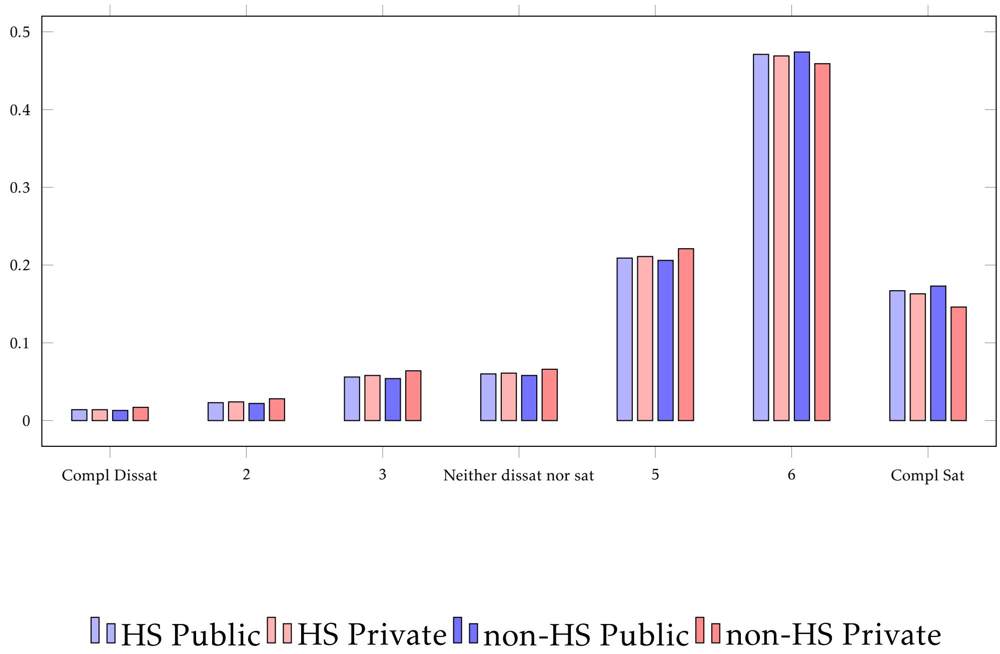


FIGURE 5.4.6: Waiting room for a *university graduate* within periods $t-1$ and t; Restricted Subsample

Note: Averages over the panel. s.e. in parenthesis. Each circle represents the state a university graduate is in period $t-1$. Probabilities to end up in a matched (or perfect) job is placed over each arrow. Difference between public and private sectors is significant at 5%.
Source: Own elaboration based on BHPS/UKHLS



(A) High-skilled female employee



(B) Any female employee

FIGURE 5.4.7: Marginal outcomes of offers on job satisfaction
Note: HS stands for High-skilled. Outcomes of offers include: (1) Unemployment; (2) High-skilled public-sector job; (3) High-skilled private-sector job; (4) non-High-skilled public-sector job; (5) non-High-skilled private-sector job. Probability of unemployment was equal to zero and omitted. Interestingly, the more satisfied a woman is with her job, the greater the gap of accepting a non-high-skilled job in the public sector. In other words, more satisfied female employees prefer to wait in mismatch in the public-sector. Difference between the outcomes is significant in 1%.
Source: Own elaboration, based on BHPS/UKHLS

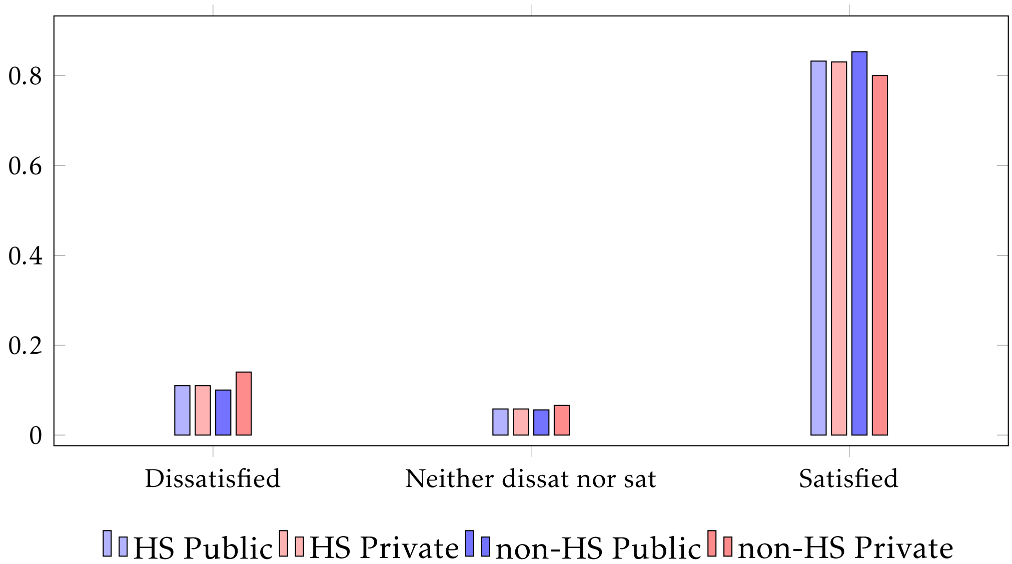


FIGURE 5.4.8: Marginal outcomes of offers on job satisfaction, recoded

Note: HS stands for High-skilled. Outcomes of offers include: (1) Unemployment; (2) High-skilled public-sector job; (3) High-skilled private-sector job; (4) non-High-skilled public-sector job; (5) non-High-skilled private-sector job. Probability of unemployment was equal to zero and omitted. Interestingly, the more satisfied a woman is with her job, the greater the gap of accepting a non-high-skilled job in the public sector. In other words, more satisfied female employees prefer to wait in mismatch in the public-sector. Difference between the outcomes is significant in 1%. This graph differs from the previous one in terms of coding the level of satisfaction from 7 categories to 3.

Source: Own elaboration, based on BHPS/UKHLS

Appendix

5.A Sample Characteristics

Table 5.A.1: Descriptive Statistics

	All	Private	Public	p-value
Highest Qualification				0.000
Higher Degree	3.76	2.26	6.59	
1st Degree or equiv	12.95	9.53	19.38	
other higher degree	11.42	8.84	16.25	
A-level etc	23.96	25.46	21.13	
GCSE etc	27.18	29.62	22.61	
other qualification	10.21	11.97	6.92	
No qf	10.51	12.32	7.12	
No of hrs overtime	3.79	4.01	3.41	0.000
	(6.20)	(6.32)	(5.95)	
No of hrs worked	34.07	35.25	31.94	0.000
	(10.99)	(11.08)	(10.49)	
Has dependent child(ren)	42.29	41.81	43.14	0.000
Real hourly wage	13.33	12.77	14.3	0.000
	(7.11)	(7.26)	(6.72)	
Number of children				0.000
0	57.71	58.19	56.86	
1	18.69	18.41	19.2	
2	17.72	17.43	18.26	
3	4.97	5.01	4.89	
4	0.77	0.81	0.71	
5+	0.13	0.16	0.08	
Older employee (35+ yrs.old)	62.66	59.04	69.24	0.000
Closer to retirement (55+ yrs. old)	8.75	8.14	9.84	0.000
Single parent	3.7	3.11	4.77	0.000
Married	61.29	60.22	63.22	0.000
Ln(hwage)	2.47	2.42	2.56	0.000
	(0.55)	(0.57)	(0.51)	
Age	39.84	39.05	41.26	0.000
	(9.99)	(10.06)	(9.69)	
Entered LM in t-1	6.01	6.42	5.25	0.000

Note: For the continuous outcomes, means are reported in the first cell and standard deviations are reported in parentheses. The rightmost column reports p-values from tests of equality of distributions between public- and private-sector employees, based on a Wilcoxon rank-sum tests for ordinal variables and χ^2 tests for categorical variables.
Source: Own elaboration based on BHPS/UKHLS

5.B Conditional Transition Probabilities

If individuals are employed in period $t-1$, they can (i) maintain their job (or move from private to public sector, and *vice versa*). Alternatively, (ii) they can exit from work (OoW).[36]

$$\Pr(OoW_t|\text{empl}_{t-1}) = \frac{\exp(x_i\beta_u)}{1+\exp(x_i\beta_u)+\exp(x_i\beta_{in})} \tag{5.4}$$

where x_i includes the control variables of age (and its square); level of education, region, year, occupation, a dummy to capture the increasing influx into retirement (=1 if individual is older than 55 years old.). Control for the gender and public sector, and their interaction has been included.

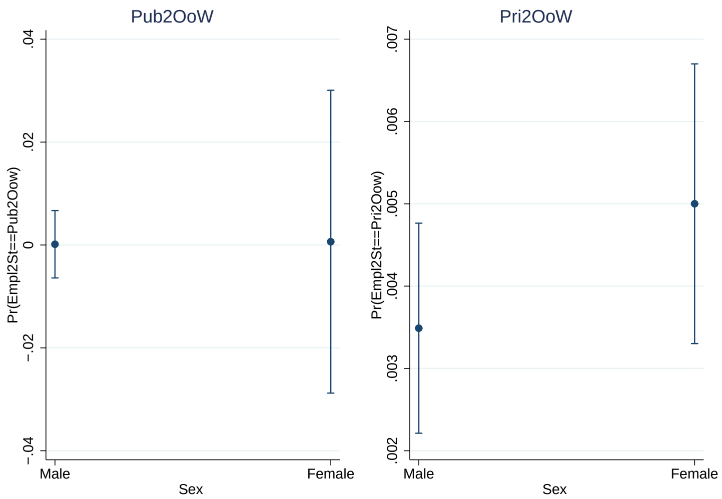


FIGURE 5.B.1: Conditional transition probabilities to unemployment and retirement

Note: Estimates from a multinomial logit regression of the change after employment on age (and its square), education level, occupation. To account for the increasing influx to retirement, a dummy =1 when age is in the range of 55 to 65 is also used. Estimation includes a public sector dummy, the gender dummy and their interaction. Region and year fixed effects included. The first row illustrates the transition into unemployment and the second into inactivity. The first and second columns represent the estimates for private and public sectors, respectively.
Source: Own elaboration, based on BHPS/UKHLS

[36] Here, I poorly define out-of-work state. It includes unemployment and inactivity, as in the unconditional setting.

5.C Robustness Checks

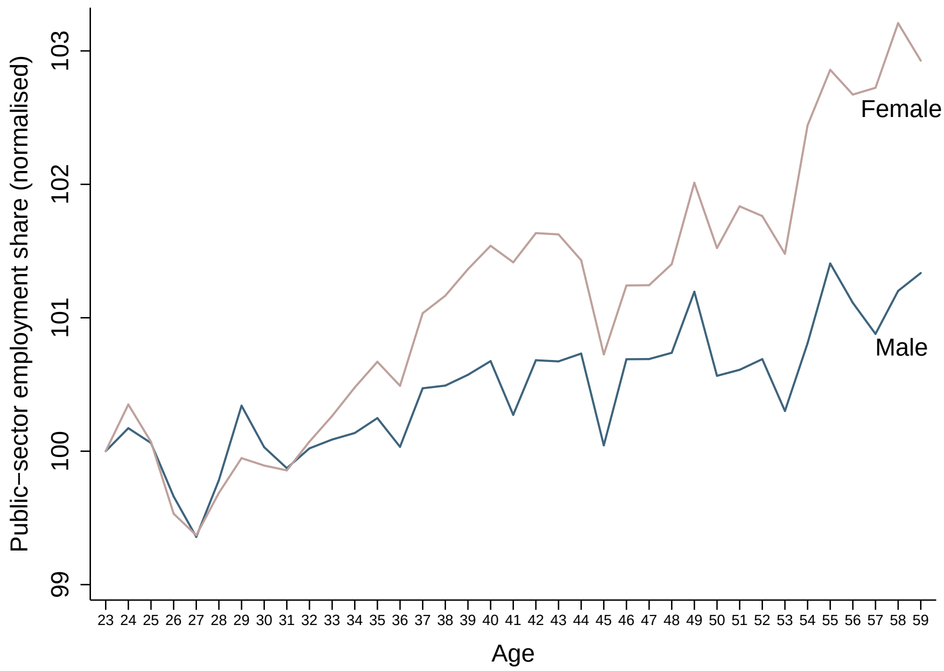


FIGURE 5.C.1: Public employment shares by gender, variation over age groups
Note: Profiles have been normalised around 26yo and the share of public-sector employment of women. Significant changes appear after 33yo.
Source: Own elaboration based on BHPS/UKHLS

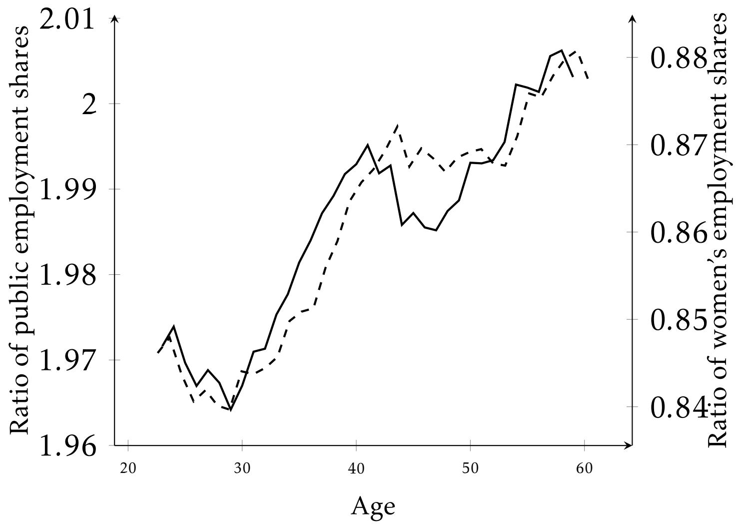


FIGURE 5.C.2: Ratios of public and women's employment shares, by age
Note: *Ratio of public employment share* (solid line) equals the share of women relative to men's employment. *Ratio of women's employment share* (dashed line) equals the sare in public relative the one in private sectors for female workers. Both figures declare that older workers are employed in the public sector; the slope becomes steeper over the age.
Source: Own elaboration based on BHPS/UKHLS

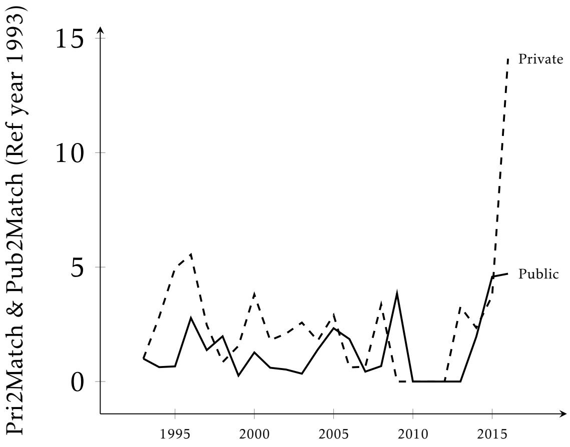


Figure 5.C.3: Transitions: Pri2Match and Pub2Match; Restricted female subsample
Note: Reference year 1993. The solid (dashed) line reports the annual transition rates from a job in the public (private) sector in mismatch to one in any sector but in match. Around the Great Recession, it is evident that the private sector reacted quicker than the public one. This is consistent with the changes on employment rates (overall and by gender) and the participation rates.
Source: Own elaboration based on BHPS/UKHLS

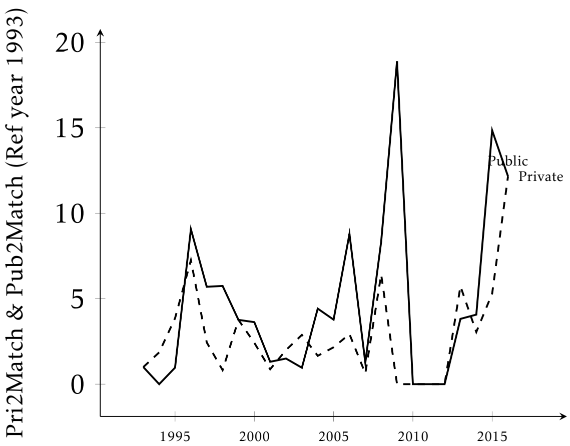


Figure 5.C.4: Transitions: Pri2Match and Pub2Match; Relative to overall population
Note: Reference year 1993. The solid (dashed) line reports the annual transition rates from a job in the public (private) sector in mismatch to one in any sector but in match. Around the Great Recession, it is evident that the private sector reacted quicker than the public one. This is consistent with the changes on employment rates (overall and by gender) and the participation rates. Around this period, spikes are consistent with literature evidence (see Fontaine et al. (2020))
Source: Own elaboration based on BHPS/UKHLS

Chapter 6

Unobserved Productivity and Mismatch: Evidence from the British Cohort Study 1970

Abstract

This paper examines the intersection of unobserved productivity and mismatch in the British labour market. Using the British Cohort Study 1970 (BCS70) data, individual unobserved heterogeneity is measured by the cognitive and non-cognitive skill test scores throughout childhood. Replicating the identification strategy of chapter 2, I derive the incidence of mismatch for cohort participants. A comparison to earlier estimates follows. Results show that the incidence does not fluctuate significantly over time and increases when accounting for skills of those born in 1970. Evidence suggests that unobserved productivity does not contribute to mismatch in the market. Finally, I explore the effect of parental background on getting a graduate job. Higher skilled parents increase the probability of being in match. When controlling for skills, the effect shrinks but the pattern persists.

6.1 Introduction

Several studies examine the incidence and effects of mismatch on wages, career mobility and job satisfaction (see for a review chapter 2). Chapter 3 shows that search frictions generate mismatch in the labour market. Empirically an employee is identified to be in mismatch if they work in a more skills-demanding job (chapter 2). Skills[1] play an important role in the matching process between employers and employees. The novel multidimensional measure of mismatch developed in chapter 2 strongly depends on the accurate estimate of returns to education. Based on the estimates of their returns to skills, workers are in mismatch if their returns exceed the median premium paid in a more skills-demanding occupation. If returns are underestimated, the incidence of mismatch will be downwards biased. Hence, a richer definition of human capital accounting for individual heterogeneity would generate a more robust mismatch measure.

[1]The setting of this paper will not examine the skills mismatch as discussed in Felstead, Gallie, and Green (2017).

Furthermore, job allocation is important if skills and physical capital are complements.[2] In that case, job allocation can explain the inequality observed among high-skilled workers. However, skills acquisition is not a sufficient condition to get a good job and improve overall productivity. If it is not the skills, what is the ticket to a good job? It can be related to the privilege of certain groups of workers to access particular jobs. In that case, the market does not use fully the available workers skills and raises barriers to occupational mobility. An example of privilege can be considered the parental background. For instance, high-skilled parents (or parents from high socio-economic class) have access to resources that enhance skills transmission and increase the probability of getting a degree. Getting a degree would increase the probability of getting a good job.

This paper discusses how unobserved productivity interacts with mismatch in the labour market. It replicates the identification strategy followed in chapter 2 and uses the British Cohort Study 1970 (BSC70) data[3] for the overall population. Furthermore, it compares BCS70 estimates with those from BHPS. The comparison exercises follow the same definition, while some specifications control for skills using cognitive and non-cognitive test scores[4] throughout childhood. If estimates of mismatch with and without control for cognitive and non-cognitive skills are similar, any differences would come from individual unobserved heterogeneity. One would expect that the incidence of mismatch should decrease in a richer definition which controls for skills. In this paper, skills are based on both cognitive and non-cognitive[5] assessments. Results suggest that the incidence of mismatch for cohort participants does not fluctuate much over time. Individual unobserved productivity does not generate mismatch; this is robust regardless of worker's gender. A twofold battery of robustness check verifies the aforementioned argument. First, the paper shows that workers in mismatch do not have particularly different cognitive and non-cognitive skills than those in match. Second, a skill principle component analysis shows that cognitive and non-cognitive skills are substitutes given the number of components needed for those who hold or not a degree. Determinants of individual personality or character seems to drive wages, and hence, the returns to skills which identify the mismatch here. Finally, *Propensity Score Matching* matches the sample on the average characteristics of skills. By this way, we can see the impact of parental background on the mismatch. Results show that higher skilled parents positively affect the likelihood of getting a graduate job.

[2] In perfect competition, the job title would not matter much. The job would be a label for a particular match.

[3] In this chapter, I use the BCS70 to better define human capital employing the cognitive and non-cognitive skills test scores data offer.

[4] The literature has established the use of test scores in labour market outcomes. For instance, military test scores are significant on earnings and unemployment (Lindqvist and Vestman, 2011), and affect job-skill mismatch on labour mobility (Fredriksson, Hensvik, and Skans, 2018).

[5] In the literature, alternative terminology includes *socio-emotional* or *character skills* (Deming, 2017b; Heckman, Humphries, and Kautz, 2014). Papageorge, Ronda, and Zheng (2019) acknowledge the flourishing literature which incorporates non-cognition into human capital definition. For a literature summary, see Almlund et al. (2011).

Empirical work establishes a causal relationship between education and wages to address several practical and policy-oriented questions. Psacharopoulos and Patrinos (2018) offer an overview of the literature for 139 countries, including the UK. Most estimates are based on the traditional Mincear wage equation. According to the authors, the private returns to education in the UK range between 11% - 12.2% depending on the level of education. These estimates, though, may be biased. As Gunderson and Oreopolous (2020) recognise, highly educated workers can have other characteristics,[6] which are associated with higher earnings, but they are not controlled in the usual estimation. Skills - cognitive and non-cognitive - seem to be the primary determinant of the wage. If wages are set according to the law of one price for each level of skills, then ignoring the aforementioned controls would not be extreme to estimate the returns. Especially in the long-run, skills play an essential role in career mobility. In the short-run, though, these "frictional" determinants may matter more in earnings determination.

The causality between cognition and wages may seem evident and is well-documented. However, literature mostly remains suggestive for non-cognition and labour market outcomes.[7] This is because omitted variable bias that drive non-cognitive skills estimates.[8] An interesting result arises from the estimates of Papageorge, Ronda, and Zheng (2019). They argue that some skills penalised at school may be valuable in the labour market. They explain that the productivity of non-cognitive skills may differ depending on the economic context seen. Misbehaviour, for instance, is associated with lower educational outcomes, but higher wages regardless of the gender of the worker. Similarly, misbehaviour contributes to greater female exposure in the market. An equivalent interpretation for career choices, originated from Roy model and extended by Willis and Rosen (1979) for selection into occupations, regards the differences in returns to academic and non-academic skills across occupations. Collapsing worker skills into a single index generates a loss of information. Ranking across occupations varies due to firms heterogeneity, and hence, a multi-dimensional sorting occurs (Böhm, Esmkhani, and Gallipoli, 2020; Lindenlaub and Postel-Vinay, 2020). In this paper, I include several test scores for cohort members from the age of 5, 10, 16 and when adults. However, some individual tests may contribute more than others and genearate significant differences between those in match and mismatch. To alleviate this concern, following Attanasio et al. (2020), I further construct an index which horizontally aggregates individual non-cognition. Heckman, Jagelka, and Kautz (2019, p.28) support that treating cognitive and non-cognitive skills as bundles generate the "greatest economic return".

The rest of the paper has the following structure. Section 2 describes the data and outlines the methodology followed. Section 3 presents the results,

[6] We may think of controls related to industry of occupation, firm characteristics, union power.

[7] Non-cognition is acknowledged more in recent literature because of the technological changes (Webb, 2020; Deming, 2017b; Autor, Katz, and Kearney, 2006). Though, little evidence exists on the causal relationship of non-cognitive skills and market success or the signalling value to potential employers.

[8] See Noray (2020) overviews recent literature emphasing on new work in Economics.

while section 4 concludes.

6.2 Data and Methodology

6.2.1 Data

This analysis uses the British Cohort Study 1970 (BCS70), which follows around 17,000 individuals born in England, Scotland and Wales in the first week of April 1970. Cohort members have been interviewed at age 5, 10, 16, 26, 30, 34, 38, 42 and 46. I use test scores from age 5, 10, 16 sweeps to construct cognitive and non-cognitive skills measures for each member. Additional non-cognitive question from age 30 sweep has been included. A list of the test scores used can be found in the appendix 6.A. From sweeps at age 26 and later, I further use the employment and partnership data to construct the mismatch index as in Galanakis (2019ch01).

To contribute to the discussion on the returns to skills, I compare these estimates with earlier findings from the British Household Panel Survey (BHPS). To this end, I restrict my sample until the sweep of age 42 (or year 2008).

6.2.2 Methodology

In this paper, I replicate the identification strategy followed in chapter 2. To compare the incidence of mismatch between the BHPS and BCS70, I restrict the estimates to those years that the cohort study runs. This raises sample sizes issues regarding the BHPS. For example, in 1996, BHPS does not include 17,000 26-years-old individuals. Hence, the difference, if any, in the incidence of mismatch between the two datasets may be attributable to some extent to sampling variation.

To eliminate such concerns, I compare the BCS70 index, which controls for skills throughout childhood,[9] with 3 different measures. First, I compare directly with the BHPS estimates, restricting for the age and particular year (e.g. the incidence for 26-years-old employees in 1996). This may be still exposed to the concerns regarding sampling variation. It can work, though, as a benchmark case. Second, since BCS70 index controls for skills, I need to make sure whether skills affect the magnitude of mismatch. To this end, I identify those in mismatch between the two samples using the exact same strategy; i.e. I only control for the level of education in both samples. If estimates of mismatch resulting from BHPS and BCS70 without control for skills are similar, any difference observed when controlling for skills would not be attributed to sampling variation. Third, I construct a weight using the BHPS data. In BHPS, I calculate weights as the average wage by occupation and education group. Note that education is commonly defined and occupations have been classified in the same way across samples. Then, I estimate the incidence of mismatch using the second exercise and apply the weights.

[9] Specifications including parental education and social class attempted. Blundell, Dearden, and Sianesi (2005) show that controlling for these background characteristics, one takes account of the selection into higher education for those with at least one A level exam.

By this way, I treat the cohort members as being interviewed in BHPS. If the estimates coming from the last two exercises are the same with (or very close to) the BHPS (in exercise 1), any difference will result from the control of skills. In other words, any difference seen in the first exercise will come from the cognitive and non-cognitive skills, or what is usually acknowledged as unobserved productivity.

The identification of mismatch works if the returns to education are estimated correctly. If there is a significant magnitude of mismatch in a particular group of workers, the returns are downward biased for this group. Hence, one could trust estimates coming from BCS70 which controls for additional individual characteristics and has a richer definition of human capital.

Finally, for the robustness check, I show that those in mismatch do not have particularly lower/higher cognitive or non-cognitive skills than those in match. This exercise is focused on the entire workforce without disaggregating by gender. A by-gender analysis is presented in the appendix.

6.3 Results

In this section, I outline the estimates stemming from the BCS70. Further, I compare these estimates with those from earlier analysis (chapters 2 and 4) to highlight the how much mismatch changes when accounting for other dimensions (i.e. unobserved productivity).

6.3.1 Mismatch in BCS70

Figure 6.3.1 reports the incidence of mismatch for the 1970 cohort based on BHPS and BCS70. For comparability purposes, this figure only looks at the same years (and hence same age) of the cohort study, i.e. individuals aged 26, 30, 34 and 38. The three rightmost bars referring to BCS70 are common between figures 6.3.1a and 6.3.1b. Their difference comes from the incidence of mismatch reported from BHPS. In, figure 6.3.1a, I report the estimate of mismatch using BHPS for a particular year and only for those who share the same age with the cohort participants. This allows to see any particular issues in the labour market within a certain year. Though, it may not be an accurate comparison, because workers in a given age may face certain frictions. For example, chapter 4 shows that recent female entrants in the labour market face a greater probability of mismatch. Later, women may face some period off the market for childbearing purposes. To this end, figure 6.3.1b reports the average incidence for a given age, to make a direct comparison with the estimates based on BCS70.

The main contribution of this paper is the account for the unobserved productivity utilising the measures of cognitive and non-cognitive skills throughout childhood.[10] The rightmost bar of each group on both panels of figure 6.3.1 shows the magnitude of mismatch in BCS70 when accounting for the

[10]Harmon, Oosterbeek, and Walker (2003) use the National Child Development Survey (NCDS). NCDS is an earlier cohort study of those born in 1958. Harmon, Oosterbeek,

test scores. The incidence does not fluctuate much over the years for this particular cohort remaining constant around 18%. This might be explained if one looks at the mobility between match and mismatch status. Table 6.3.1 summarises the transition rates between the two consecutive periods ($t-1$ and t) as in chapter 2. The majority of those born in 1970 do not move to a better job.[11] On average, only 11% of the workforce finds a better job and is in match. Almost 1 out of 5 people is (11.2%) or remains (7.8%) in mismatch.

Table 6.3.1: Mismatch transitions (in %)

	Matched		Mismatched	
	remained	became	remained	became
2000	70.87	10.68	6.93	11.51
2004	69.79	11.1	7.62	11.5
2008	68.85	11.68	9.2	10.27
Total	69.91	11.11	7.82	11.16

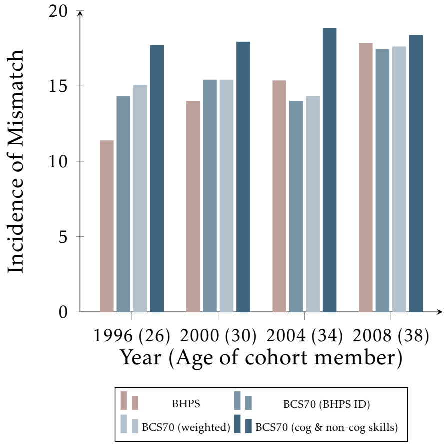
Note: Transitions calculated between two consecutive periods ($t-1$ and t) as in chapter 2.
Source: Own elaboration, based on BCS70

To show the significance of skills in the estimation of mismatch, I further estimate specifications which only control for the level of education. This compares the second bar (BCS70 [BHPS ID]) with the rightmost one in both panels of figure 6.3.1. From the graph, we notice that the incidence increases when controlling for the unobserved productivity. If individual productivity plays an important role in the matching process, controlling for skills would have resulted in more workers being in match and lower incidence of mismatch. Hence, for validity of the argument, we need to compare these estimates with earlier ones based on BHPS. If the estimates coming from the two datasets are close when using the same identification, mismatch is not driven by just unobserved individual skill heterogeneity. This is why, I compare the two leftmost bars in each panel. Both employ the same identification of mismatch - namely, they only control for the level of education. The comparison is made possible by maintaining a constant definition of education and same occupation classification. To this end, one can notice that for the latter three years of the cohort study (2000-2008) estimates are very close. 1996 estimates are not as close as later years.

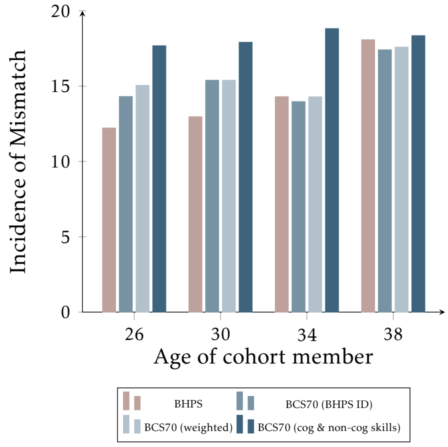
Finally, a reasonable concern might regard the sample size variation between the two datasets. BHPS in a particular year does not question the same amount of individuals born in 1970. Hence, any difference arisen between samples could be driven by the size of observations. To alleviate this concern, I calculate a weight from the BHPS to apply on BCS70. The same observation

and Walker (2003) look at the role of controlling for cognitive skills. Their findings suggest little signalling value to education; education picks up innate ability at age 7 and not later in life.

[11]The same argument holds if we look those specifications which only control for education (BCS70 [BHPS ID]). There, the incidence of mismatch is lower and transitions more limited.



(A) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.



(B) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

FIGURE 6.3.1: Incidence of mismatch: Overall population
Source: Own elaboration based on BHPS and BCS70

between BCS70 commonly identified with BHPS occurs here. The estimates of mismatch are very close and 1996 shows a difference. In 2008, the gap of all estimates bridges and minimal differences exist between any BCS70 specification and BHPS.

Therefore, figure 6.3.1 supports the argument that individuals may be in mismatch not due to their skills. This also holds if one looks at either women (appendix 6.B.1) or men (appendix 6.B.2). Women follow the pattern of the overall population. The estimates of mismatch for men when controlling for skills are slightly higher than when not controlling for them.

Robustness Check 1: Differences in Skills by mismatch

To further validate the aforementioned argument, I show that those in mismatch do not have significantly lower cognitive and non-cognitive skills than those in match. This is consistent among degree and non-degree holders.

Table 6.3.2 summarises the cognitive and non-cognitive skill test scores of those who hold a degree or not by mismatch statues, and reports their difference. This table excludes the low-skilled individuals, who by definition cannot be in mismatch. The table reports all test scores individually.

Looking at the non-cognitive skill test scores, the majority has no difference by mismatch both for degree and non-degree holders. Some tests, individually, seem to have a significant difference. The second index aggregates horizontally all the non-cognitive test scores,[12] as in Attanasio et al. (2020). This index may be seen as a joint test for non-cognition. It shows no statistical difference between those in match and mismatch. Regardless the degree and matching status, women have greater non-cognitive test scores. This may suggest that they mature earlier than men. Looking at the cognitive skill test scores, middle-skilled workers in match have lower cognitive skills than their counterparts in mismatch. This is not the case for the high-skilled, whose difference is not statistically significant in most tests. Regardless the degree, matched women outperform men in test scores on average. Hence, there is no evidence that unobserved skill would explain mismatch for degree holders. On the contrary, there is weak evidence for middle-skilled individuals without a degree.

[12] All the non-cognitive skill test scores have been included to inform about differences each may have.

Table 6.3.2: Differences in skills, by mismatch and degree

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
I. Non-Cognitive Skills														
Maternal Malaise Score	2.03	1.87	1.49	1.71	-0.54	***	0.18	2.15	1.91	2.07	1.94	-0.07		0.13
Combined non-cognitive skills	17.32	3.46	17.21	3.25	-0.10		0.34	15.74	3.51	15.89	3.42	0.15		0.22
(bin) Complains of headaches	0.87	0.34	0.88	0.33	0.004		0.03	0.91	0.29	0.90	0.30	-0.007		0.02
(bin) Complains of stomach-ache or has vomited	0.94	0.24	0.95	0.21	0.01		0.02	0.96	0.21	0.90	0.30	-0.05	***	0.02
(bin) Has temper tantrums (that is, complete loss of temper with shouting, angry)	0.90	0.30	0.90	0.31	-0.005		0.03	0.88	0.32	0.89	0.32	0.002		0.02
(scl) Very restless. Often running about or jumping up and down. Hardly ever still	29.22	27.00	26.79	27.46	-2.44		2.86	35.47	30.93	31.68	29.34	-3.79	**	1.93
(scl) Is squirmy or fidgety	26.01	24.97	24.52	25.38	-1.49		2.64	30.25	29.39	27.48	27.48	-2.77		1.81
(scl) Often destroys own or others belongings	9.64	9.01	10.15	9.19	0.51		0.96	12.82	15.42	11.45	11.27	-1.37	*	0.78
(scl) Frequently fights with other children	10.81	9.24	12.29	11.61	1.48		1.16	15.59	18.09	15.34	16.72	-0.25		1.10
(scl) Not much liked by other children	11.17	10.65	12.97	14.78	1.80		1.46	13.58	16.76	14.27	16.11	0.69		1.06
(scl) Often worried, worries about many things	32.48	25.51	34.87	30.21	2.39		3.06	26.08	25.05	32.83	28.48	6.75	***	1.83
(scl) Tends to do things on his/her own rather solitary	27.0085	25.3198	32.5500	28.76	5.54	*	2.93	24.68	25.98	29.53	27.97	4.86	***	1.81
(scl) Irritable. Is quick to fly off the handle	27.18	25.55	24.56	23.95	-2.62		2.54	30.33	28.99	30.15	28.96	-0.18		1.89
(scl) Often appears miserable, unhappy, tearful or distressed	14.30	10.13	16.84	16.34	2.54		1.59	14.26	12.85	18.61	19.55	4.36	***	1.23
(scl) Sometimes takes things belonging to others	9.50	8.78	10.46	9.17	0.97		0.95	12.64	15.71	11.90	12.49	-0.74		0.84
(scl) Has twitches, mannerisms or tics of the face or body	10.13	12.96	11.71	13.99	1.58		1.44	11.46	14.09	11.89	13.63	0.42		0.89
(scl) Frequently sucks thumb or finger	23.12	30.07	21.16	27.05	-1.96		2.90	16.82	23.74	22.36	28.18	5.53	***	1.81

Continued overleaf

Table 6.3.3Differences in skills, by mismatch and degree (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
(scl) Frequently bites nails or fingers	19.20	25.02	30.68	32.68	11.48	***	3.26	21.84	27.57	34.00	34.16	12.16	***	2.18
(scl) Is often disobedient	18.85	15.89	18.30	17.59	-0.55		1.80	21.96	22.02	23.92	22.60	1.96		1.47
(scl) Cannot settle to anything for more than a few moments	16.27	19.12	16.18	18.80	-0.09		1.97	23.18	23.69	21.28	22.66	-1.90		1.49
(scl) Tends to be fearful or afraid of new things or new situations	25.62	24.79	28.37	26.43	2.75		2.73	19.25	19.83	28.31	27.94	9.06	***	1.77
(scl) Is over fussy or over particular	16.86	17.71	22.50	24.28	5.64	**	2.41	27.22	27.84	27.39	27.67	0.17		1.81
(scl) Often tells lies	13.01	13.71	14.79	14.45	1.78		1.49	17.83	18.68	16.21	15.81	-1.62		1.06
(scl) Bullies other children	10.38	9.01	11.89	10.66	1.51		1.08	14.88	17.04	13.35	13.23	-1.53	*	0.90
Tried smoking (16)	0.57	0.50	0.49	0.50	-0.08		0.05	0.57	0.50	0.62	0.49	0.05		0.03
Tried alcohol (16)	0.96	0.19	0.92	0.28	-0.05	*	0.03	0.95	0.22	0.94	0.23	-0.01		0.02
Alcohol in past week (16)	0.76	0.43	0.68	0.47	-0.07		0.05	0.72	0.45	0.73	0.45	0.005		0.03
Ever been drunk (16)	0.50	0.50	0.46	0.50	-0.05		0.05	0.59	0.49	0.64	0.48	0.05		0.03
Porn in past month (16)	0.19	0.40	0.19	0.40	-0.001		0.04	0.29	0.46	0.34	0.47	0.05		0.03
Had sex (16)	0.13	0.33	0.16	0.36	0.03		0.04	0.33	0.47	0.32	0.47	-0.01		0.03
Tried drugs (16)	0.07	0.26	0.07	0.25	-0.004		0.03	0.06	0.25	0.05	0.23	-0.01		0.02
Tried cannabis (16)	0.04	0.20	0.05	0.21	0.01		0.02	0.03	0.16	0.03	0.18	0.01		0.01
Read book for pleasure in past week (16)	0.81	0.40	0.73	0.45	-0.08	*	0.05	0.59	0.49	0.55	0.50	-0.04		0.04
Damaged other's property in past year (16)	0.05	0.22	0.05	0.22	-0.002		0.03	0.16	0.37	0.11	0.32	-0.04	*	0.03
Shoplifted >£5 in past year (16)	0.03	0.18	0.06	0.23	0.02		0.03	0.04	0.19	0.07	0.26	0.03	*	0.02
II. Cognitive Skills														
English Picture Vocabulary Test (y5)	0.77	0.98	0.53	0.92	-0.24	**	0.10	0.46	0.87	0.05	0.92	-0.41	***	0.06
Copying Designs Test (5y)	0.77	0.86	0.66	0.89	-0.11		0.09	0.36	0.93	0.04	0.95	-0.32	***	0.06
Human Figure Drawing Test (y5)	0.43	1.10	0.44	1.04	0.01		0.11	0.04	0.91	0.03	0.92	-0.01		0.06
PLCT (y10)	0.69	0.11	0.68	0.09	-0.01		0.01	0.64	0.09	0.60	0.09	-0.04	***	0.01
FMT (y10)	0.80	0.11	0.78	0.12	-0.02	*	0.01	0.71	0.13	0.61	0.15	-0.10	***	0.01
SERT (y10)	0.81	0.13	0.79	0.14	-0.02		0.01	0.71	0.16	0.65	0.17	-0.06	***	0.01
Reading (y16)	0.76	0.31	0.73	0.33	-0.02		0.03	0.71	0.26	0.60	0.30	-0.11	***	0.02
BAS (similarities; y10)	0.79	0.11	0.79	0.10	0.002		0.01	0.73	0.14	0.72	0.11	-0.01		0.01
BAS (matrices; y10)	0.76	0.18	0.77	0.14	0.01		0.02	0.71	0.16	0.67	0.15	-0.03	***	0.01
BAS (Recall of digits; y10)	0.78	0.11	0.75	0.13	-0.03	**	0.01	0.75	0.12	0.72	0.12	-0.03	***	0.01
BAS (Word Definitions; y10)	0.61	0.12	0.57	0.10	-0.03	***	0.01	0.51	0.12	0.46	0.11	-0.05	***	0.01
Spelling (y10)	0.83	0.20	0.84	0.14	0.01		0.02	0.76	0.22	0.74	0.19	-0.01		0.01

Continued overleaf

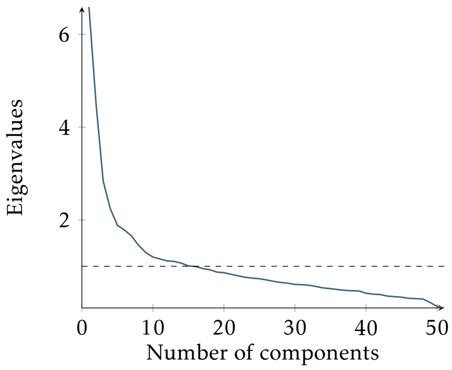
Table 6.3.3Differences in skills, by mismatch and degree (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
Spelling (y16)	0.85	0.18	0.85	0.16	-0.003		0.02	0.78	0.23	0.75	0.26	-0.03	**	0.02
Arithmetic scores (y16)	0.80	0.28	0.76	0.32	-0.04		0.03	0.77	0.27	0.71	0.30	-0.06	***	0.02
Vocabulary scores (y16)	0.69	0.15	0.67	0.15	-0.02		0.02	0.58	0.17	0.52	0.19	-0.07	***	0.01
Numeracy MC and OR assessment	0.83	0.20	0.92	0.08	0.10	***	0.03	0.84	0.13	0.76	0.16	-0.08	***	0.02

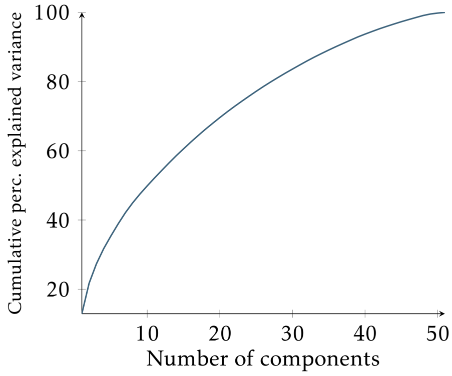
Rutter Recoding Index: (b): bin; 1 is better. (scl): measured in scale
Cognitive Skills Test scores have been normalised
* p<0.1, ** p<0.05, *** p<0.01

Note: non-Degree excludes low-skilled employees, who by definition cannot be classified as in mismatch. Stars show the significance of two-tailed t-test of the difference.

Source: Own elaboration based on BCS70



(A) Eigenvalues by component
Note: In the analysis, we include those components whose eigenvalue is greater than 1. The dashed line shows this threshold.



(B) Cumulative variance explained
Note: The first 15 components explain, cumulatively, 61% of the variation.

FIGURE 6.3.2: Cognitive and non-cognitive skills
Source: Own elaboration based on BCS70

Robustness check 2: Skills Principal Component Analysis

Principal Component Analysis (PCA) of skills help us to reduce the dimensionality of the data. This is particularly important when cognitive and non-cognitive variables are highly correlated.[13] From the PCA, we take the (i) eigenvalues for each component, (ii) the difference in eigenvalue size among the principle components, (iii) the proportion of variation explained by each component and (iv) the cumulative proportion explained. For example, the first three components explain 27.3% of the variation when accounting for both cognitive and non-cognitive skills. Empirical rule requires using as many components as their eigenvalue is greater than 1. This is satisfied in the first 15 components. Following, we receive the eigenvectors with which we can inspect exactly how each variable loaded onto each component. The coefficients on each variable are the linear combinations that make up each of the components (Henderson, 2017).

The first 2 out of 15 components explain the major variation. This is why figure 6.3.3 plots the coefficients of eigenvectors by pca. For instance, the combination of non-cognition (purple dot) loads much on the first component, but low on component 2. More precisely, individual non-cognitive skills of early childhood (blue dots) mostly load in component 2 than in component 1. Non-cognitive skills of teenagehood (pink dots) load negatively in both components. Green, petrol and light blue dots present cognitive skills in the age of 5, 10 and 16 years old, respectively. Most of them load positively on both. However, there seems to be a greater concentration of cognition on the first component and lower on the second one.

[13]Correlation matrix available upon request.

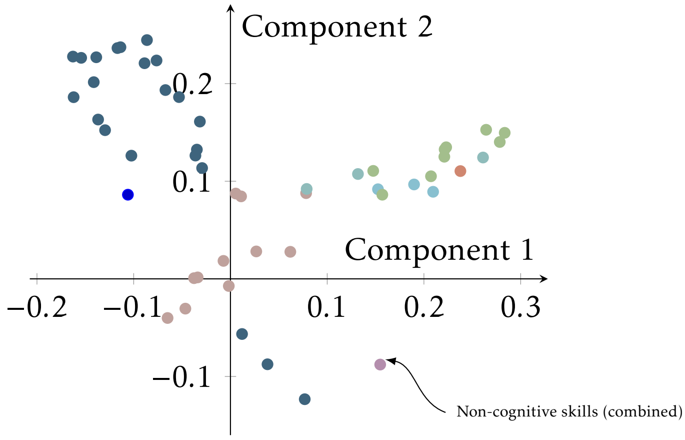


FIGURE 6.3.3: Loading plot
Note: Overall Kaiser-Meyer-Olkin measure of sampling adequacy 0.8046 for both cognitive and non-cognitive test scores.
Source: Own elaboration based on BCS70

Here, we are interested in how the model performs in predicting out-of-sample variation. To do so, we employ the k-fold cross-validation.[14] I compute the estimated RMSE for a model with only $pc1$ as a predictor with $k = 10$. Then, I repeat the process with two principle components, namely $pc1$ and $pc2$, as predictors. I continue adding principal components to the model until RMSE does not decrease significantly. K-fold cross-validation is simple to compute using the function STATA ‘crossfold‘. Figure 6.3.4 plots the RMSE against the number of principle components by holding a degree. Different specifications control for both cognitive and non-cognitive skills or solely for one type of skills. When jointly controlling for cognition and non-cognition or solely for cognition, more components are needed for non-degree holders. When controlling for non-cognition only, one component is required for non-degree holders, while 2 for degree holders. This shows that the explanatory power of this specification is similar. On the other hand, cognition plays an important role in the prediction of out-of-sample observations, since the number of principle components changes by holding a degree. In some cases, as for the degree holders when accounting for cognitive skills only, additional components seem to increase RMSE. This may imply that further components add up noise; the number of components is not correlated with the dependent variable.

Appendix 6.D includes estimates of eigenvalues and cumulative explanatory power by the number of principle components and the loading plot for cognitive and non-cognitive skills separately. This analysis offers a twofold interpretation on how skills interact with mismatch. First, cognitive and non-cognitive skills substitute each other given the number of components

[14]We split the data in $k = 10$ parts. The first part will be a test dataset while the $k - 1$ parts will be our "training" dataset. We run the regression on the training dataset and use those coefficients to run the model on the test data. We record the root mean squared error (RMSE) on the test data. We repeat this process until each of the k parts has been used as a test dataset and then take the average of the RMSE’s.

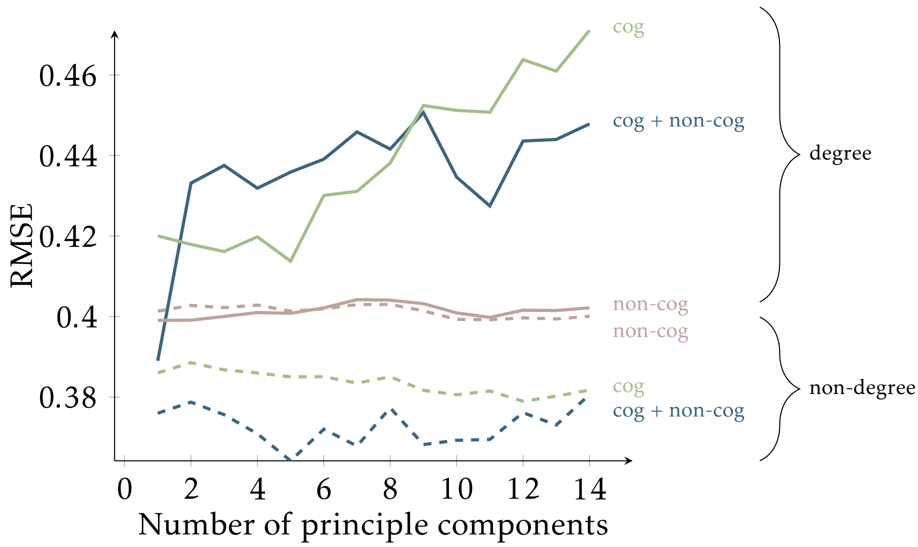


Figure 6.3.4: RMSE of regressions with number of principle components

Note: Solid line presents estimates for those who hold a degree, while dashed line for those who do not have a degree. When controlling for both cognitive and non-cognitive skills, 1 component is sufficient for those with degree, but 5 components are required for non-degree holders. When only non-cognitive skills are controlled for, 2 principle components are needed for degree holders and 1 component for non-degree ones. When accounting only for cognitive skills, 5 components are required for those with a degree, while 12 components for those without a degree.
Source: Own elaboration

needed for degree and non-degree holders. Second, what drives the individual personality or character seems to drive wages, and hence, the returns to skills which identify mismatch in this setting.

6.3.2 Parental background and offspring's mismatch

Another interesting aspect in terms of the individual allocation to jobs regards the parental background. The question is whether members of Generation X are more or less likely to climb the working ladder compared to the Baby Boomers before them and work in a better job. Does parents' social class and/or education explain the offspring's probability to get a graduate job? In this setting, the social class is defined by the occupation one holds. The graduate job is the one in which the worker is in match and holds a degree. This section complements a broader discussion of an upward or downward mobility in the social or economic ladder. A poor parental background would have a twofold contribution. First, the offspring is less likely to access higher education and hence get a degree. Second, this reduces the alternatives of the offsprings, given their degree, to get a high-skilled (or graduate) job. Blanden et al. (2002) find that cohort members in 1970 are less likely to move socially than older generations. In their study, they explain that educational choices are determined by parental background.

Occupation, and hence social class, plays a different role between degree and non-degree holders. Pooling the earlier estimates on the incidence of mismatch by social class, table 6.3.4 shows that for the degree-holders the incidence of mismatch decreases when controlling for skills. However, for the non-degree holders the incidence of mismatch increases when accounting for the unobserved heterogeneity.

TABLE 6.3.4: Incidence of mismatch, pooled by social class (average; in %)

	Degree		Non-Degree**	
	Cognitive & Non-cog skills	Educ only	Cognitive & Non-cog skills	Educ only
I Professional	0.99	0.9	0	0
II Managerial - technical	12.37	20.16	9.51	0.65
IIINM Skilled non-manual	53.56	55.48	10.79	2.12
IIIM Skilled manual	49.39	60.12	25.4	5.48
IV Partly skilled	84.68	85.1	13.44	9.41
V Unskilled	100.00*	100.00*	16.22	6.56
Others (Unempl/unclass/army)	0	27.47	30.22	14
Total	15.03	20.66	13.57	4.5

Note: * only one observation included. ** Middle-skilled workers excluding low-skilled people who by definition cannot be in mismatch.
Source: Own elaboration based on BCS70

To investigate the explanatory power of the parental background on the probability of getting a graduate job (or not being in mismatch), I use the *Propensity Score Matching* (PSM). PSM is useful to overcome the challenges of the questions I set here. Differences in outcomes between the treated (high-skilled parents) and untreated (middle- and low-skilled parents) groups may be the result of confounding variables and not necessarily the treatment. I match individuals on the average characteristics of the sample with the same cognitive and non-cognitive skills. The matching estimator regards the single nearest neighbour within a caliper of 0.25sd. Several specifications have been considered. I perform analysis using (a) only father or mother's education (baseline); (b) parental education and cognitive skills; (c) parental education and non-cognitive skills; and (d) parental education and cognitive and non-cognitive skills. Figures 6.3.5 and 6.3.6 report results from specifications (a) and (d).

Figure 6.3.5 depicts the difference between the baseline model and the one which accounts for skills. It shows the marginal effects compared to the first category of the father's education. It further compares the estimates coming from the PSM and a simple ordered logit estimation. The latter comparison emphasises the importance of the score matching in avoiding any underestimation of the father's education effect. We note that having a better educated father increases the probability of one's getting a graduate job. The magnitude reduces when controlling for own skills. However, the pattern remains the same. The average treatment effect (table 6.3.5) is very small yet positive for those who have a high-skilled father. This can be explained by the following mechanism. More paternal skills allow him access to resources enhancing transmission of skills to their children. To this end, if fathers work in good jobs, they are exposed to a stronger network which facilitates offsprings' upward mobility in the social ladder.

TABLE 6.3.5: Average Treatment Effects: High-skilled father vs. Graduate job.

Average Treatment Effect on the Treated (ATT)	0.0123	**
	(0.0704)	
Average Treatment Effect on the Untreated (ATU)	-0.0357	
	(0.0695)	
Average Treatment Effect (ATE)	-0.0121	*
	(0.0642)	

Bootstrapped s.e. in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: Treatment is whether the father is high-skilled. Outcome is to get a graduate job. Bootstrapped s.e.
Source: Own elaboration based on BCS70

Figure 6.3.6 replicates the analysis for mother's education. Here, I further pool estimates by offspring's gender and by mother's labour market attachment. The offspring's gender is important to see whether the effect differs between men and women. Chapter 4 finds greater probability of women to be in mismatch. Regarding mother's labour supply, there is no strong evidence suggesting that children whose mother works perform worse (Joshi, 2013; Cooksey, Joshi, and Verropoulou, 2009; Gregg et al., 2005). Ermisch and Francesconi (2013) find stronger adverse effects for children of lower skilled mothers. Results verify the same pattern we found earlier about father's education. Higher-educated mothers increase the probability of getting a graduate job for both boys and girls. However, controlling for skills seems to be more important for boys outcomes. Better male employment outcomes dominate those of female. This evidence does not differ much by mother's employment attachment. Slightly higher probability of getting a graduate job is observed for mothers in the labour market.

6.4 Conclusion

This paper uses the British Cohort Study 1970 to discuss how the unobserved productivity intersects with the mismatch in the labour market. A richer definition of human capital uses cognitive and non-cognitive test scores throughout childhood to control for individual ability. To this end, this study can answer whether the incidence of mismatch stems from the unobserved heterogeneity of workers.

Comparing the BCS70 estimates to the earlier estimates from the BHPS, we notice that the incidence of mismatch increases despite the control for cognitive and non-cognitive skills. This suggests that unobserved productivity does not impact the mismatch. If unobserved productivity is an important matching tool, controlling for skills should result in more people being in match, and hence, in lower incidence of mismatch. Instead, labour market frictions may play a more essential role generating imperfections (chapter 3). Finally, this result may have an alternative interpretation. Identification is based on the accurate estimate of the returns to skills. Since the magnitude of mismatch increases, estimates based on the BHPS may not fully capture the

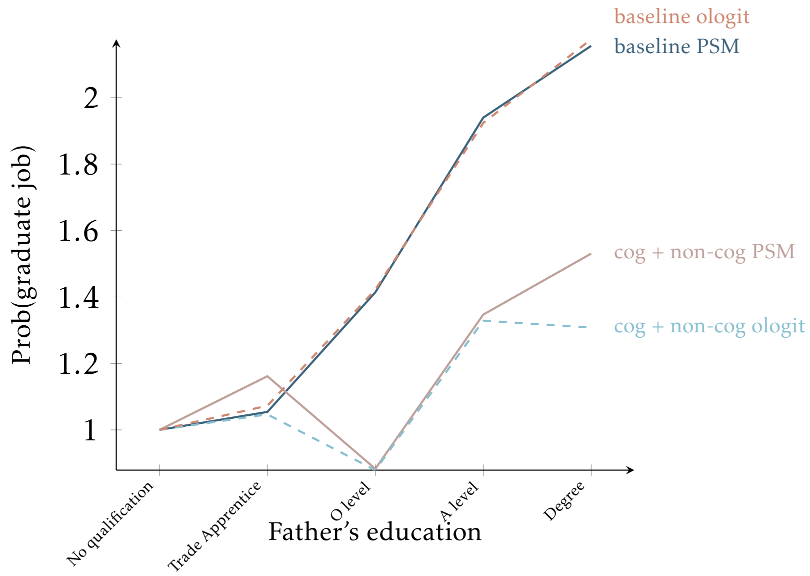
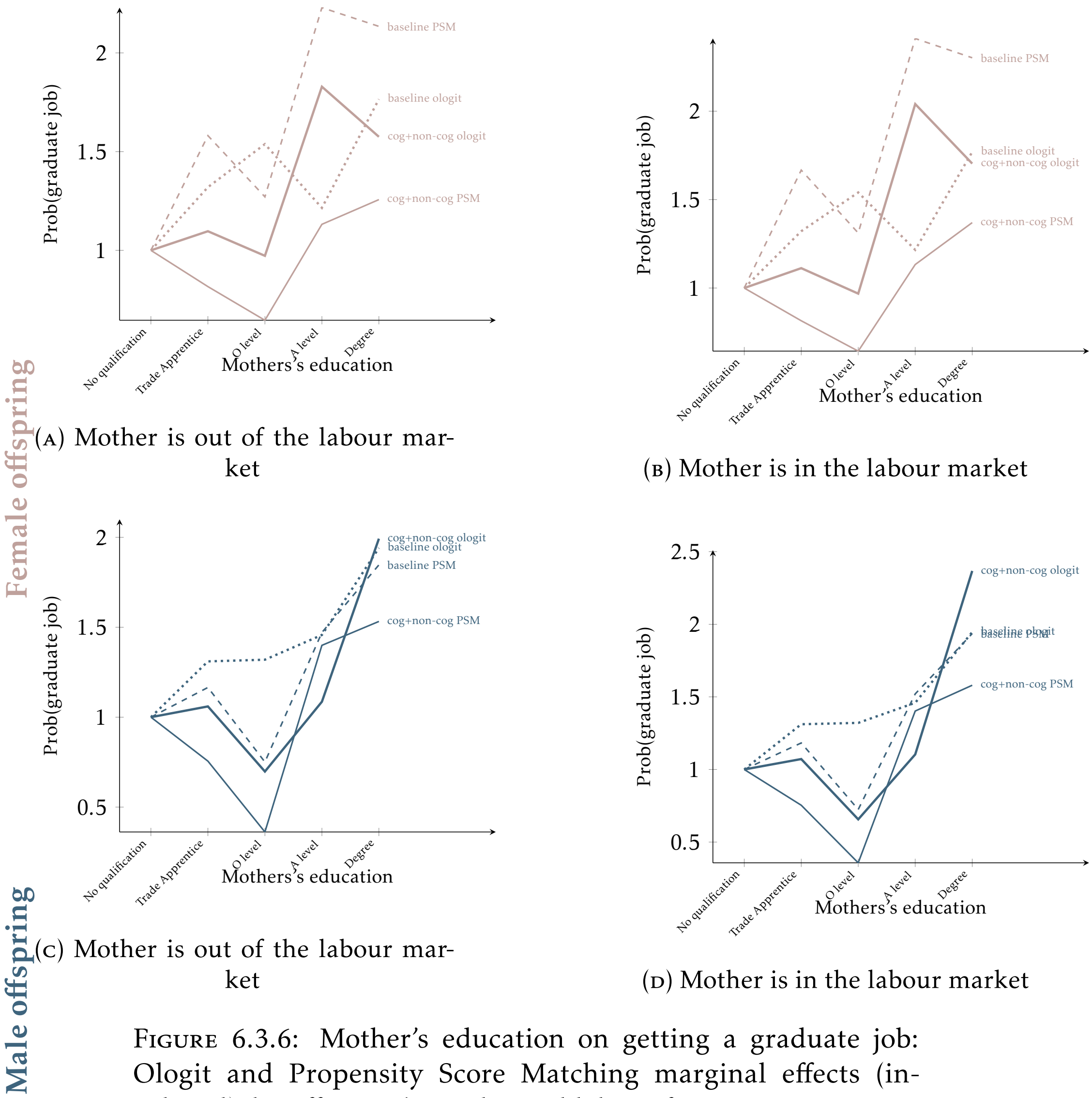


FIGURE 6.3.5: Father's education on getting a graduate job: Ologit and Propensity Score Matching marginal effects (indexed)

Note: *PSM* stands for propensity score matching. *Ologit* stands for ordered logit model. *Baseline* includes only father's education and *Cog + non-cog* controls for cognitive and non-cognitive skills.
Source: Own elaboration based on BCS70

realised individual returns to skills. Therefore, the estimates based on the cohort study may be more accurate. Looking at the skills of those in match and mismatch, there are no significant differences regarding the non-cognitive skills regardless the level of education. However, middle-skilled workers in match have lower cognitive test scores than their mismatched counterparts. This is not true, though, for the high-skilled workers.

Finally, using propensity score matching, I estimate the effect of parental education on the probability of getting a graduate job. Higher-skilled parents generate a higher probability of getting a graduate job. What this study further adds regards the control of skills on this probability. In particular, when accounting for cognition and non-cognition the positive trend in getting a graduate job persists. However, the probability is lower than in the baseline case where no skills are controlled for. The effect of mother's education does not differ from that of the father's education. Greater effect of mother's education is observed on male offspring's employment potential.



(A) Mother is out of the labour market

(B) Mother is in the labour market

(C) Mother is out of the labour market

(D) Mother is in the labour market

FIGURE 6.3.6: Mother's education on getting a graduate job: Ologit and Propensity Score Matching marginal effects (indexed), by offspring's gender and labour force participation

Note: *PSM* stands for propensity score matching. *Ologit* stands for ordered logit model. *Baseline* includes only mother's education and *Cog + non-cog* controls further for cognitive and non-cognitive skills.

Source: Own elaboration based on BCS70

Appendix

6.A Test scores for skills

Table 6.A.1: Cognitive skills tests used in BCS70

Age	Test
5	HFDT: Human Figure Drawing Test CDT: Copying Designs Test EPVT: English Picture Vocabulary Test PT: Profile Test
10	PLCT: Pictorial Language Comprehension Test FMT: Friendly Math Test SERT: Shortened Edinburgh Reading Test BAS: British Ability Scales (Recall of Digits; Matrices; Word Definitions; Similarities)
16	AT: Arithmetic Test VT: Vocabulary Test ST: Spelling Test
30	Numeracy MC and OR assessment

Tests have been normalised using the min/max method.

Table 6.A.2: Non-cognitive skills tests used in BCS70 (summary)

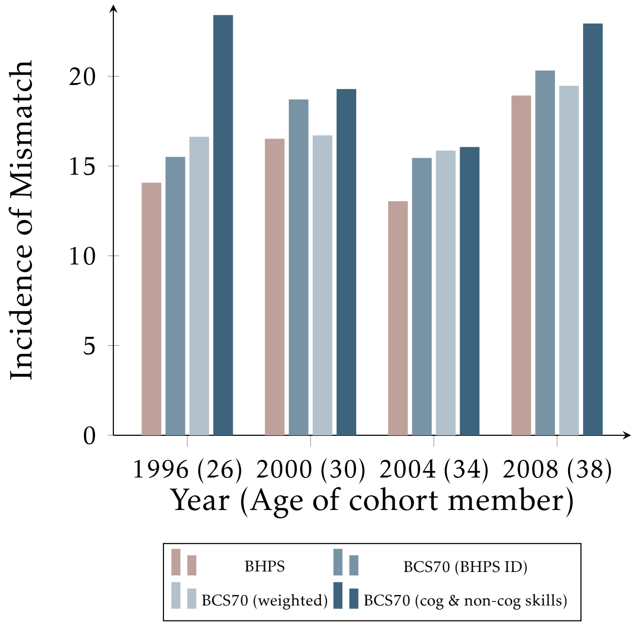
Age	Test
Birth	Mother Malaise
5	Mother Malaise Child Behavioural Measures (on Rutter Scale)
10	Child Behavioural Measures (on Rutter Scale)
26	Malaise score

For details, see Attanasio et al. (2020, table A1)

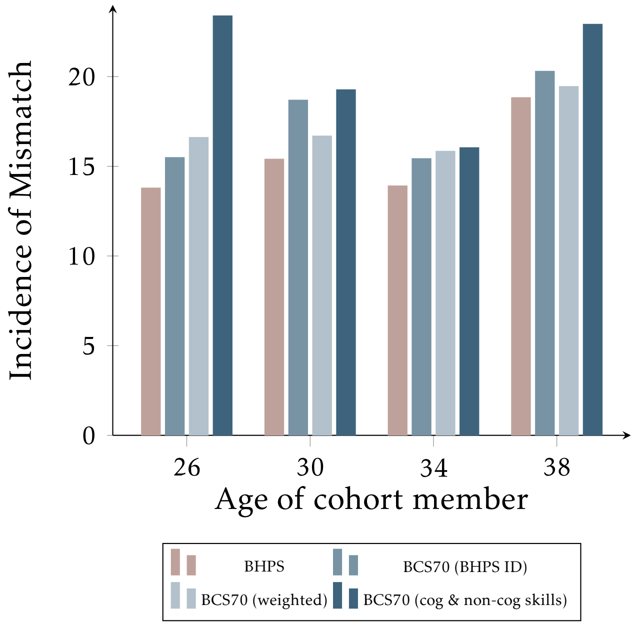
6.B Incidence of mismatch by gender

6.B.1 Women

This section replicates the three indices shown in chapter 4 for women. The weighted index here is applied only to the restricted subsample. The estimates for the remaining exercises are available upon request.

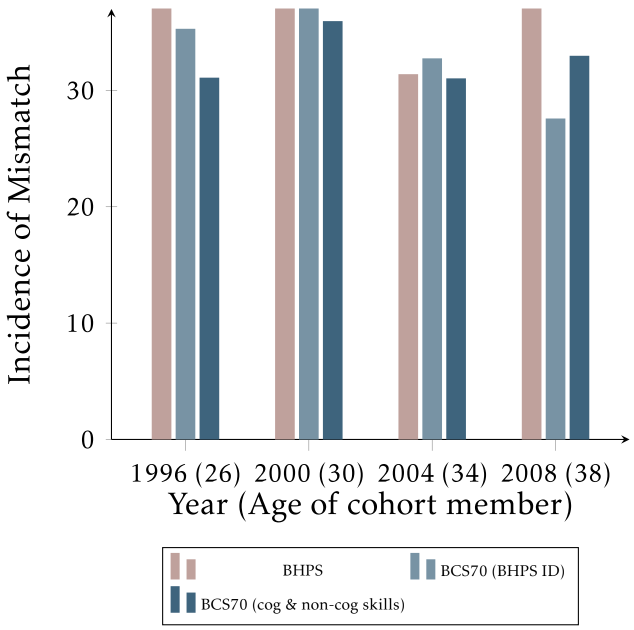


(A) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

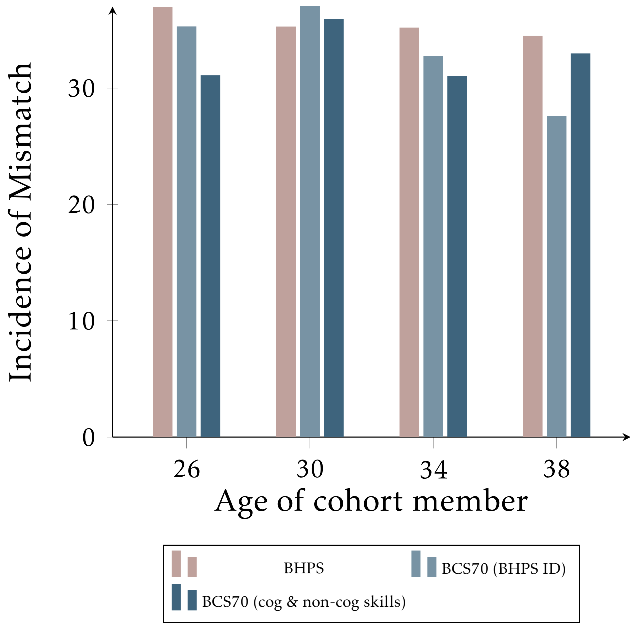


(B) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

FIGURE 6.B.1: Incidence of mismatch: Women (restricted sub-sample)
Source: Own elaboration based on BHPS and BCS70

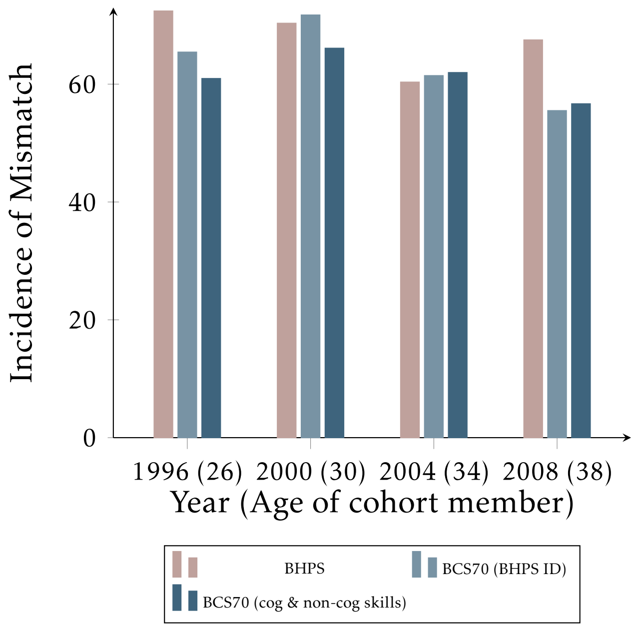


(A) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

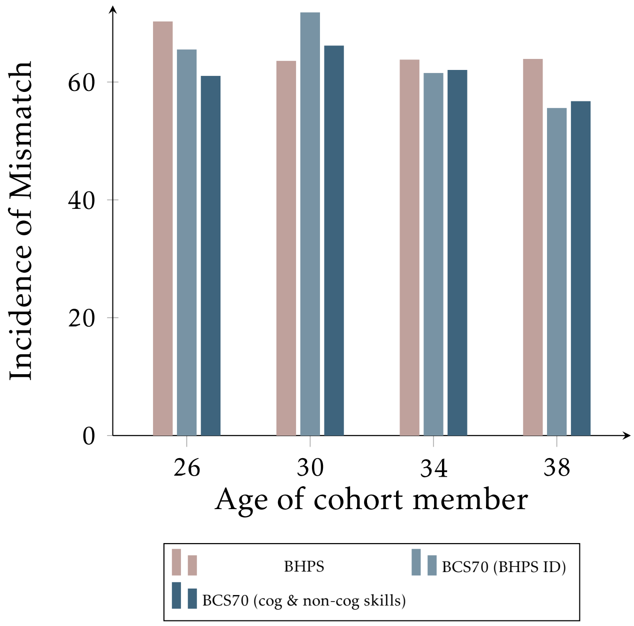


(B) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

FIGURE 6.B.2: Incidence of mismatch: Women (relative to overall population)
Source: Own elaboration based on BHPS and BCS70

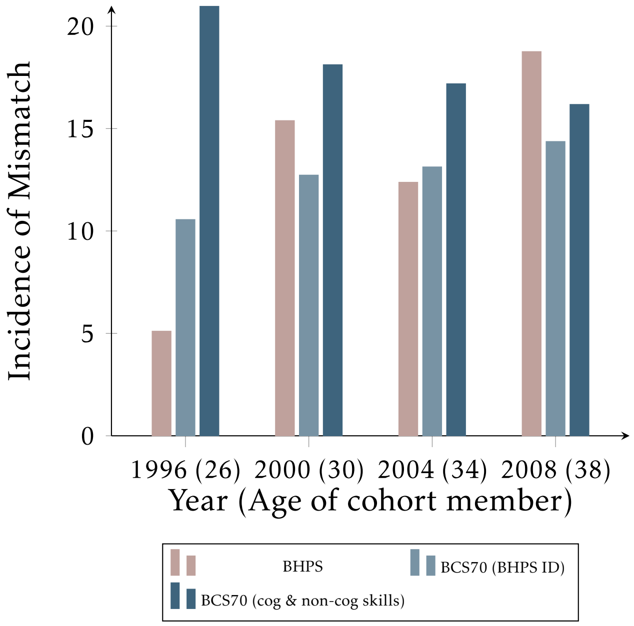


(A) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

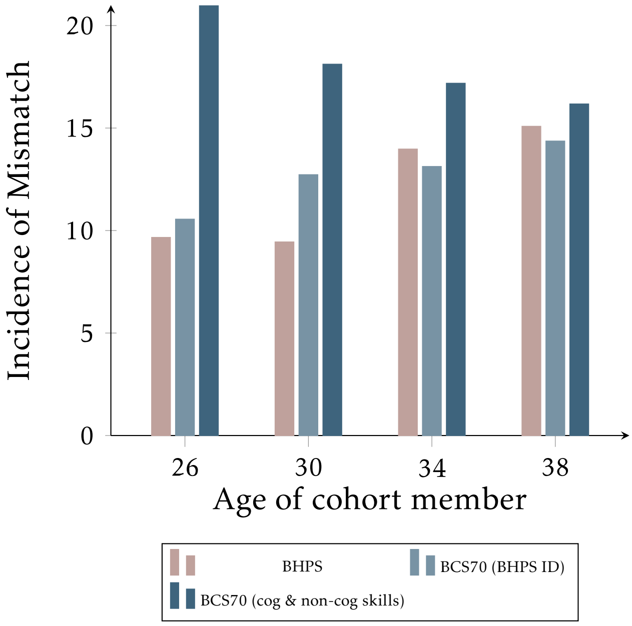


(B) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

FIGURE 6.B.3: Incidence of mismatch: Women (counterfactual)
Source: Own elaboration based on BHPS and BCS70



(A) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.



(B) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog and non-cog skills) controls not only for education but also for cognitive and non-cognitive skills.

FIGURE 6.B.4: Incidence of mismatch: Men (restricted subsample)
Source: Own elaboration based on BHPS and BCS70

6.B.2 Men

For male employees, I repeat the exercise only for the restricted subsample for comparability purposes.

6.C Skills by gender

Looking at the tables 6.C.1 and 6.C.3, two main points may be observed. First, non-cognition difference by degree remains non-significant for men, but not for women. Middle-skilled female employees in match, namely non-degree holders, show a significant lower non-cognitive skill test scores. Second, women perform better than men in both cognitive and non-cognitive tests. Given that both were tested at the same age, this implies that female maturity occurs earlier than male.

Table 6.C.1: Differences in skills, by mismatch and degree: Men

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
I. Non-Cognitive Skills														
Maternal Malaise Score	2.5294	1.9935	1.7382	1.7605	-0.7912	***	0.2855	2.2690	1.8843	1.9937	1.9205	-0.2753	*	0.1614
Rutter Index (Combined all)	16.4314	3.4015	16.7853	3.2656	0.3540		0.5193	15.2281	3.5794	15.6952	3.4558	0.4671		0.2932
(bin) Complains of headaches	0.9216	0.2715	0.9110	0.2855	-0.0106		0.0445	0.8830	0.3223	0.9068	0.2909	0.0238		0.0250
(bin) Complains of stomach-ache or has vomited	0.9608	0.1960	0.9895	0.1021	0.0287		0.0201	0.9825	0.1317	0.9345	0.2475	-0.0479	**	0.0195
(bin) Has temper tantrums (that is, complete loss of temper with shouting, angry	0.9020	0.3003	0.9058	0.2929	0.0038		0.0464	0.8713	0.3358	0.8690	0.3376	-0.0023		0.0284
(scl) Very restless. Often running about or jumping up and down. Hardly ever sti	39.5294	29.9208	31.9372	32.1009	-7.5922		4.9900	37.9123	31.5358	36.8136	30.8022	-1.0987		2.6078
(scl) Is squirmy or fidgety	33.1373	27.7770	26.2094	28.4499	-6.9278		4.4623	33.6725	30.7460	30.7393	29.1456	-2.9332		2.4815
(scl) Often destroys own or others belongings	10.1373	11.4333	9.6859	11.6811	-0.4514		1.8331	14.4620	18.2896	12.5995	13.9365	-1.8625		1.2476
(scl) Frequently fights with other children	10.7843	7.9983	11.5602	12.5482	0.7759		1.8515	17.8538	20.9923	16.2015	17.7853	-1.6523		1.5506
(scl) Not much liked by other children	10.1961	12.3061	12.2304	17.0467	2.0343		2.5493	13.7310	17.6994	14.5932	17.1228	0.8622		1.4522
(scl) Often worried, worries about many things	34.3529	25.5075	32.0942	30.5347	-2.2587		4.6589	26.5673	25.4759	32.2280	29.0128	5.6607	**	2.3960
(scl) Tends to do things on his/her own â rather solitary	27.4902	24.8720	33.8325	29.2201	6.3423		4.4715	24.9006	26.4590	28.4408	27.9401	3.5402		2.3339
(scl) Irritable. Is quick to fly off the handle	27.7647	26.9745	23.1361	24.4328	-4.6286		3.9379	33.8830	30.7234	33.5390	30.5425	-0.3440		2.5776

Continued overleaf

Table 6.C.2Differences in skills, by mismatch and degree: Men (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
(scl) Often appears miserable, unhappy, tearful or distressed	13.8235	8.9927	15.1047	16.8860	1.2812		2.4549	13.9532	13.3217	16.9610	17.7419	3.0077	**	1.4370
(scl) Sometimes takes things belonging to others	8.9412	9.6962	9.6335	10.5910	0.6923		1.6410	13.7778	18.1295	12.4811	13.0303	-1.2967		1.1858
(scl) Has twitches, mannerisms or tics of the face or body	8.5098	12.4505	10.2251	15.8056	1.7153		2.3907	12.1404	15.9412	12.5479	14.3318	0.4075		1.2333
(scl) Frequently sucks thumb or finger	14.6863	22.3647	18.4188	26.5352	3.7326		4.0543	17.7018	25.6762	21.0642	27.7941	3.3625		2.3127
(scl) Frequently bites nails or fingers	16.5490	23.1951	24.8377	30.3296	8.2887	*	4.5691	23.7193	30.3065	35.3539	35.0247	11.6346	***	2.8865
(scl) Is often disobedient	20.5686	17.0637	17.9948	17.8132	-2.5739		2.7835	24.7544	23.9882	25.9899	24.4383	1.2355		2.0536
(scl) Cannot settle to anything for more than a few moments	15.8824	20.1342	16.1780	21.5169	0.2957		3.3472	25.3684	24.9715	24.3048	25.0494	-1.0636		2.1106
(scl) Tends to be fearful or afraid of new things or new situations	27.9020	26.8419	26.5288	27.2983	-1.3732		4.2878	18.6608	19.8690	26.3715	27.8399	7.7107	***	2.2431
(scl) Is over fussy or over particular	17.8431	20.0862	21.2513	25.9856	3.4082		3.9203	28.8012	30.1673	27.0353	28.6707	-1.7659		2.4398
(scl) Often tells lies	12.6275	14.4305	13.9686	15.9687	1.3411		2.4684	21.2339	21.0639	17.7456	17.1847	-3.4883	**	1.5116
(scl) Bullies other children	8.0588	7.8623	9.4136	8.5981	1.3548		1.3319	16.4152	19.9499	12.8501	12.4867	-3.5651	***	1.1882
Tried smoking (16)	0.5918	0.4966	0.5189	0.5010	-0.0729		0.0803	0.5862	0.4942	0.5435	0.4985	-0.0427		0.0453
Tried alcohol (16)	1.0000	0.0000	0.9341	0.2489	-0.0659	*	0.0364	0.9542	0.2099	0.9289	0.2572	-0.0253		0.0239
Alcohol in past week (16)	0.8125	0.3944	0.7541	0.4318	-0.0584		0.0688	0.7029	0.4586	0.7541	0.4310	0.0512		0.0407
Ever been drunk (16)	0.5652	0.5012	0.6236	0.4859	0.0584		0.0809	0.6822	0.4674	0.6610	0.4737	-0.0212		0.0456
Porn in past month (16)	0.1837	0.3912	0.3222	0.4686	0.1385	*	0.0731	0.3471	0.4780	0.4323	0.4958	0.0852	*	0.0490
Had sex (16)	0.1489	0.3599	0.1967	0.3986	0.0478		0.0640	0.3485	0.4783	0.3509	0.4776	0.0024		0.0454
Tried drugs (16)	0.0769	0.2700	0.0942	0.2932	0.0173		0.0523	0.0962	0.2962	0.0592	0.2363	-0.0369		0.0270
Tried cannabis (16)	0.0513	0.2235	0.0942	0.2932	0.0429		0.0507	0.0500	0.2190	0.0385	0.1927	-0.0115		0.0219
Read book for pleasure in past week (16)	0.6809	0.4712	0.6774	0.4687	-0.0034		0.0766	0.4737	0.5012	0.4375	0.4965	-0.0362		0.0473
Damaged other's property in past year (16)	0.0526	0.2263	0.0870	0.2828	0.0343		0.0498	0.2427	0.4308	0.2489	0.4328	0.0061		0.0474
Shoplifted >č5 in past year (16)	0.0789	0.2733	0.1087	0.3124	0.0297		0.0558	0.0385	0.1932	0.1230	0.3289	0.0846	**	0.0335
II. Cognitive Skills														

Continued overleaf

Table 6.C.2Differences in skills, by mismatch and degree: Men (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
English Picture Vocabulary Test (y5)	0.9306	1.0241	0.6990	0.8526	-0.2316		0.1404	0.4710	0.9155	0.1940	0.9219	-0.2770	***	0.0776
Copying Designs Test (5y)	0.8019	0.9507	0.6539	0.8813	-0.1480		0.1413	0.3064	0.9237	0.0101	0.9587	-0.2964	***	0.0803
Human Figure Drawing Test (y5)	0.3372	1.2494	0.2685	1.0750	-0.0687		0.1755	-0.0822	0.9261	-0.1513	0.9328	-0.0691		0.0785
PLCT (y10)	0.6785	0.1051	0.6861	0.0879	0.0076		0.0145	0.6429	0.0877	0.6118	0.0919	-0.0312	***	0.0077
FMT (y10)	0.8072	0.0976	0.7825	0.1227	-0.0247		0.0186	0.7186	0.1325	0.6176	0.1619	-0.1010	***	0.0132
SERT (y10)	0.7964	0.1094	0.7710	0.1404	-0.0254		0.0212	0.6895	0.1678	0.6294	0.1720	-0.0601	***	0.0144
Reading (y16)	0.7028	0.3340	0.7731	0.2873	0.0704		0.0469	0.6970	0.2621	0.6005	0.2925	-0.0964	***	0.0242
BAS (similarities; y10)	0.7897	0.1380	0.7931	0.1185	0.0034		0.0194	0.7276	0.1558	0.7156	0.1307	-0.0120		0.0114
BAS (matrices; y10)	0.7573	0.1053	0.7662	0.1037	0.0090		0.0164	0.7043	0.1515	0.6597	0.1583	-0.0446	***	0.0132
BAS (Recall of digits; y10)	0.7761	0.1333	0.7460	0.1188	-0.0301		0.0192	0.7485	0.1259	0.7109	0.1347	-0.0377	***	0.0112
BAS (Word Definitions; y10)	0.6112	0.1280	0.5901	0.1048	-0.0211		0.0173	0.5106	0.1225	0.4662	0.1205	-0.0444	***	0.0102
Spelling (y10)	0.8355	0.1311	0.8094	0.1660	-0.0261		0.0251	0.7276	0.2303	0.7112	0.2101	-0.0164		0.0180
Spelling (y16)	0.8039	0.2294	0.8285	0.1526	0.0246		0.0270	0.7615	0.2445	0.7200	0.2668	-0.0415	*	0.0222
Arithmetic scores (y16)	0.7745	0.2869	0.8067	0.2752	0.0322		0.0438	0.7651	0.2749	0.6974	0.3026	-0.0677	***	0.0251
Vocabulary scores (y16)	0.6656	0.1810	0.6643	0.1479	-0.0012		0.0245	0.5577	0.1839	0.5091	0.1943	-0.0486	***	0.0162
Numeracy MC and OR assessment	0.8333	0.2164	0.9360	0.0834	0.1026	**	0.0459	0.8303	0.1383	0.7956	0.1556	-0.0348		0.0212

Rutter Recoding Index: (b): bin; 1 is better. (scl): measured in scale
Cognitive Skills Test scores have been normalised
* p<0.1, ** p<0.05, *** p<0.01

Note: non-Degree excludes low-skilled male employees, who by definition cannot be classified as in mismatch. Stars show the significance of two-tailed t-test of the difference.
Source: Own elaboration based on BCS70

TABLE 6.C.3: Differences in skills, by mismatch and degree: Women

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
I. Non-Cognitive Skills														
Maternal Malaise Score	1.6515	1.6870	1.2838	1.6418	-0.3677		0.2308	1.9286	1.9491	2.1359	1.9581	0.2074		0.2067
Rutter Index (Combined all)	18.0000	3.3650	17.5677	3.1983	-0.4323		0.4521	16.6327	3.2217	16.0361	3.3912	-0.5965	*	0.3567
(bin) Complains of headaches	0.8333	0.3755	0.8472	0.3606	0.0138		0.0509	0.9490	0.2212	0.8954	0.3061	-0.0535	*	0.0317
(bin) Complains of stomach-ache or has vomited	0.9242	0.2666	0.9258	0.2627	0.0015		0.0368	0.9082	0.2903	0.8764	0.3293	-0.0317		0.0344
(bin) Has temper tantrums (that is, complete loss of temper with shouting, angry	0.8939	0.3103	0.8821	0.3232	-0.0118		0.0448	0.9082	0.2903	0.8992	0.3012	-0.0089		0.0317
(scl) Very restless. Often running about or jumping up and down. Hardly ever sti	21.2576	21.5559	22.4891	22.0606	1.2315		3.0665	31.2041	29.5244	27.8004	27.5707	-3.4037		2.9299
(scl) Is squirmy or fidgety	20.5000	21.1713	23.1092	22.4752	2.6092		3.1005	24.2755	25.9320	25.0247	25.9140	0.7492		2.7371
(scl) Often destroys own or others belongings	9.2576	6.6340	10.5459	6.4260	1.2883		0.9043	9.9592	7.6075	10.5884	8.6361	0.6292		0.9034
(scl) Frequently fights with other children	10.8333	10.1627	12.9039	10.7565	2.0706		1.4848	11.6531	10.3546	14.6911	15.8516	3.0380	*	1.6331
(scl) Not much liked by other children	11.9242	9.2075	13.5939	12.5916	1.6696		1.6659	13.3163	15.0714	14.0295	15.3074	0.7131		1.6146
(scl) Often worried, worries about many things	31.0303	25.6071	37.1878	29.8056	6.1575		4.0413	25.2245	24.3888	33.2890	28.0690	8.0645	***	2.9337
(scl) Tends to do things on his/her own â rather solitary	26.6364	25.8443	31.4803	28.3859	4.8440		3.8898	24.2857	25.2403	30.3555	27.9769	6.0698	**	2.9315
(scl) Irritable. Is quick to fly off the handle	26.7273	24.5930	25.7467	23.5334	-0.9805		3.3212	24.1224	24.6138	27.5865	27.4369	3.4641		2.8738

Continued overleaf

Table 6.C.4Differences in skills, by mismatch and degree: Women (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
(scl) Often appears miserable, unhappy, tearful or distressed	14.6667	10.9844	18.2795	15.7575	3.6128	*	2.0721	14.7857	12.0174	19.8574	20.7277	5.0717	**	2.1269
(scl) Sometimes takes things belonging to others	9.9242	8.0600	11.1572	7.7523	1.2330		1.0927	10.6531	9.9743	11.4667	12.0551	0.8137		1.2561
(scl) Has twitches, mannerisms or tics of the face or body	11.3788	13.2906	12.9520	12.1797	1.5732		1.7372	10.2857	10.0647	11.4011	13.0664	1.1154		1.3561
(scl) Frequently sucks thumb or finger	29.6364	33.6089	23.4454	27.3201	-6.1909		4.0283	15.2857	19.9567	23.3317	28.4453	8.0460	***	2.9391
(scl) Frequently bites nails or fingers	21.2424	26.3422	35.5459	33.8208	14.3034	***	4.5142	18.5612	21.7436	32.9819	33.4798	14.4207	***	3.4485
(scl) Is often disobedient	17.5303	14.9288	18.5590	17.4324	1.0286		2.3623	17.0918	17.1393	22.3555	20.9745	5.2637	**	2.1839
(scl) Cannot settle to anything for more than a few moments	16.5606	18.4559	16.1790	16.2375	-0.3816		2.3408	19.3673	20.8462	18.9943	20.3905	-0.3731		2.1577
(scl) Tends to be fearful or afraid of new things or new situations	23.8636	23.1310	29.9170	25.6381	6.0534	*	3.5072	20.2857	19.8302	29.7757	27.9359	9.4900	***	2.8880
(scl) Is over fussy or over particular	16.1061	15.7530	23.5415	22.7560	7.4354	**	2.9899	24.4490	23.1040	27.6540	26.8856	3.2050		2.8080
(scl) Often tells lies	13.3030	13.2351	15.4672	13.0382	2.1642		1.8277	11.8878	11.4260	15.0428	14.5965	3.1550	**	1.5162
(scl) Bullies other children	12.1818	9.4786	13.9607	11.7441	1.7789		1.5760	12.2041	9.6538	13.7310	13.7592	1.5269		1.4217
Tried smoking (16)	0.5469	0.5017	0.4574	0.4993	-0.0895		0.0709	0.5567	0.4994	0.6743	0.4689	0.1176	**	0.0501
Tried alcohol (16)	0.9365	0.2458	0.9037	0.2957	-0.0328		0.0408	0.9451	0.2291	0.9514	0.2151	0.0064		0.0237
Alcohol in past week (16)	0.7143	0.4554	0.6256	0.4851	-0.0887		0.0684	0.7473	0.4370	0.7053	0.4561	-0.0419		0.0498
Ever been drunk (16)	0.4603	0.5024	0.3180	0.4668	-0.1423	**	0.0680	0.4505	0.5003	0.6221	0.4851	0.1715	***	0.0534
Porn in past month (16)	0.2031	0.4055	0.0876	0.2833	-0.1156	**	0.0448	0.2258	0.4204	0.2772	0.4479	0.0514		0.0485
Had sex (16)	0.1094	0.3146	0.1233	0.3295	0.0139		0.0464	0.3043	0.4627	0.2912	0.4545	-0.0132		0.0497
Tried drugs (16)	0.0702	0.2577	0.0492	0.2168	-0.0210		0.0345	0.0247	0.1561	0.0507	0.2195	0.0260		0.0251
Tried cannabis (16)	0.0351	0.1856	0.0112	0.1057	-0.0239		0.0197	0.0000	0.0000	0.0298	0.1702	0.0298		0.0189
Read book for pleasure in past week (16)	0.9032	0.2981	0.7668	0.4238	-0.1364	**	0.0574	0.7609	0.4289	0.6221	0.4851	-0.1387	***	0.0524
Damaged other's property in past year (16)	0.0526	0.2253	0.0219	0.1466	-0.0308		0.0256	0.0494	0.2180	0.0300	0.1708	-0.0193		0.0207
Shoplifted >č5 in past year (16)	0.0000	0.0000	0.0165	0.1277	0.0165		0.0172	0.0370	0.1900	0.0399	0.1958	0.0028		0.0229
II. Cognitive Skills														

Continued overleaf

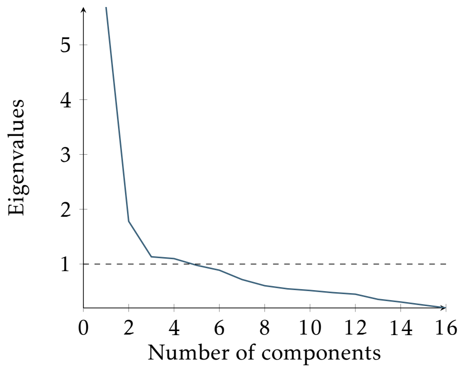
Table 6.C.4Differences in skills, by mismatch and degree: Women (continued)

	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
English Picture Vocabulary Test (y5)	0.6448	0.9248	0.3903	0.9501	-0.2545	*	0.1320	0.4331	0.7859	-0.0643	0.9052	-0.4974	***	0.0946
Copying Designs Test (5y)	0.7505	0.7804	0.6632	0.8997	-0.0873		0.1222	0.4474	0.9310	0.0640	0.9494	-0.3834	***	0.1001
Human Figure Drawing Test (y5)	0.5021	0.9772	0.5776	0.9873	0.0755		0.1376	0.2473	0.8584	0.1633	0.8906	-0.0840		0.0938
PLCT (y10)	0.6909	0.1174	0.6683	0.0878	-0.0227	*	0.0133	0.6416	0.0955	0.5995	0.0942	-0.0420	***	0.0100
FMT (y10)	0.7934	0.1145	0.7752	0.1247	-0.0182		0.0171	0.7016	0.1142	0.6055	0.1400	-0.0962	***	0.0146
SERT (y10)	0.8119	0.1368	0.8013	0.1387	-0.0106		0.0193	0.7369	0.1381	0.6584	0.1621	-0.0785	***	0.0169
Reading (y16)	0.7976	0.2849	0.6987	0.3513	-0.0989	**	0.0472	0.7383	0.2677	0.6067	0.3066	-0.1316	***	0.0321
BAS (similarities; y10)	0.7847	0.0838	0.7868	0.0726	0.0020		0.0105	0.7287	0.1024	0.7253	0.0954	-0.0034		0.0101
BAS (matrices; y10)	0.7555	0.2198	0.7658	0.1570	0.0103		0.0242	0.7137	0.1667	0.6837	0.1516	-0.0301	*	0.0162
BAS (Recall of digits; y10)	0.7854	0.0971	0.7611	0.1432	-0.0243		0.0188	0.7648	0.1145	0.7289	0.1098	-0.0360	***	0.0116
BAS (Word Definitions; y10)	0.6005	0.1199	0.5564	0.0975	-0.0441	***	0.0144	0.5092	0.1216	0.4585	0.1035	-0.0508	***	0.0111
Spelling (y10)	0.8202	0.2426	0.8629	0.1075	0.0427	**	0.0207	0.8058	0.1989	0.7697	0.1780	-0.0361	*	0.0190
Spelling (y16)	0.8901	0.1205	0.8657	0.1624	-0.0245		0.0215	0.8254	0.1924	0.7746	0.2508	-0.0508	*	0.0260
Arithmetic scores (y16)	0.8270	0.2775	0.7282	0.3559	-0.0989	**	0.0475	0.7849	0.2513	0.7235	0.3020	-0.0613	*	0.0315
Vocabulary scores (y16)	0.7140	0.1136	0.6797	0.1548	-0.0343	*	0.0205	0.6284	0.1223	0.5227	0.1885	-0.1057	***	0.0194
Numeracy MC and OR assessment	0.8232	0.2026	0.9101	0.0811	0.0869	**	0.0401	0.8571	0.0664	0.7294	0.1653	-0.1278	***	0.0444

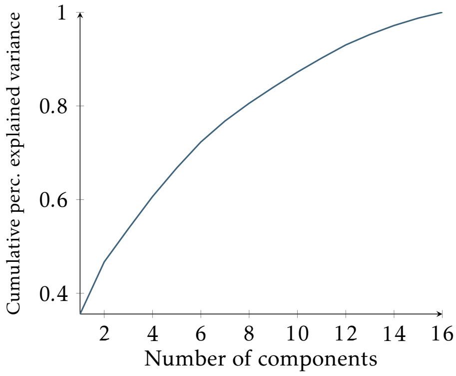
Rutter Recoding Index: (b): bin; 1 is better. (scl): measured in scale
Cognitive Skills Test scores have been normalised
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: non-Degree excludes low-skilled female employees, who by definition cannot be classified as in mismatch. Stars show the significance of two-tailed t-test of the difference.

Source: Own elaboration based on BCS70



(A) Eigenvalues by component
Note: In the analysis, we include those components whose eigenvalue is greater than 1. The dashed line shows this threshold.



(B) Cumulative variance explained
Note: The first 4 components explain, cumulatively, 60.6% of the variation.

FIGURE 6.D.1: Cognitive skills
Source: Own elaboration based on BCS70

6.D Principal Component Analysis by skills

6.D.1 Cognitive skills only

6.D.2 Non-cognitive Skills only

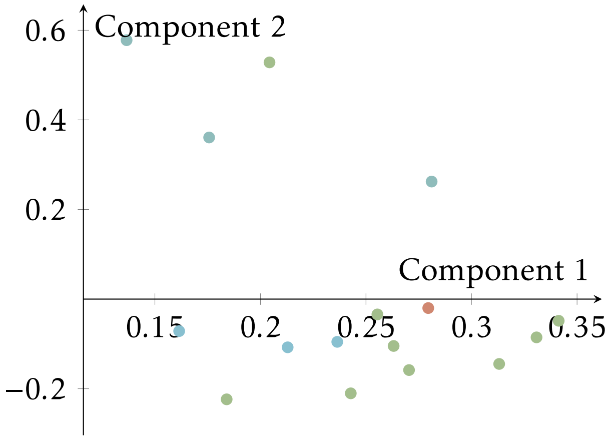
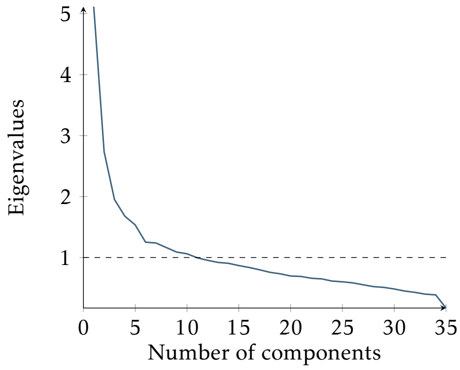
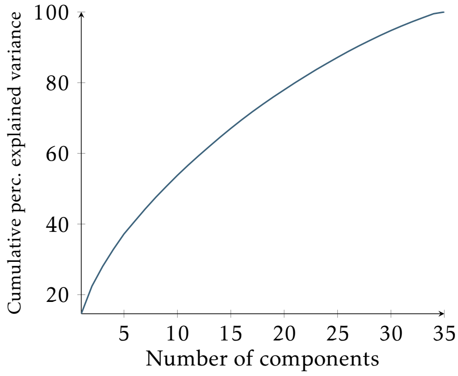


FIGURE 6.D.2: Loading plot; cognitive skills only



(A) Eigenvalues by component
Note: In the analysis, we include those components whose eigenvalue is greater than 1. The dashed line shows this threshold.



(B) Cumulative variance explained
Note: The first 15 components explain, cumulatively, 61% of the variation.

FIGURE 6.D.3: Non-cognitive skills
Source: Own elaboration based on BCS70

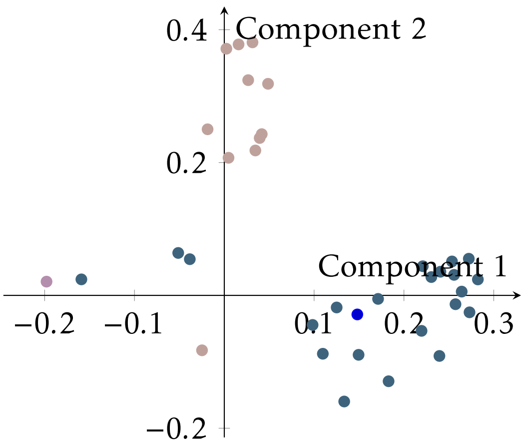


FIGURE 6.D.4: Loading plot; non-cognitive skills only

Conclusions

THIS section outlines the conclusions, policy implications and limitations of this research from a broader perspective. Each individual chapter has been treated as a separate paper. Hence, here I will not repeat conclusions and particular limitations chapter by chapter.

This Thesis

This Thesis explores the Human Capital Mismatch in the British labour market. It shows that the mismatch arises because of the workers' allocation into jobs as a result of between-group inequalities in the UK. There is no evidence that it results from an oversupply of graduates in the market. Frictions in the labour market generate mismatch and hinder perfect competition among workers. As a result, workers are not efficiently allocated into jobs. Their cognitive and non-cognitive skills substitute each other and do not contribute to greater mismatch.

Chapter 1 reviews the theories of overeducation and skills mismatch to motivate the research question the Thesis answers. It further reviews the empirical tools to measure overeducation to motivate a novel measure of mismatch which depends on the distributions of skills and jobs. Chapter 2 presents the BHPS/UKHLS data and constructs this empirical novel multidimensional measure of mismatch. It explores how transitions in the labour market may change the individual matching status in a dynamic framework. The main result postulates that the mismatch distorts the prices, i.e. wages. Workers find a better job or their transition occurs earlier than the overall change of skills. However, is this true in theory? Chapter 3 extends the Burdett and Mortensen (1998) model, allowing for heterogeneous workers and firms. It shows that frictions generate mismatch. The model simulation, in a continuous-skills setting, shows that higher-skilled workers have a lower expected wage if they face more frictions. Different groups face different frictions, e.g. women face more frictions. This is why chapter 4 and 5 focus on women. Chapter 4 explores the instance of mismatch among female employees accounting for any potential a priori discrimination women might face. It shows that the incidence changes when the control group changes. Chapter 5 is a case study for the British public sector and controls for the endogenous self-selection into jobs. It finds that the public sector is more attractive as a waiting room for highly-qualified graduates.

The above empirical measure of mismatch is dependent on the accurate estimate of the returns to education. How much does individual heterogeneity, namely worker ability, contribute to mismatch? Chapter 6 estimates the incidence of mismatch controlling for cognitive and non-cognitive skills, using test scores throughout childhood. This chapter uses data from the BCS70 and finds no evidence that skills contribute to mismatch.

Policy implications

The main argument of this Thesis claims that mismatch arises because of the worker allocation into jobs. Hence, policy implications would regard their efficient allocation in the market. To this end, it could stress the importance of policies for female labour force participation. Women face more frictions in the labour market. First, policies regarding childcare could increase female job arrival rate and decrease their destruction rate. Second, reallocation of housework could further help their labour market affiliation. It is not necessarily true that they are more productive in the house since the out-of-house alternative is not equally probable for women. A motivation for this root of research could further come from the COVID-19 "Stay at home" restriction requirements.

Another between-group inequality examined here regarded those who come from a more favoured parental background. If one's father is higher-skilled, they are more likely to gain a degree and a good job. To this end, first, the policy recommendation stemming from this could regard equal training opportunities for all regardless their background. This may offer a ticket to higher education for those who do not have a chance in the first place. As a result, their training will help them get a better job. Second, without parental wealth, individuals can afford less time in unemployment. As a result they would get any job available. For lower-skilled individuals, this may be translated not only in unemployment but an exit from the labour market. Hence, an unemployment benefit that assures enough time to search for a good job and cover individual needs should be supported.

Limitations

I came across several challenges while working on this Ph.D. Thesis since the beginning. These challenges concerned the methodology to use and how to frame a story that does not follow the most conventional narrative. However, this research has limitations that could motivate further contributions.

First, the empirical part could enjoy better data. At the moment, I infer how the labour demand works from the individual data. However, the next step of this research is to use employee-employer matched administrative data so that I gain greater information on the firm side. I plan to estimate the exact share of each type of firm. This would inform the theoretical model and generate a more precise level of frictions workers face in the market.

Second, I wish BHPS and its successor UKHLS could collect the same data and in the same format. Not only the transition would be smoother, but also we could gain more precise information for individuals since 1991. In the questionnaire, I notice that some questions are no longer questionned. To this end, a harmonisation by the data issuer should be attempted. However, a success of UKHLS is the expansion of the sample on ethnic minorities motivating further research ideas.

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