“Are you in the right job?” Human Capital Mismatch in the UK[*]

Yannis Galanakis[†]

King’s College London

Current Version: 2022–11–20

Latest Version

Abstract

This paper examines a problem of worker misallocation into jobs. A theoretical model, allowing for heterogeneous workers and firms, shows that job search frictions generate mismatch between employees and employers. In the empirical analysis, the British Household Panel Survey (BHPS), the UK household Longitudinal Study (UKHLS) and British Cohort Study 1970 (BCS70) data are used to measure the incidence of mismatch, how it changes over time and whether it can be explained by unobserved ability. Results show that (i) the incidence of mismatch increases after the Great Recession. (ii) Individual transitions to/from matching 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. (iv) Controlling for individual heterogeneity, measured by cognitive and non-cognitive skill test scores throughout childhood, does not decrease the incidence of mismatch. This suggests that unobserved productivity does not generate mismatch in the labour market.

Key words: Human Capital Mismatch; frictions; individual heterogeneity

JEL Classification: I26, J24, J31, J64

[*]**Acknowledgements**: I am indebted to Amanda Gosling and Olena Nizalova for their support throughout this project. Further, I would like to thank Amrit Amirapu, Alex Bryson, Irma Clots-Figueras, Bansi Malde, Steve McIntosh, Miltos Makris, Anthony Savagar and participants of the MicroForum seminars (University of Kent), WPEG Annual Conference 2021 (University of Sheffield and DWP), Irish Postgraduate and Early Career Economics (IPECE) Workshop 2021, the Workshop on Labour Economics 2022 (Trier University), XXIV Applied Economics Meeting (ALdE; Universitat de les Illes Balears) and 15th Annual Meeting of the Portuguese Economic Journal (University of Azores) for useful comments on earlier versions of this paper. The financial support from the Vice Chancellor’s Research Scholarship Award is greatly acknowledged.

Interactive app: An interactive application to perform your own parametrisation of the simulation is available here.

[†]**Correspondence**: Yannis Galanakis, King’s Business School, Bush House, 30 Aldwych, King’s College London, London, WC2B 4BG; E: yannis.galanakis@kcl.ac.uk; W: yannisgalanakis.com

1 Introduction

If the labour market is perfectly competitive, the job title matters less. It acts as a label for a particular type of match between individual skills and a job. However, if human and physical capital are complements, the job allocation process plays an important role allowing room for market imperfections (Zentler-Munro, 2021). Job allocation can explain wage heterogeneity relative to individual skills. It would be expected that controlling for skills, the probability of getting a graduate job would be higher. Lower skilled workers, whose productivity is lower, earn less than higher skilled workers. If not, any mismatch may not be the result of individual skill heterogeneity, but of search frictions in the labour market. In this framework, labour market frictions are related to the privilege of a particular group of workers to access certain jobs. The market does not fully utilise worker's skills and barriers to occupational progress arise. Different groups of workers have different access to jobs or face different frictions in job search. Therefore, individual heterogeneity may result in a worker's different relative position between the skills and jobs distributions. This paper questions whether a worker's relative position differs between these two observed distributions. How much of this structural inequality in the British labour market can be explained by the differences in search frictions across different groups of workers? To this end, I measure the incidence of mismatch and how it changes over time. I further explore whether controlling for individual unobserved productivity reduces the incidence of mismatch.

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 skills differs across firms, frictions have an important efficiency implication. When heterogeneity[1] from both firms and workers arises, workers are allocated into sub-optimal jobs given their characteristics (e.g. Gautier and Teulings (2015); Papageorgiou (2014); Hornstein et al. (2011); 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.

Frictions arise when deviating from the perfectly competitive frameworkand allowing on-

[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.

the-job search. Under the neoclassical perspective, frictions generate an inefficiency in the market. Due to mismatch,[2] realised wages may compress workers' productivity.[3]

Contribution and background

This paper has a twofold contribution: a theoretical and empirical one. Theoretically, I extend the general equilibrium Burdett and Mortensen (1998) (henceforth BM) search model. The original BM model assumes on-the-job search and endogeneity in wages distribution. It explains the wage dispersion among homogeneous individuals in the labour market. This assumption of identical-skills workers does not allow an exploration of the *between-group* differentials which contribute to the wage inequality. Low-, middle- and high-productive employers may coexist for two reasons. First, it is time-consuming to generate offers.[4] Second, the flow of new entrants into the non-employment (or unemployment) status is constant.

My extension allows heterogeneity of firms in productivity and workers in skills. I show how the relative wage and employment of higher-skilled workers evolves in lower-productivity jobs, in equilibrium. In my setting, the labour market takes the following form. An individual chooses between work and non-employment (leisure). Skills are the main sorting device[5] 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, 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 leisure. Hence, they wait for a better job in which they will be matched. There is a positive relationship between firm productivity and worker skills: the greater the firm productivity, the greater the skill requirement of the worker. This setting echoes Uren and Virag (2011) to a certain extent. Even though Uren and Virag (2011) allow for heterogeneity in both sides, they do not quantify the mismatch that arises and drives the observed inequality. Albrecht and Vroman (2002) consider a labour market where workers differ in their skills and jobs in their requirements. However, they do

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

[3] 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.

[4] If non-employed and firms were sharing the same characteristics, new contract could be issued immediately.

[5] Bagger and Lentz (2019) quantify the sources of wage dispersion and find that sorting is its major contributor. Song et al. (2019) and Card et al. (2013) argue that increased sorting of high-skilled workers in high-productivity firms contribute to an increasing inequality.

not consider any on-the-job search and skill continuity, which is usually met in the data.

The arising heterogeneity from both worker and firm sides demands a broader measure of mismatch than the existent empirical over- or under-education measures.[6] The model developed here shows that market frictions generate a mismatch in a horizontal setting[7] between employers and workers. My model argues that ranking of workers is not the same in the observed distributions of skills and jobs. This is the reason why workers cannot seek all potential alternative jobs. To capture the continuity in skills, I replicate the initial exercise for more than three types of firms and workers. In this way, I construct a more realistic measure of mismatch.

Empirically, I construct a multidimensional measure of human capital mismatch that accounts for individual heterogeneity in more than one dimension. It considers the worker's relative position in the skills and job distributions. Employees fail any match if their skills exceed the median estimates of the more skills-demanding occupation. Using the BHPS/UKHLS data allows the estimate of distributions of wage offers of employed and unemployed/out-of-employment. Therefore, I can report any transition from/to matching and the occupation mobility in any two periods. Results show that, first, the incidence of mismatch increases after the Great Recession. Second, individual transitions to/from matching take place due to workers' occupational mobility and over-time skills development. Third, employees can find better jobs or their mobility occurs earlier than the aggregate change of skills.

To investigate the role of cognitive and non-cognitive skills, I use the test scores throughout childhood from the British Cohort Study (BCS70) and I replicate the same identification strategy as before. 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. I find that unobserved productivity does not generate mismatch in the market when controlling for skills.

This paper stands at the literature intersection of job search models, individual skills, mobility and inequality. Job search models have been employed to better comprehend, among other things, wage inequality (e.g. Mortensen (2003)), wage growth (e.g. Bontemps et al. (2000); Burdett and Mortensen (1998)) and the allocation of workers in firms (e.g.Shimer and Smith (2000)). Burdett and Mortensen (1998) and Bontemps et al. (2000) argue that frictions generate wage dispersion and firm heterogeneity is reflected in wages. The literature has acknowledged the

[6]E.g. McGuinness et al. (2018); McGuinness and Pouliakas (2016) offer a review of existing methods.

[7]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 horizontally sorted from low to high level.

importance of firm productivity and linked it to the wage policy (Card et al., 2018; Cahuc et al., 2006; Postel-Vinay and Robin, 2002; Abowd et al., 1999). A recent stream of studies highlights the role of high-wage firms in widening the wage hiatus (e.g. Barth et al. (2016); Card et al. (2013)). Other studies report a link between firm innovation[8] intensity and higher wages (e.g. Aghion et al. (2019); Van Reenen (1996)). Models inspired by Burdett and Mortensen predict that workers will move to higher-paying employers; any pay differences among employers will be reflecting the excess labour demand (Lachowska et al., 2020; Haltiwanger et al., 2018).

Employment can be seen as a two-players game in which the literature relates on-the-job search to the existing matching relationships. For instance, in models such as those of Chassamboulli (2011); Dolado et al. (2009); Cahuc et al. (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 the 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,[9] when high-quality workers accept low-wage, low-productivity jobs. Low-skilled workers, in this setting, are pushed into unemployment. High-skilled workers in mismatch have a greater incentive to look for a better job than those in match.

The literature has also linked the returns to skills to the job search. Labour market frictions may impede worker allocation into jobs by distorting the prices, i.e. the market returns to skills. This raises a discussion on human capital accumulation and schooling investment decisions before or after entering the market (e.g. Bobba et al. (2020, 2018); Flinn and Mullins (2015)). From a macroeconomic perspective, scholars have looked at the aftermath of mismatch for the productivity and growth of an economy (e.g. Restuccia and Rogerson (2013)).

From a microeconomic perspective, empirical work establishes a causal relationship between education and its (financial) returns[10] on wages and addresses several practical and policy-oriented questions. As Gunderson and Oreopolous (2020) recognise, highly educated workers can have other characteristics, which are associated with higher earnings, but they are not controlled in the usual estimation. The causality between cognition and wages may

[8]Empirically, the topic of innovation has been seen in terms of the social mobility and inequality (e.g. Aghion et al. (2019)).

[9]The Burdett and Mortensen (1998) model has been further used to analyse dynamics of economic activity fluctuations between growth and recession; e.g. Coles and Mortensen (2016); Moscarini and Postel-Vinay (2013).

[10]Psacharopoulos and Patrinos (2018) offer an overview of the literature for 139 countries, including the UK. Most estimates are based on the traditional Mincerian 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.

seem evident and is well-documented. However, literature mostly remains suggestive for non-cognition and labour market outcomes.[11] Papageorge et al. (2019) argue that some skills penalised at school may be valuable in the labour market. They explain that the returns to non-cognitive skills may differ depending on the economic context seen. Misbehaviour, for instance, is associated with lower educational outcomes, but higher wages regardless the gender of the worker. Similarly, misbehaviour contributes to greater female exposure in the market.

An equivalent interpretation for career choices, originated from the Roy model and extended from 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 et al., 2020; Lindenlaub and Postel-Vinay, 2020).

The rest of the paper is structured as follows. Section 2 sets up the model and comments on the simulation. Section 3 describes the data and outlines the empirical strategy. Section 4 presents the results stemming from the analysis and the last section concludes.

2 Model

The model presented here is akin to Burdett and Mortensen (1998) allowing for heterogeneity of both firms and workers, where labour market frictions 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.

2.1 Setting

Let an economy comprised of a continuum of firms and a continuum of workers. To simplify, both continua are assumed to be of a unitary mass.[12] Firms are heterogeneous in productivity; thus, 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. Firms employ workers who differ in their skills; low-, middle- and high-skilled workers search for a job. At any moment, jobseekers choose between

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

[12] 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.

either to enjoy leisure and not work or to work. If they are Out-of-Work (OoW),[13] they receive a flat benefit, b, regardless of their credentials. In other words, 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.

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 be 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 is the cumulative distribution of wage offers across firms. It is a weighted average of salary offer made by the 3 types of firms:

$$F(w) = \sigma_1 F_1(w) + \sigma_2 F_2(w) + \big(1 - (\sigma_1 + \sigma_2)\big) F_3(w)$$

Its respective density distribution is $f(w)$. δ is the exogenous destruction rate of the job-worker matches[14]; where $0 < \delta < \infty$.

Final important assumption regards the level of the wage. Firms are able to pay workers less than the productivity level. If $w = p$,[15] 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, an individual 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

[13] 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 et al., 2006). Later, Jones and Riddell (2019) find that the marginally-attached lie between the unemployed and the 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.

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

[15] 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 ($0 < \kappa < \infty$).

such that their profits are maximised, or

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

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 the maximisation problem, determining the level of employment is important.

2.1.1 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 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). The non-employment rate is thus determined as

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

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

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

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:

$$G(w) = \frac{F(w)}{1 + \kappa(1 - F(w))} \tag{2}$$

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 revision of the firms' profit. Assuming uniform hiring effort, the expected number of workers at a firm which pays w is

$$\ell(w) = \frac{1 + \kappa}{\Big(1 + \kappa\big(1 - F(w)\big)\Big)^2} \tag{3}$$

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

$$\pi_i = \frac{\kappa(p_i - w)}{\Big(1 + \kappa\big(1 - F(w)\big)\Big)^2} \tag{4}$$

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

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

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

2.2 Simulation

Table 1 outlines the values used to run the simulation discussed in the following sections.

Table 1: Parametrization

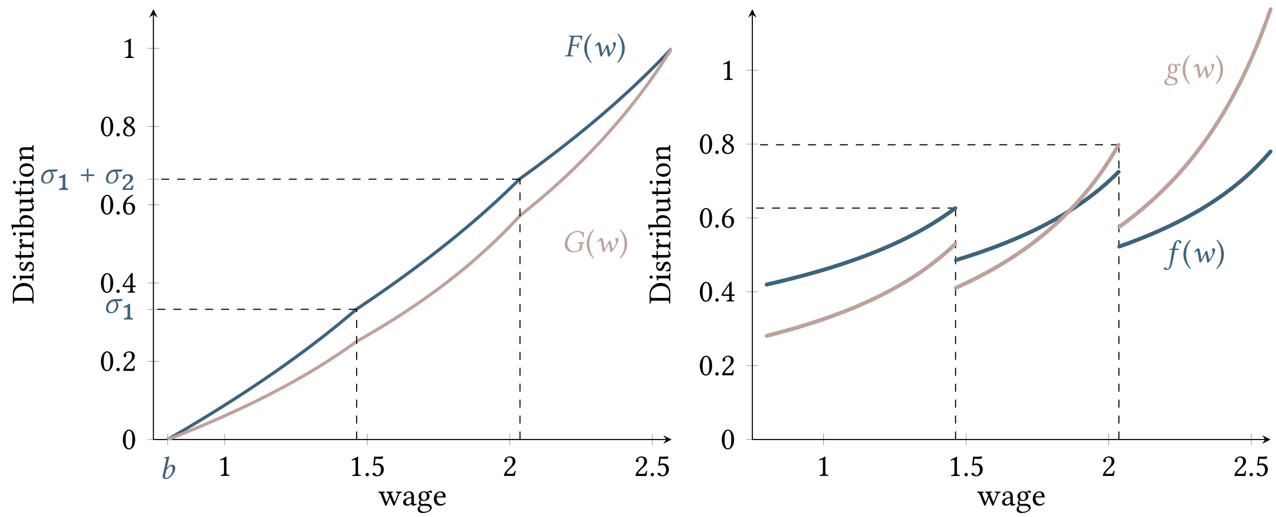
Parameter	Description	Value
b	Flat flow value to non-employment	0.8
δ	Job destruction rate	0.287
λ	Job arrival rate	0.142
p_1	Productivity of low-type firms	2
p_2	Productivity of middle-type firms	2.5
p_3	Productivity of high-type firms	3
σ_1	Share of low-productivity firms	$\frac{1}{3}$
σ_2	Share of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

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

2.2.1 Discrete Skills

Based on the model described on 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 1 depicts the cumulative (panel 1a) and density (panel 1b) distribution of wage offers (blue) and salaries (pink). Panel 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 $G(w, F)$. Both distributions are kinked; these kinks are related to how many different types of firms we employ. For j types of firms, $j - 1$ kinks are observed on the CDF. In panel 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



(a) Cumulative

(b) Density

Figure 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

them wait in a firm while searching for an alternative job that pays a higher wage.[16] A reasonable question may concern the overlap of the density distributions in the middle-productivity firms. This occurs because number of workers in middle-productivity firms exceeds the average employment per firm. Besides, this type of firms employs both middle- and high-skilled firms. Hence, the latter category of workers may wait there until they find their matched job.

The final implication is in relation to the number of workers per firm or the firm size as depicted in figure 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 fewer to other employers.

2.2.1.1 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 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

[16] 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).

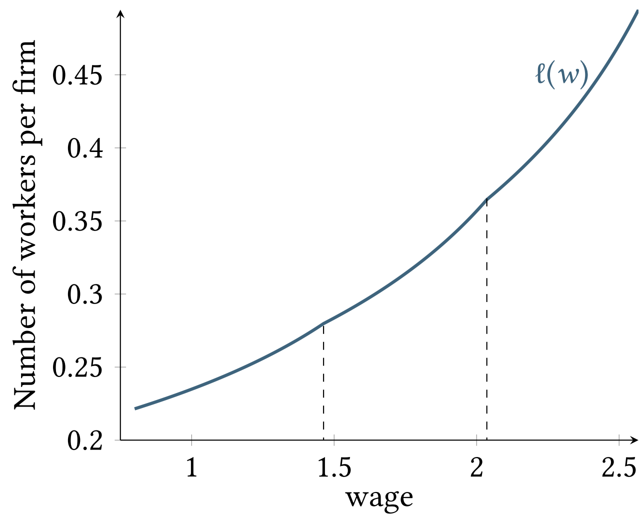


Figure 2: Labour Force
Note: $\ell(w)$ shows the number of workers per firm or the firm size. Dashed lines indicate the boundaries each type of firm dependent on the wage, as above.
Source: Own elaboration

Table 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

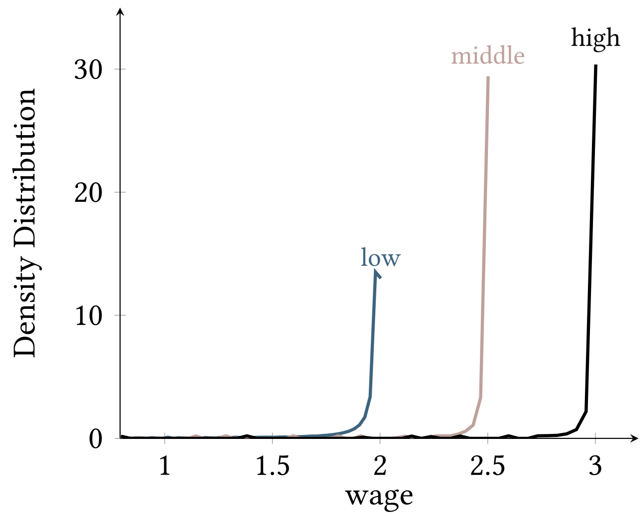


Figure 3: Identification of Mismatch
Note: This is an alternative illustration of figure 1b. The mismatch is identified on the overlap of the wage density distribution. A worker is in mismatch if she is middle-skilled, but works in a low-productivity firm ($g_2(w_1)$). A high-skilled employee is in mismatch 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 2).
Source: Own elaboration

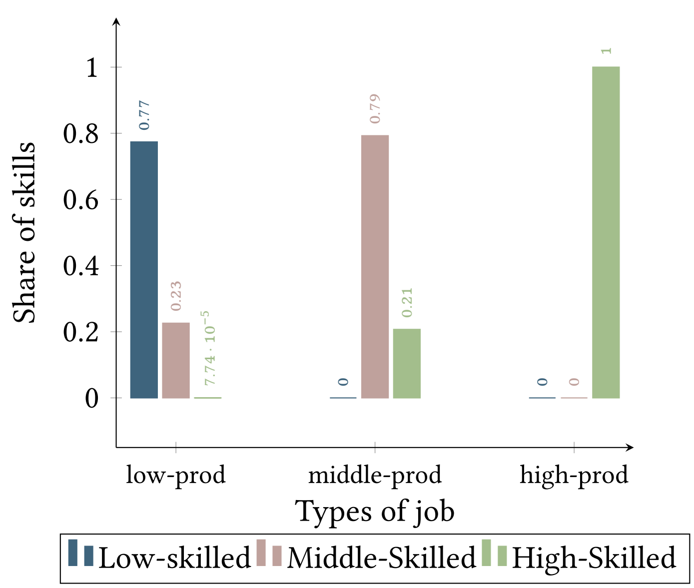


Figure 4: Workers' skills vs. types of jobs
Note: Relative share of each skill- in each job-type. For ease, I have assumed that workers are equally distributed among each skill-type; namely their share equals to $\omega_i = \frac{1}{3}$.
Source: Own elaboration

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 2 reports the method to calculate and the incidence of the mismatch in the BM labour market. One is not in match 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 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.

2.2.1.2 Frictions in the Labour Market

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

Figure 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) paradox. In that case, all workers regardless 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

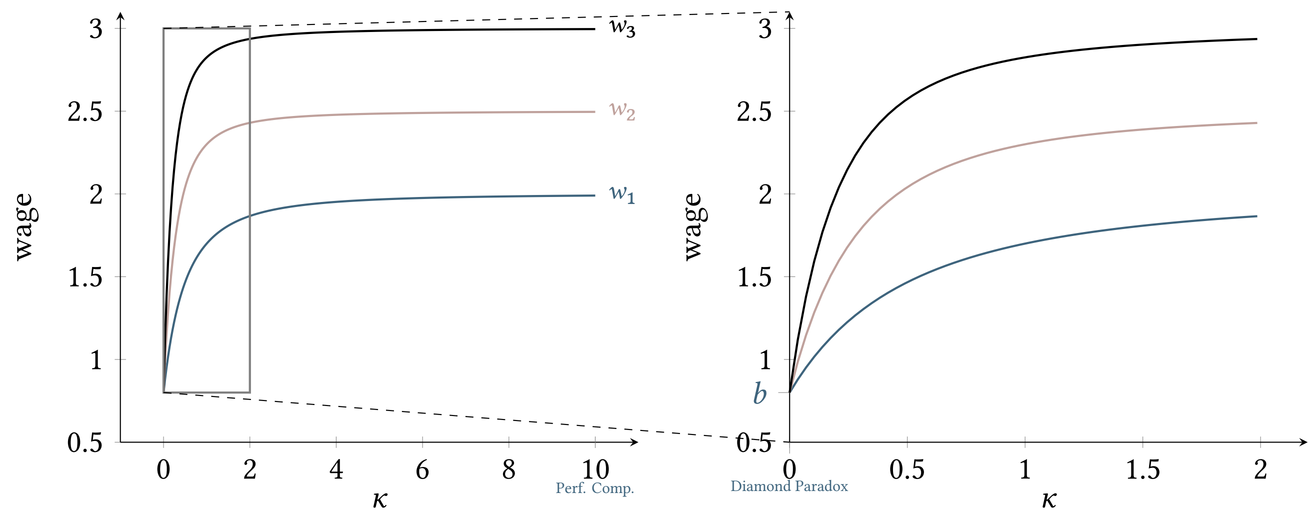


Figure 5: Change of κ with constant share of firms

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 $\kappa \le 2$ to better illustrate the differences among wages.

Source: Own elaboration

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 $\kappa \le 2$.

A similar picture might come from the study of the relative slopes of wages, or the returns to skills. Figure 6 illustrates them as κ changes. To highlight the gender differences, we may use the non-employment rate steady-state equilibrium condition (eq. 1). 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 do face more labour market frictions.[17] In fact they may face several exogenous reasons why their jobs are destroyed (greater job destruction rate). For example, they have to move because of their partner's new job opportunity, they get pregnant, or nursery may close and they are needed to childcare. On the other hand, they may have a lower job arrival rate because of the jobs that they are looking for. For instance, their job hunting is restricted to a set of firms where 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

[17] 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); 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.

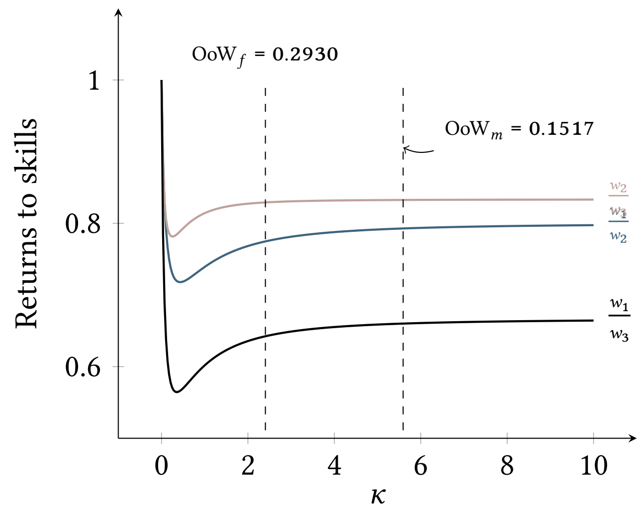


Figure 6: Gender differences in frictions and returns to skills

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

employment.

2.2.1.3 Do frictions matter? The role of firms' share

Figure 7 depicts the essential role of the firms' share (σ) on the market frictions, and hence, the 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 in the margin will migrate to the next closest type of firm.[18] Second, σ *per se* determines the "under-reward" or the 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

[18]For example, if in 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).

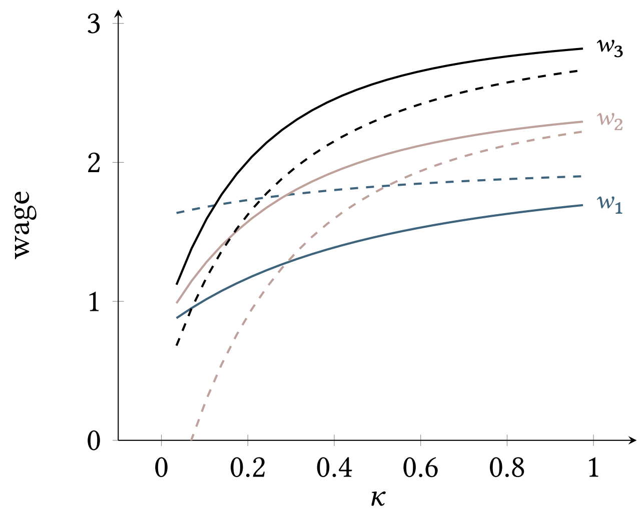


Figure 7: The role of firms' share (σ)
Note: Each profile illustrates the wages in low- (w_1), middle- (w_2) and high-productivity (w_3) firms over the market-friction parameter κ. As κ increases, the model collapses to the perfect competition where employees are awarded with their marginal product. 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

less frictions in the market decrease the incidence of mismatch.

2.2.2 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 the mismatch given the frictions in the labour market. A qualitative illustration of the frictions in a positive continuum, as in figure 8, shows that as frictions reduce (or $\kappa \longrightarrow \infty$), 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* 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.[19]

Figure 9 includes the wage profiles of each worker given their skills-type. In a frictionless market ($\kappa \longrightarrow \infty$), 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

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

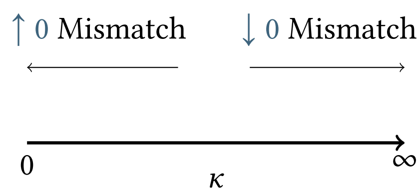


Figure 8: Frictions vs. Mismatch: A qualitative illustration
Note: Market frictions represented as a positive continuum. A greater value of κ reduces the incidence of mismatch, and *vice versa.*
Source: Own elaboration

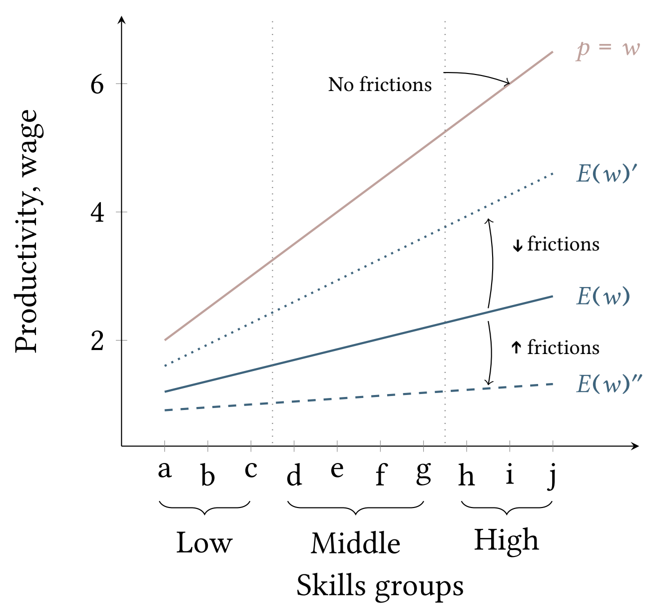


Figure 9: Productivity vs. Expected wages
Note: Let 10 types of firms and 10 types of workers. The steps of the earlier discrete measure's estimation repeated for each skill category. This framework allows to approximate a continuous skills measure. The market segmentation (vertical dotted lines) occurred 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 5. 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

the same parametrization as before, we calculate the expected wage as:

$$E(w) = \frac{1}{1+\kappa} b + \frac{\kappa}{1+\kappa} p \tag{5}$$

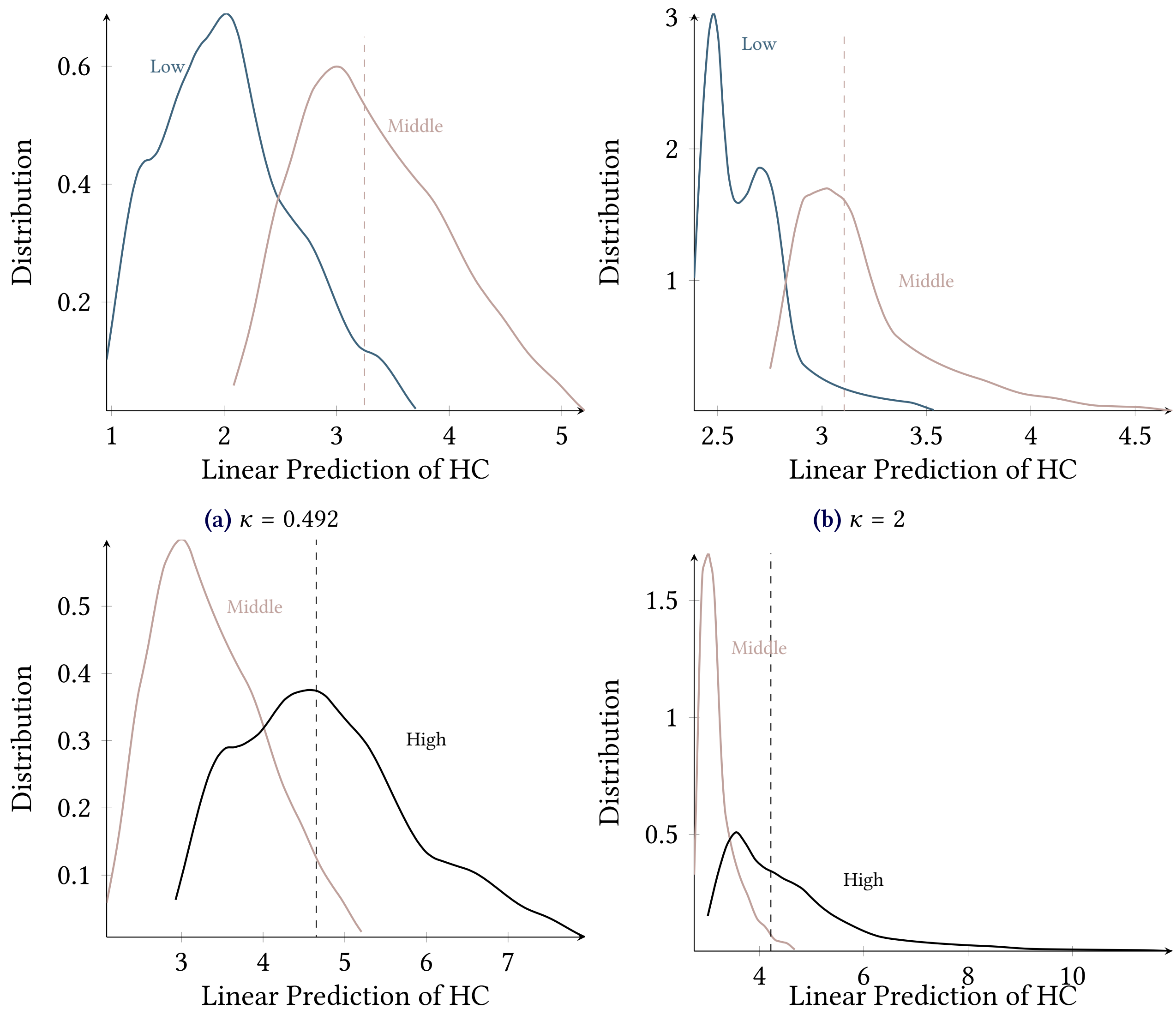
This formula reveals a positive relationship between the frictions the gap from the frictionless model. As κ decreases, the gap rises. In fact, the difference is greater at the top of the skills distribution. This is because there are cases of higher-skilled workers in mismatch. Alternatively, productivity 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. It may suggest that estimates depend on being able to observe productivity. However, it is usually compressed by realised wages due to the mismatch.

Table 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

Figure 10 plots the Kernel densities of the linear prediction of skills. 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.



(a) $\kappa = 0.492$

(b) $\kappa = 2$

(c) $\kappa = 0.492$

(d) $\kappa = 2$

Figure 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

3 Data and Empirical Strategy

From the model, we learn that frictions generate mismatch in the labour market. Yet, additional frictions increase the gap from the perfectly competitive framework the higher we stand on the skills distribution. Therefore, mismatch is a function of search frictions and unobserved productivity. Therefore, we need to measure empirically the incidence of mismatch and question whether frictions can explain the estimates. The measure of mismatch should account for individual heterogeneity in more than one dimension. It should be based on the observed distributions of skills and jobs. Looking at the differentials in returns to education or the instance of mismatch by parental background, we may pick up differences in unobserved productivity. We would expect a decrease of the incidence of mismatch when controlling for individual cognitive and non-cognitive skills. If this is not the case, unobserved worker heterogeneity does not contribute to mismatch. To this end, this section presents the data I employ and the empirical strategy I follow in this paper.

3.1 Data

3.1.1 BHPS/UKHLS

The analysis first 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.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 sample in this paper is confined to those working at least 1 hour per week, aged 23-59 years old in order to abstract from non-random selection into education and retirement. Additionally, self-employed individuals, farmers or those serving in the army and those employees who are currently enrolled in any educational level[20] 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.

3.1.2 BCS70

The final part of this paper 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

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

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 F. From sweeps at age 26 and later, I further use the employment and partnership data to construct the mismatch index as explained below.

3.2 Empirical strategy

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. My multidimensional indicator 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, I question how relative skills change over time.

3.2.1 Identification: Who is mismatched?

"Does an individual hold the appropriate skills to be employed in a better job[21]?" If so, the worker is in mismatch.[22] Attempting to answer this novel[23] question, I overcome any arguments - usually met in the overeducation literature - about an oversupply of the workforce. Instead, I focus on its current composition explaining workers' status as illustrated via their earnings and the returns to education.

Initially, I adopt the Human Capital Theory's assumptions which consider each year of education equally valuable and suggest that education enhances productivity as depicted in wage differentials (Becker, 1964). For instance, to see how human capital varies across different occupations, an estimation of the expanded Mincerian wage equation is performed;

$$\ln[\text{wage}]_{i,t} = \alpha + \beta_1 x_i + \sum_{k=2}^{7} \beta_k S_{i,k,t} + \vartheta_t + u_{i,t} \tag{6}$$

where x_i is a vector of the factors, independent to education, but (cor)related to income, personal and job-specific features; e.g. experience, age, marital status.[24] $S_{i,k,t}$ is the k^{th} attained

[21]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.

[22]In this paper, I will not consider employees' relative position *within* the same occupation accounting for the required level of education or skills.

[23]To the best of my knowledge, so far no theoretical or empirical work tries to explore any type of mismatch following this identification.

[24]Robustness checks included the number of children as additional determinant of skills; the magnitude of mis-

level of education. $\ln[\text{wage}]_{i,t}$ is the logarithm of hourly wages of individual i, in constant prices of 2015. Potential concerns may refer to those unobservable characteristics which may affect earnings (usual suspect could be individual ability or non-cognitive skills). I assume that credentials acquired demonstrate a skillset composed by (innate) individual ability and personal effort to achieve a certain level of education.[25] Besides, the credential effect may bring about earnings premia supporting the idea that higher level of education does not increase productivity directly, but a better educated workforce is prone to be more productive (Patrinos, 2016).

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:

$$\begin{aligned} \text{labour force}_{i,t} = \alpha + \delta_{\mathbf{1}} z_{i,t} + \sum_{n=\mathbf{1}}^{5} \delta_n FS_{i,n,t} + \sum_{j=\mathbf{1}}^{\mathbf{12}} \delta_j \text{ region}_{i,j,t} + \delta_k \mathbf{HHmembers}_{i,t} \\ + \vartheta_t + v_{i,t} \end{aligned} \tag{7}$$

where labour force is a dummy variable, which equals to 1 if the individual is in a paid job or unemployed and 0 otherwise.[26] 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} NUTS 1 statistical region of residence.[27] Finally, **HHmembers** denotes a vector counting for the number of household's

match, though, did not differ significantly.

[25] Heckman et al. (2006) claim that 'sociability', which is strongly related with the grades and schooling abilities affects labour market outcomes. Baum et al. (2008) claim that any individual displacements in the labour market are not unaffected by the social networks. Finally, Deming (2017b), 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.

[26] 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 et al., 2018).

[27] 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 region's dummy. Besides, regional unemployment generally follows the national unemployment rate. However, its deviations among the regions persist for greater

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 et al., 2017; Marelli and Vakulenko, 2016; Addabbo et al., 2015).

The continuity of the wage variable allows an estimation with the Heckman's (?) 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.

3.2.1.1 Identification Algorithm

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

Step 1: Estimate the wage equation 6, corrected for the sample selection bias (eq. 7) 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 D.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.

periods (Lolos and Papapetrou, 2012).

(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,

$$\text{mismatched}_i = \begin{cases} 1 & \text{if } \widehat{w}_i | occ_j > \left(\tilde{\widehat{w}} | occ_{j-\mathbf{1}}\right) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

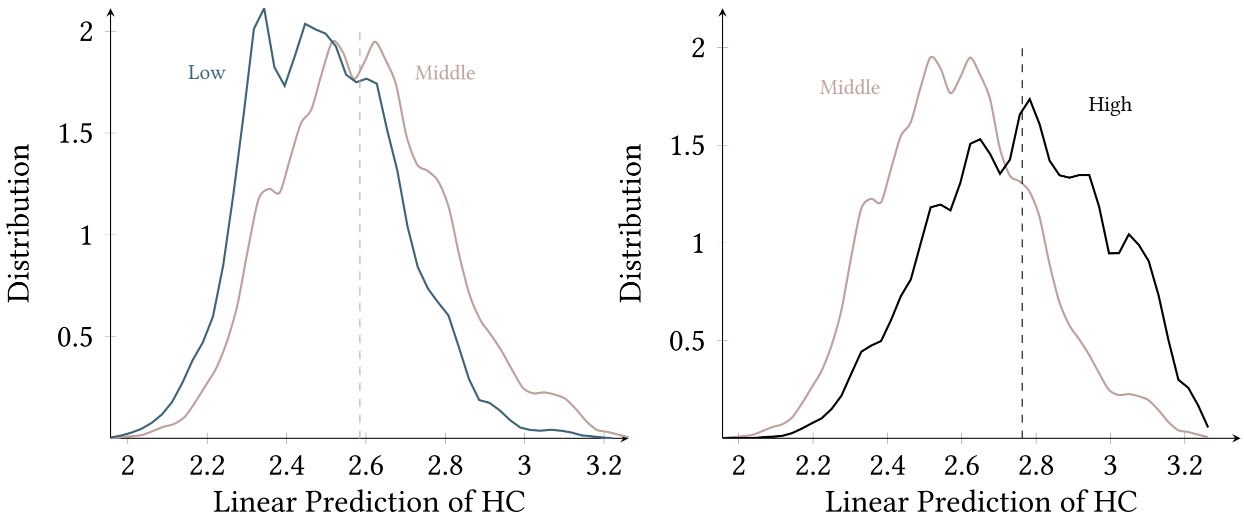
where $\tilde{\widehat{w}}$ is the median of the estimated wages.

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 11).[28] 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.

3.2.2 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

[28] 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 11: 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

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 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.

4 Results - Discussion

4.1 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 the ratio (8.65%; figure 12). 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. In fact, the immediate effect was not only restricted to 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. Only in 2015, the percentage of mismatched workforce returned to the pre-crisis level; thereafter, there was an increase.[29]

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 across 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 the mismatch of men around 2006. Regardless the various definitions used in the 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).

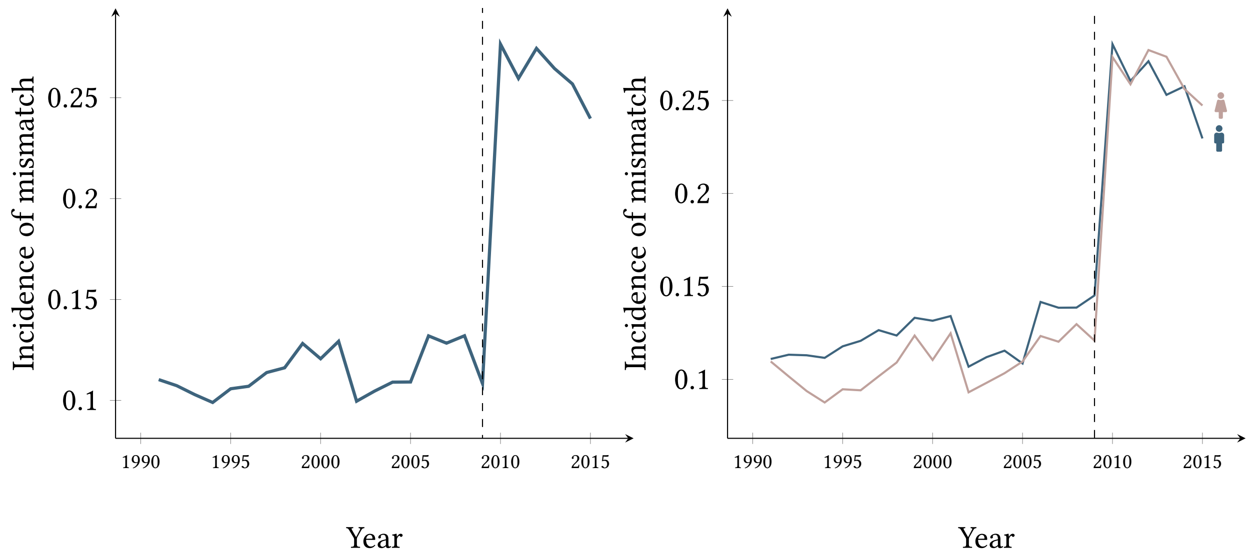
In figure 12, we observe the sudden increase of the incidence after 2009. One the one hand, this can be explained partly by the transition from BHPS to UKHLS and the small number of observations we have for 2009.[30] Postel-Vinay and Sepahsalari (2019) harmonise these two datasets and validate its consistency with equivalent time series by other sources (e.g. 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. The difference, they point out, comes from the different sample composition. On the other hand, recent evidence on labour mobility and earnings support the idea of the recession's impact.

4.2 Transitions and Occupational Mobility

Table 4 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 the non-matched, and *vice versa.* The main diagonal has been intentionally omitted to pay attention to the occupational transitions. The stagnation in the same set of jobs is not part of this study. Yet, by this way, the role of over-time change

[29] 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.

[30] 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.



(a) Total population

(b) Pooled by gender

Figure 12: 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

of relative skills is revealed. Firstly, those who were occupied in a high-skilled position are allowed, by assumption, to a downward mobility. 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 to 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 finding a better job. 2.66% accept a subjacent job and are currently matched. Around 24% of the British employees (or roughly 400 in our sample) suffer from mismatch. The promotion case might be more obvious than the latter one; those who moved from the middle to the low 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 a lower occupation. Alternatively, it may imply a skills atrophy or potential lost opportunities for training[31] (McGuinness et al., 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 matched in both periods given that their stock of HC exceeded the median worker in a more skilled group.

[31] 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 (see ch. 2).

Table 4: 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

However, upgrading[32] 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 instance is moving across the occupational groups. As a result, a twofold reasoning can explain this change. Firstly, employees can find jobs where their profile is a better fit to the needs; alternatively, the efficiency is restored since the supply meets the demand. Secondly, the workforce's 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.

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

4.3 Mismatch in BCS70

Figure 13 reports the incidence of mismatch for the BHPS and cohort members. To alleviate sample sizes concerns, I treat the cohort members as participants of the BHPS. 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 are common between figures 13a and 13b. Their difference regards the incidence reported from BHPS. In, figure 13a, BHPS reports the mismatch for a particular year and only for those who share the same age with the BCS70 participants. This allows to see any particular issues in the labour market within a certain year. However, it may not be an accurate comparison, because workers in a given age may face certain frictions which attenuate over time. For example, Galanakis (2021) 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 13b reports the average incidence for a given age, to make a direct comparison with BCS70.

The main contribution of this paper is the control for the unobserved productivity through the cognitive and non-cognitive skills throughout childhood. The rightmost bar of figure 13 shows the magnitude of mismatch in BCS70 when accounting for the test scores. The incidence does not fluctuate much over the years for this particular cohort; instead, it remains constant around 18%. This might be explained if one looks at the mobility between match and mismatch status. Table 5 summarises the transition rates between two consecutive sweeps. The majority of those born in 1970 does not move to a better job.[33] 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 5: 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 sweeps. Each sweep is 4 years apart, i.e. transitions are calculated between $t - 4$ and t.
Source: Own elaboration, based on BCS70

[33]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.

To show the significance of skills in the 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 figure 13. From the graph, one can notice that controlling for the unobserved productivity, the incidence increases. If it is important tool in the matching process, controlling for skills would result in more people being in match and lower incidence of mismatch. For the validity of this argument, we need to compare these estimates with earlier ones based on BHPS. If estimates coming from the two datasets are close, mismatch is not driven by just unobserved individual skill heterogeneity. This is why, I compare the two leftmost bars. Both employ the same identification of mismatch - namely, they only control for the level of education. Maintaining a constant definition of education and same occupation classification, the comparison is possible. 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. This may stem from some data noise.

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 between BCS70 commonly identified with BHPS occurs here. Estimates 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.

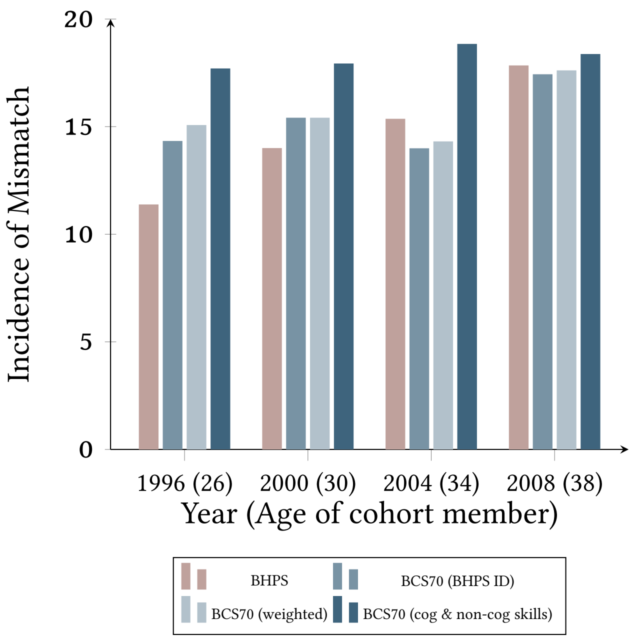
Therefore, figure 13 supports the argument that individuals may be in mismatch not due to their skills. This also holds if one looks at either women (appendix G.1) or men (appendix G.2). Women follow the pattern of the overall population. Estimates for men are slightly higher when controlling for skills.

4.3.1 Robustness Check 1: Differences in Skills by mismatch

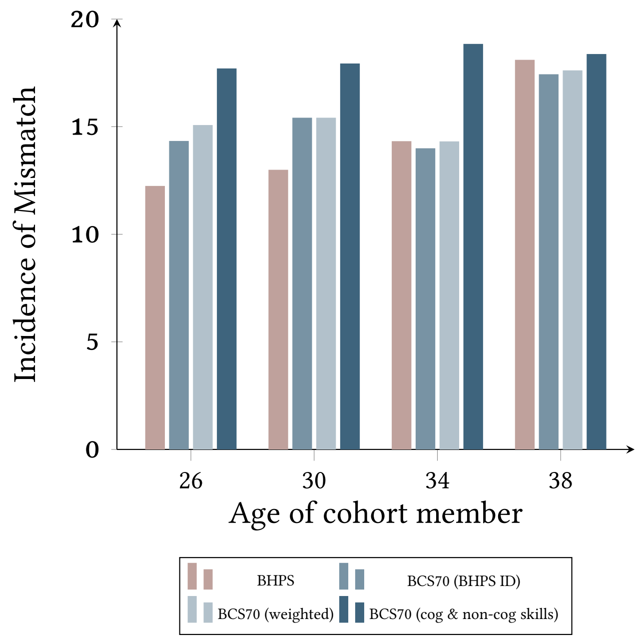
To further validate the aforementioned argument, I show that those in mismatch do not have significantly lower cognitive and non-cognitive skills than those in match. This is consistent among degree and non-degree holders.

Table 6 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



(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 13: Incidence of mismatch: Overall population
Source: Own elaboration based on BHPS and BCS70

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,[34] 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.

4.3.2 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.[35] From the PCA, we take the (i) eigenvalues for each component, (ii) the difference in eigenvalue size between 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 whom we can inspect exactly how each variable loaded onto each component. The coefficients on each variable are the linear combinations that make up the each component.

The first 2 out of 15 components explain the major variation. This is why figure 15 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.

Here, we are interested in how the model performs in predicting out-of-sample variation.

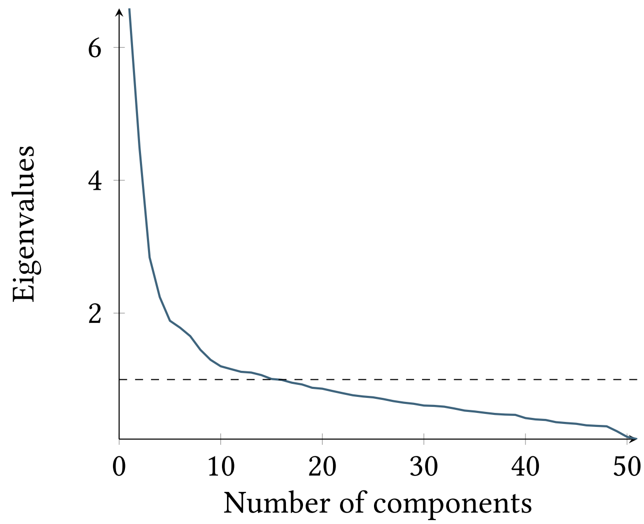
[34]All the non-cognitive skill test scores have been included to inform about differences each may have.
[35]The correlation matrix is available upon request.

Table 6: Differences in skills, by mismatch and degree

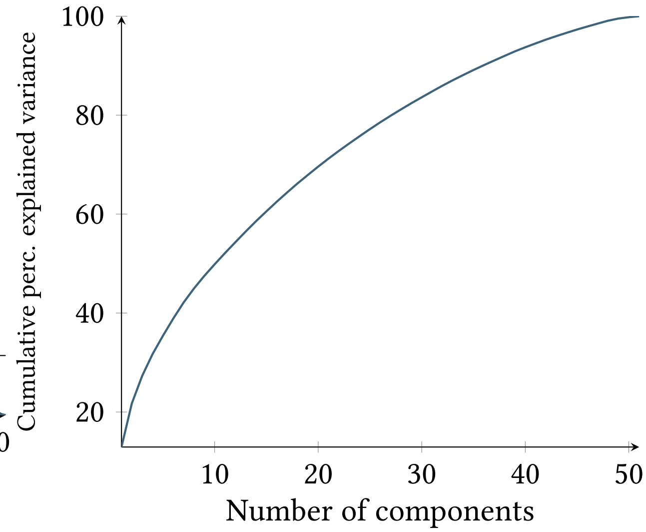
	Degree							non-Degree						
	Mismatch		Match					Mismatch		Match				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error	Mean	Std. Dev.	Mean	Std. Dev.	Diff.		Std. Error
I. Non-Cognitive Skills														
Maternal Malaise Score	2.0342	1.8705	1.4905	1.7098	-0.5437	***	0.1825	2.1450	1.9116	2.0748	1.9428	-0.0702		0.1265
Combined non-cognitive skills	17.3162	3.4558	17.2119	3.2487	-0.1043		0.3444	15.7398	3.5132	15.8895	3.4223	0.1497		0.2241
(bin) Complains of headaches	0.8718	0.3358	0.8762	0.3298	0.0044		0.0346	0.9071	0.2909	0.9003	0.2996	-0.0067		0.0195
(bin) Complains of stomach-ache or has vomited	0.9402	0.2382	0.9548	0.2081	0.0146		0.0225	0.9554	0.2068	0.9014	0.2982	-0.0540	***	0.0188
(bin) Has temper tantrums (that is, complete loss of temper with shouting, angry	0.8974	0.3047	0.8929	0.3097	-0.0046		0.0323	0.8848	0.3199	0.8862	0.3176	0.0015		0.0207
(scl) Very restless. Often running about or jumping up and down. Hardly ever sti	29.2222	27.0010	26.7857	27.4643	-2.4365		2.8606	35.4684	30.9322	31.6771	29.3382	-3.7913	**	1.9282
(scl) Is squirmy or fidgety	26.0085	24.9667	24.5190	25.3828	-1.4895		2.6441	30.2491	29.3864	27.4827	27.4892	-2.7664		1.8102
(scl) Often destroys own or others belongings	9.6410	9.0110	10.1548	9.1939	0.5137		0.9570	12.8216	15.4223	11.4534	11.2676	-1.3681	*	0.7750
(scl) Frequently fights with other children	10.8120	9.2438	12.2929	11.6107	1.4809		1.1646	15.5948	18.0909	15.3407	16.7228	-0.2541		1.1031
(scl) Not much liked by other children	11.1709	10.6547	12.9738	14.7820	1.8029		1.4626	13.5799	16.7621	14.2719	16.1113	0.6920		1.0569
(scl) Often worried, worries about many things	32.4786	25.5071	34.8714	30.2101	2.3928		3.0582	26.0781	25.0480	32.8326	28.4759	6.7545	***	1.8315
(scl) Tends to do things on his/her own â€“ rather solitary	27.0085	25.3198	32.5500	28.7576	5.5415	*	2.9321	24.6766	25.9759	29.5320	27.9696	4.8554	***	1.8094
(scl) Irritable. Is quick to fly off the handle	27.1795	25.5500	24.5595	23.9532	-2.6200		2.5411	30.3271	28.9859	30.1468	28.9561	-0.1803		1.8900
(scl) Often appears miserable, unhappy, tearful or distressed	14.2991	10.1313	16.8357	16.3376	2.5366		1.5898	14.2565	12.8454	18.6116	19.5472	4.3551	***	1.2289
(scl) Sometimes takes things belonging to others	9.4957	8.7844	10.4643	9.1730	0.9686		0.9503	12.6394	15.7089	11.9030	12.4906	-0.7364		0.8447
(scl) Has twitches, mannerisms or tics of the face or body	10.1282	12.9552	11.7119	13.9947	1.5837		1.4401	11.4647	14.0947	11.8944	13.6331	0.4297		0.8936
(scl) Frequently sucks thumb or finger	23.1197	30.0661	21.1595	27.0503	-1.9601		2.8990	16.8216	23.7424	22.3564	28.1819	5.5349	***	1.8050
(scl) Frequently bites nails or fingers	19.1966	25.0239	30.6762	32.6811	11.4796	***	3.2596	21.8401	27.5668	34.0022	34.1637	12.1620	***	2.1797
(scl) Is often disobedient	18.8547	15.8958	18.3024	17.5877	-0.5523		1.8017	21.9628	22.0223	23.9187	22.5951	1.9559		1.4699
(scl) Cannot settle to anything for more than a few moments	16.2650	19.1236	16.1786	18.7993	-0.0864		1.9726	23.1822	23.6899	21.2784	22.6596	-1.9037		1.4875
(scl) Tends to be fearful or afraid of new things or new situations	25.6239	24.7873	28.3762	26.4282	2.7523		2.7264	19.2528	19.8333	28.3115	27.9380	9.0587	***	1.7650
(scl) Is over fussy or over particular	16.8632	17.7117	22.5000	24.2752	5.6368	**	2.4056	27.2156	27.8368	27.3879	27.6616	0.1723		1.8067
(scl) Often tells lies	13.0085	13.7122	14.7857	14.4462	1.7772		1.4939	17.8290	18.6816	16.2053	15.8142	-1.6237		1.0576
(scl) Bullies other children	10.3846	9.0113	11.8929	10.6637	1.5082		1.0796	14.8810	17.0386	13.3521	13.2306	-1.5289	*	0.8988
Tried smoking (16)	0.5664	0.4978	0.4853	0.5004	-0.0811		0.0531	0.5744	0.4955	0.6201	0.4855	0.0457		0.0334
Tried alcohol (16)	0.9636	0.1880	0.9175	0.2755	-0.0461	*	0.0279	0.9505	0.2175	0.9422	0.2335	-0.0083		0.0166
Alcohol in past week (16)	0.7568	0.4310	0.6841	0.4655	-0.0727		0.0491	0.7205	0.4497	0.7253	0.4465	0.0048		0.0315
Ever been drunk (16)	0.5046	0.5023	0.4557	0.4987	-0.0489		0.0540	0.5864	0.4936	0.6380	0.4807	0.0516		0.0347
Porn in past month (16)	0.1947	0.3977	0.1940	0.3959	-0.0007		0.0423	0.2944	0.4568	0.3394	0.4736	0.0450		0.0344
Had sex (16)	0.1261	0.3335	0.1567	0.3640	0.0306		0.0383	0.3304	0.4714	0.3159	0.4650	-0.0144		0.0332
Tried drugs (16)	0.0729	0.2614	0.0685	0.2531	-0.0044		0.0297	0.0649	0.2470	0.0540	0.2262	-0.0108		0.0181
Tried cannabis (16)	0.0417	0.2009	0.0475	0.2130	0.0058		0.0245	0.0276	0.1643	0.0332	0.1792	0.0056		0.0142
Read book for pleasure in past week (16)	0.8073	0.3962	0.7262	0.4465	-0.0812	*	0.0470	0.5911	0.4927	0.5471	0.4979	-0.0440		0.0354
Damaged other's property in past year (16)	0.0526	0.2245	0.0498	0.2180	-0.0028		0.0256	0.1576	0.3654	0.1143	0.3184	-0.0433	*	0.0258
Shoplifted >£5 in past year (16)	0.0323	0.1776	0.0563	0.2308	0.0240		0.0259	0.0378	0.1913	0.0722	0.2590	0.0344	*	0.0199
II. Cognitive Skills														
English Picture Vocabulary Test (y5)	0.7693	0.9755	0.5307	0.9190	-0.2387	**	0.0974	0.4572	0.8692	0.0468	0.9211	-0.4104	***	0.0597
Copying Designs Test (5y)	0.7729	0.8553	0.6590	0.8903	-0.1139		0.0923	0.3578	0.9271	0.0408	0.9535	-0.3170	***	0.0620
Human Figure Drawing Test (y5)	0.4302	1.1022	0.4370	1.0384	0.0068		0.1100	0.0378	0.9143	0.0280	0.9220	-0.0099		0.0601
PLCT (y10)	0.6855	0.1119	0.6764	0.0882	-0.0091		0.0098	0.6424	0.0904	0.6048	0.0934	-0.0376	***	0.0061
FMT (y10)	0.7994	0.1073	0.7785	0.1237	-0.0209	*	0.0126	0.7124	0.1262	0.6107	0.1499	-0.1018	***	0.0096
SERT (y10)	0.8051	0.1253	0.7875	0.1401	-0.0176		0.0143	0.7068	0.1590	0.6459	0.1670	-0.0609	***	0.0108
Reading (y16)	0.7563	0.3095	0.7326	0.3255	-0.0237		0.0337	0.7120	0.2644	0.6040	0.3005	-0.1080	***	0.0193
BAS (similarities; y10)	0.7869	0.1102	0.7897	0.0961	0.0027		0.0104	0.7280	0.1385	0.7211	0.1120	-0.0069		0.0076
BAS (matrices; y10)	0.7563	0.1785	0.7660	0.1353	0.0097		0.0152	0.7077	0.1570	0.6734	0.1549	-0.0344	***	0.0101
BAS (Recall of digits; y10)	0.7814	0.1139	0.7543	0.1327	-0.0271	**	0.0135	0.7545	0.1219	0.7211	0.1214	-0.0334	***	0.0079
BAS (Word Definitions; y10)	0.6052	0.1230	0.5717	0.1022	-0.0335	***	0.0112	0.5101	0.1220	0.4618	0.1112	-0.0483	***	0.0073
Spelling (y10)	0.8269	0.2011	0.8386	0.1396	0.0117		0.0162	0.7561	0.2222	0.7445	0.1946	-0.0116		0.0129
Spelling (y16)	0.8526	0.1807	0.8488	0.1589	-0.0038		0.0171	0.7848	0.2286	0.7511	0.2592	-0.0337	**	0.0167
Arithmetic scores (y16)	0.8041	0.2816	0.7639	0.3237	-0.0402		0.0329	0.7723	0.2662	0.7123	0.3024	-0.0600	***	0.0195
Vocabulary scores (y16)	0.6929	0.1481	0.6727	0.1517	-0.0202		0.0158	0.5835	0.1674	0.5169	0.1911	-0.0666	***	0.0123
Numeracy MC and OR assessment	0.8273	0.2005	0.9230	0.0828	0.0958	***	0.0299	0.8348	0.1293	0.7564	0.1645	-0.0784	***	0.0189

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

To do so, we employ the k-fold cross-validation.[36] 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 16 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 for the prediction of out-of-sample observation, 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;

[36] We split the data in $k = \mathbf{10}$ parts. The first part will be a test dataset while the $k - \mathbf{1}$ 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.

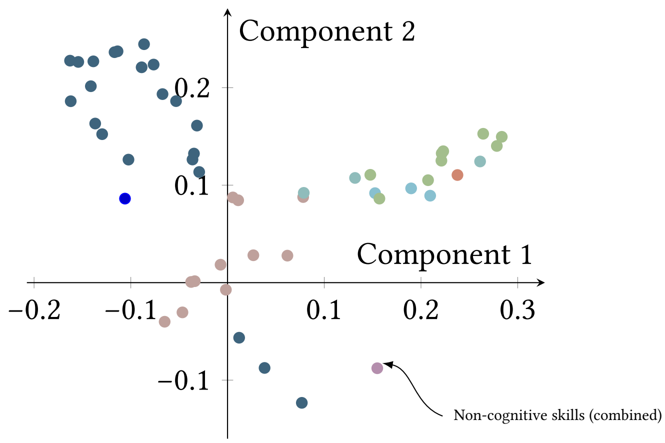


Figure 15: Loading plot

Note: Overall Kaiser-Meyer-Olkin measure of sampling adequacy 0.8046 for both cognitive and non-cognitive test scores. Colours correspond to different test scores categories; dark blue: Child behavioural measures (in Rutter scale); red: Non-cognition in age 16; light blue: cognition in age 5; green: cognition in age 10; petrol: cognition in age 16; orange: cognition in age 30. Purple: combines all non-cognitive skills similar to Attanasio et al. (2020).

Source: Own elaboration based on BCS70

the number of components is not correlated to the dependent variable.

Appendix H includes estimates of eigenvalues and cumulative explanatory power by number of principle components and the loading plot for only cognitive and only non-cognitive skills. 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 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.

5 Conclusion

This papers presents a structural search-and-matching model akin to Burdett and Mortensen (1998) with on-the-job search. Its extension allows for a heterogeneity in worker skills and in firm productivity. People search in the same labour market. If they are low-skilled, their alternatives are not to work (OoW), 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.

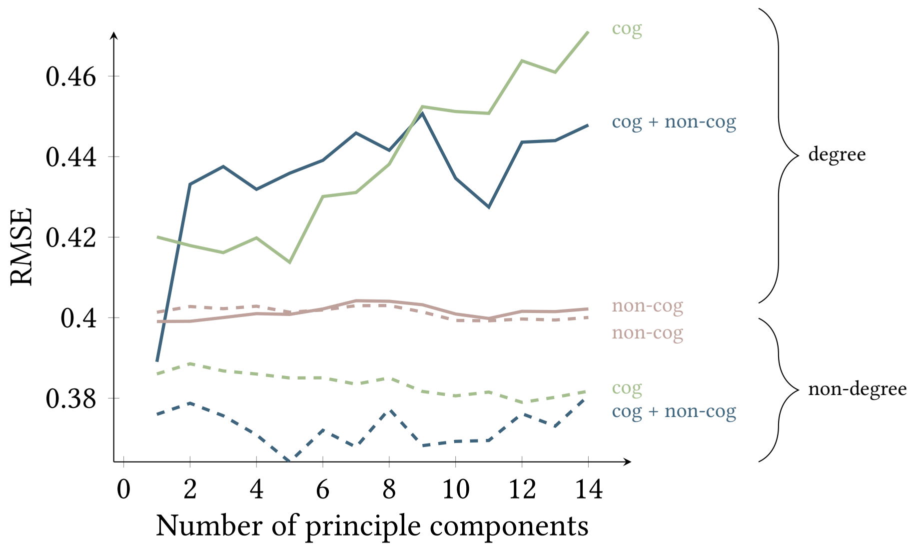


Figure 16: RMSE of regressions with number of principle components
Note: Solid line presents estimates for those who hold a degree, while dashed line for those who do not have a degree. When controlling for both cognitive and non-cognitive skills, 1 component is sufficient for those with degree, but 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 based on BCS70

Having simulated the market (offers) and wage distributions in the economy and the labour supply curve, I have estimated the incidence of mismatch. 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" for the mismatch.

To better approximate the data, I have replicated the same exercise assuming ten types of workers and firms. In this case I segmented 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.

Empirically, I have estimated the instance of mismatch using the BHPS/UKHLS and the BCS70 data. Using the BHPS/UKHLS, the incidence of mismatch 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. Mismatch 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, the incidence of mismatch 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.

Finally, I have used a richer index of human capital including 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 earlier estimates from the BHPS, we have noticed 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. 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 BHPS may not fully capture the 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.

Policy implications should regard the efficient allocation of workers in the market. To this end, the paper stresses the importance of policies for groups of people who suffer the most from frictions in the market. For example, 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 female labour market affiliation. It is not necessarily true that women 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 a person's father is higher skilled, they are more likely to pursue a degree and work in a good job. To this end, first, the policy recommendation stemming from this could regard equal training opportunities for all regardless of their background. This may offer a ticket to higher education for those who do not have the 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 may take any job available. For lower-skilled individuals, this may be translated not only into unemployment but into 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.

References

Abowd, John M, Francis Kramarz, and David N Margolis (1999) "High wage workers and high wage firms," *Econometrica*, 67 (2), 251–333. (Cited on page 5.)

Addabbo, Tindara, Paula Rodríguez-Modroño, and Lina Gálvez-Muñoz (2015) "Young people living as couples: How women's labour supply is adapting to the crisis. Spain as a case study," *Economic Systems*, 39 (1), 27–42, 10.1016/J.ECOSYS.2014.10.003. (Cited on page 24.)

Aghion, Philippe, Antonin Bergeaud, Richard W Blundell, and Rachel Griffith (2019) "The innovation premium to soft skills in low-skilled occupations," *Available at SSRN 3489777.* (Cited on page 5.)

Albrecht, James and Susan Vroman (2002) "A matching model with endogenous skill requirements," *International Economic Review*, 43 (1), 283–305. (Cited on page 3.)

Attanasio, Orazio, Richard Blundell, Gabriella Conti, and Giacomo Mason (2020) "Inequality in socio-emotional skills: A cross-cohort comparison," *Journal of Public Economics*, 104171. (Cited on pages 4, 33, 36, and 55.)

Bagger, Jesper and Rasmus Lentz (2019) "An empirical model of wage dispersion with sorting," *The Review of Economic Studies*, 86 (1), 153–190. (Cited on page 3.)

Banerjee, Abhijit V and Sandra Sequeira (2020) "Spatial Mismatches and Imperfect Information in the Job Search." (Cited on page 2.)

Barth, Erling, Alex Bryson, James C Davis, and Richard Freeman (2016) "It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States," *Journal of Labor Economics*, 34 (S2), S67–S97. (Cited on page 5.)

Baum, Scott, Anthea Bill, and William Mitchell (2008) "Labour Underutilisation in Metropolitan Labour Markets in Australia: Individual Characteristics, Personal Circumstances and Local Labour Markets," *Urban Studies*, 45 (5-6), 1193–1216, 10.1177/0042098008089865. (Cited on page 23.)

Becker, GS (1964) *Human capital: A theoretical and empirical analysis, with special reference to education*, 412. (Cited on page 22.)

Bobba, Matteo, Luca Flabbi, and Santiago Levy (2018) "Labor market search, informality and schooling investments." (Cited on page 5.)

Bobba, Matteo, Luca Flabbi, Santiago Levy, and Mauricio Tejada (2020) "Labor market search, informality, and on-the-job human capital accumulation," *Journal of Econometrics*. (Cited on page 5.)

Böckerman, Petri, Mika Haapanen, and Christopher Jepsen (2018) "More skilled, better paid: labour-market returns to postsecondary vocational education," *Oxford Economic Papers*, 70 (2), 485–508, 10.1093/oep/gpx052. (Cited on page 23.)

Böhm, Michael J, Khalil Esmkhani, and Giovanni Gallipoli (2020) "Firm Heterogeneity in Skill Returns." (Cited on page 6.)

Bonhomme, Stephane and Gregory Jolivet (2009) "The pervasive absence of compensating differentials," *Journal of Applied Econometrics*, 24 (5), 763–795. (Cited on page 15.)

Bontemps, Christian, Jean-Marc Robin, and Gerard J Van den Berg (2000) "Equilibrium search with continuous productivity dispersion: Theory and nonparametric estimation," *International Economic Review*, 41 (2), 305–358. (Cited on pages 4 and 48.)

Brandolini, Andrea, Piero Cipollone, and Eliana Viviano (2006) "Does the ILO definition capture all unemployment?" *Journal of the European Economic Association*, 4 (1), 153–179. (Cited on page 7.)

Bredtmann, Julia, Sebastian Otten, and Christian Rulff (2017) "Husband's Unemployment and Wife's Labor Supply: The Added Worker Effect across Europe," *ILR Review*, 001979391773961, 10.1177/0019793917739617. (Cited on page 24.)

Burdett, Kenneth and Dale T Mortensen (1998) "Wage differentials, employer size, and unemployment," *International Economic Review*, 257–273. (Cited on pages 3, 4, 5, 6, and 36.)

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin (2006) "Wage bargaining with on-the-job search: Theory and evidence," *Econometrica*, 74 (2), 323–364. (Cited on page 5.)

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline (2018) "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 36 (S1), S13–S70. (Cited on page 5.)

Card, David, Jörg Heining, and Patrick Kline (2013) "Workplace heterogeneity and the rise of West German wage inequality," *The Quarterly journal of economics*, 128 (3), 967–1015. (Cited on pages 3 and 5.)

CEDEFOP (2018) "Insights into skill shortages and skill mismatch learning from Cedefop's European skills and jobs survey,"Technical report, European Centre for the Development of Vocational Training (Cedefop), Luxembourg. (Cited on page 28.)

Chassamboulli, Andri (2011) "Cyclical upgrading of labor and employment differences across skill groups," *The BE Journal of Macroeconomics*, 11 (1). (Cited on pages 3 and 5.)

Coles, Melvyn G and Dale T Mortensen (2016) "Equilibrium labor turnover, firm growth, and unemployment," *Econometrica*, 84 (1), 347–363. (Cited on page 5.)

Conlon, John J, Laura Pilossoph, Matthew Wiswall, and Basit Zafar (2018) "Labor market search with imperfect information and learning,"Technical report, National Bureau of Economic Research. (Cited on page 2.)

Coulter, Steve (2016) "The UK labour market and the 'great recession'," in Myant, Martin, Sotiria Theodoropoulou, and Agnieszka Piasna eds. *Unemployment, Internal Devaluation and Labour Market Deregulation in Europe*, Chap. Chapter 6, 197–227, Brussels, Belgium: European Trade Union Institute. (Cited on page 27.)

DeLoach, Stephen B and Mark Kurt (2018) "On-the-Job search, mismatch and worker heterogeneity," *Journal of Labor Research*, 39 (2), 219–233. (Cited on page 3.)

Deming, David J (2017a) "The growing importance of social skills in the labor market," *The Quarterly Journal of Economics*, 132 (4), 1593–1640. (Cited on page 6.)

Deming, David J. (2017b) "The Growing Importance of Social Skills in the Labor Market," *The Quarterly Journal of Economics*, 132 (4), 1593–1640, 10.1093/qje/qjx022. (Cited on page 23.)

Di Pietro, Giorgio and Andrea Cutillo (2006) "University Quality and Labour Market Outcomes in Italy," *Labour*, 20 (1), 37–62. (Cited on page 24.)

Dolado, Juan J, Marcel Jansen, and Juan F Jimeno (2009) "On-the-job search in a matching model with heterogeneous jobs and workers," *The Economic Journal*, 119 (534), 200–228. (Cited on page 5.)

Flinn, Christopher and Joseph Mullins (2015) "Labor market search and schooling investment," *International Economic Review*, 56 (2), 359–398. (Cited on page 5.)

Galanakis, Yannis (2020) "Female Human Capital Mismatch: An extension for the British Public Sector," working paper, GLO Discussion Paper, GLO DP No. 669. (Cited on pages 15 and 16.)

——— (2021) *Human Capital Mismatch in the British labour market* Ph.D. dissertation, University of Kent. (Cited on pages 30 and 55.)

Gautier, Pieter A and Coen N Teulings (2015) "Sorting and the output loss due to search frictions," *Journal of the European Economic Association*, 13 (6), 1136–1166. (Cited on page 2.)

Green, Francis and Yu Zhu (2010) "Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education," *Oxford Economic Papers*, 62, 740–763, 10.1093/oep/gpq002. (Cited on page 53.)

Greene, William H. (2012) *Econometric analysis*: Prentice Hall, 1188. (Cited on page 23.)

Gunderson, Morley and Philip Oreopolous (2020) "Returns to education in developed countries," in *The economics of education*, 39–51: Elsevier. (Cited on page 5.)

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer (2020) "Multidimensional skill mismatch," *American Economic Journal: Macroeconomics*, 12 (1), 210–44. (Cited on page 3.)

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer (2018) "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 10 (2), 52–85. (Cited on page 5.)

Heckman, James J., Jora Stixrud, and Sergio Urzua (2006) "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24 (3), 411–482, 10.1086/504455. (Cited on page 23.)

Hornstein, Andreas, Per Krusell, and Giovanni L Violante (2011) "Frictional wage dispersion in search models: A quantitative assessment," *American Economic Review*, 101 (7), 2873–98. (Cited on page 2.)

Jones, Stephen RG and W Craig Riddell (1999) "The measurement of unemployment: An empirical approach," *Econometrica*, 147–161. (Cited on page 7.)

——— (2019) "Unemployment, Marginal Attachment, and Labor Force Participation in Canada and the United States," *Journal of Labor Economics*, 37 (S2), S399–S441. (Cited on page 7.)

Joona, Pernilla, Nabanita Gupta, and Eskil Wadensjö (2014) "Overeducation among immigrants in Sweden: incidence, wage effects and state dependence," *IZA Journal of Migration*, 3 (1), 9, 10.1186/2193-9039-3-9. (Cited on page 21.)

Kankaraš, Miloš, Guillermo Montt, Marco Paccagnella, Glenda Quintini, and William Thorn (2016) *Skills matter : further results from the survey of adult skills.*: OECD Publishing. 2, rue Andre Pascal, F-75775 Paris Cedex 16, France. Tel: +33-145-24-8200; Fax: +33-145-24-8500; Web site: http://www.oecd.org, 158, `https://eric.ed.gov/?id=ED567018`. (Cited on page 53.)

Krueger, Alan B and Andreas I Mueller (2012) "The lot of the unemployed: a time use perspective," *Journal of the European Economic Association*, 10 (4), 765–794. (Cited on page 7.)

Lachowska, Marta, Alexandre Mas, and Stephen A Woodbury (2020) "Sources of displaced workers' long-term earnings losses," *American Economic Review*, 110 (10), 3231–66. (Cited on page 5.)

Lindenlaub, Ilse and Fabien Postel-Vinay (2020) "Multidimensional sorting under random search," Working Paper. (Cited on page 6.)

Lolos, Sarantis and Evangelia Papapetrou (2012) "Unemployment disparities and persistence Assessing the evidence from Greek regions, 1981-2008," *Regional and Sectoral Economic Studies*, 12 (1), 69–90. (Cited on page 24.)

Marelli, Enrico and Elena Vakulenko (2016) "Youth unemployment in Italy and Russia: Aggregate trends and individual determinants," *The Economic and Labour Relations Review*, 27 (3), 387–405, 10.1177/1035304616657959. (Cited on page 24.)

Martins, Pedro S. and Pedro T. Pereira (2004) "Does education reduce wage inequality? Quantile regression evidence from 16 countries," *Labour Economics*, 11 (3), 355–371, 10.1016/J.LABECO.2003.05.003. (Cited on page 25.)

McGuinness, Seamus and Konstantinos Pouliakas (2016) "Deconstructing Theories of Overeducation in Europe: A Wage Decomposition Approach." (Cited on page 4.)

McGuinness, Seamus, Konstantinos Pouliakas, and Paul Redmond (2018) "SKILLS MISMATCH: CONCEPTS, MEASUREMENT AND POLICY APPROACHES," *Journal of Economic Surveys*, 1–31, 10.1111/joes.12254. (Cited on pages 4 and 28.)

McGuinness, Seámus (2006) "Overeducation in the Labour Market," *Journal of Economic Surveys*, 20 (3), 387–418. (Not cited.)

Mortensen, Dale (2003) *Wage dispersion: why are similar workers paid differently?*: MIT press. (Cited on pages 4 and 10.)

Moscarini, Giuseppe and Fabien Postel-Vinay (2013) "Stochastic search equilibrium," *Review of Economic Studies*, 80 (4), 1545–1581. (Cited on page 5.)

Papageorge, Nicholas W, Victor Ronda, and Yu Zheng (2019) "The economic value of breaking bad: Misbehavior, schooling and the labor market,"Technical report, National Bureau of Economic Research. (Cited on page 6.)

Papageorgiou, Theodore (2014) "Learning your comparative advantages," *Review of Economic Studies*, 81 (3), 1263–1295. (Cited on page 2.)

Patrinos, Harry Anthony (2016) "Estimating the return to schooling using the Mincer equation," 10.15185/izawol.278. (Cited on page 23.)

Piper, Alan (2015) "Heaven knows I'm miserable now: overeducation and reduced life satisfaction," *Education Economics*, 23 (6), 667–669, 10.1080/09645292.2013.870981. (Cited on page 53.)

Postel-Vinay, Fabien and Jean-Marc Robin (2002) "Equilibrium wage dispersion with worker and employer heterogeneity," *Econometrica*, 70 (6), 2295–2350. (Cited on page 5.)

Postel-Vinay, Fabien and Alireza Sepahsalari (2019) "Labour Mobility and Earnings in the UK, 1992-2016,"Technical report, `https://sites.google.com/site/fabienpostelvinay/working-papers/UKLM_09.pdf?attredirects=0&d=1`. (Cited on page 27.)

Psacharopoulos, George and Harry Anthony Patrinos (2018) "Returns to investment in education: a decennial review of the global literature," *Education Economics*, 26 (5), 445–458. (Cited on page 5.)

Restuccia, Diego and Richard Rogerson (2013) "Misallocation and productivity," *Review of Economic Dynamics*, 16 (1), 1–10, 10.1010/j.red.2012.11.003. (Cited on page 5.)

Robinson, Chris (2018) "Occupational Mobility, Occupation Distance, and Specific Human Capital," *Journal of Human Resources*, 53 (2), 513–551. (Cited on page 28.)

Shimer, Robert and Lones Smith (2000) "Assortative matching and search," *Econometrica*, 68 (2), 343–369. (Cited on page 4.)

Somers, Melline A., Sofie J. Cabus, Wim Groot, and Henriëtte Maassen van den Brink (2019) "Horizontal mismatch between employment and field of education: Evidence from a systematic literature review," *Journal of Economic Surveys*, 33 (2), 567–603, 10.1111/joes.12271. (Cited on page 29.)

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter (2019) "Firming up inequality," *The Quarterly journal of economics*, 134 (1), 1–50. (Cited on page 3.)

Stokes, L., A. Bryson, H. Bewley, and J. Forth (2017) "Older workers and the workplace : evidence from the Workplace Employment Relations Survey," `https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/584727/older-workers-and-the-workplace.pdf`. (Cited on page 53.)

Sulis, Giovanni (2012) "Gender wage differentials in Italy: a structural estimation approach," *Journal of Population Economics*, 25 (1), 53–87. (Cited on page 15.)

Sullivan, Paul and Ted To (2014) "Search and nonwage job characteristics," *Journal of Human Resources*, 49 (2), 472–507. (Cited on page 15.)

Ueno, Koji and Alexandra Krause (2018) "Overeducation, perceived career progress, and work satisfaction in young adulthood," *Research in Social Stratification and Mobility*, 55, 51–62, 10.1016/J.RSSM.2018.03.003. (Cited on page 53.)

UKCES (2014) "The Labour Market Story: The UK Following Recession | Institute for Employment Studies (IES)." (Cited on page 27.)

Uren, Lawrence and Gabor Virag (2011) "Skill requirements, search frictions, and wage inequality," *International Economic Review*, 52 (2), 379–406. (Cited on page 3.)

van den Berg, Gerard J. and Aico van Vuuren (2010) "The effect of search frictions on wages," *Labour Economics*, 17 (6), 875 – 885, https://doi.org/10.1016/j.labeco.2010.08.001. (Cited on page 2.)

Van Reenen, John (1996) "The creation and capture of rents: wages and innovation in a panel of UK companies," *The Quarterly Journal of Economics*, 111 (1), 195–226. (Cited on page 5.)

Verhaest, Dieter and Elsy Verhofstadt (2016) "Overeducation and job satisfaction: the role of job demands and control," *International Journal of Manpower*, 37 (3), 456–473. (Cited on page 53.)

Webb, Michael (2020) "The impact of artificial intelligence on the labor market," *Available at SSRN 3482150*, `https://www.michaelwebb.co/webb_ai.pdf`. (Cited on page 6.)

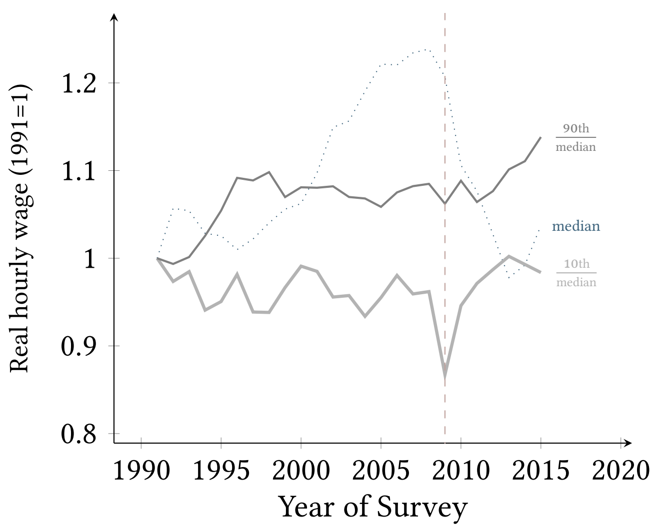
Willis, Robert J and Sherwin Rosen (1979) "Education and self-selection," *Journal of political Economy*, 87 (5, Part 2), S7–S36. (Cited on page 6.)

Yunus, NM (2017) "Sheepskin Effects in the returns to Higher Education: New Evidence for Malaysia," *Asian Academy of Management Journal*, 22 (1), 151–182. (Cited on page 52.)

Zentler-Munro, David (2021) "Rising Wage Inequality: Technological Change and Search Frictions." (Cited on page 2.)

A Wage heterogeneity in the UK

Individuals whose parents are highly educated are more likely to get a degree.[37] Given their degree, they are more likely to get a graduate job, and hence, enjoy greater returns to education. Greater paternal skills allow fathers to provide skills-enhancing resources to their children. If fathers work in a good job, they are exposed to a stronger network which facilitates their offspring's upward mobility. However, there is a wage heterogeneity among the high-skilled workers.[38] In the UK, this inequality seems to widen over time – especially, when looking at the top and bottom 10% of their wage distribution. This suggests that, even though it is important, skill acquisition is not a sufficient condition to guarantee a good job and improve overall productivity. In fact, job allocation can explain this wage heterogeneity relative to skills in the labour market (figure A.1). We can observe this heterogeneity in several dimensions. Figure A.2 shows the wage heterogeneity by gender to highlight gender-related frictions. This paper focuses parental background related frictions. An additional dimension would regard race-related frictions.

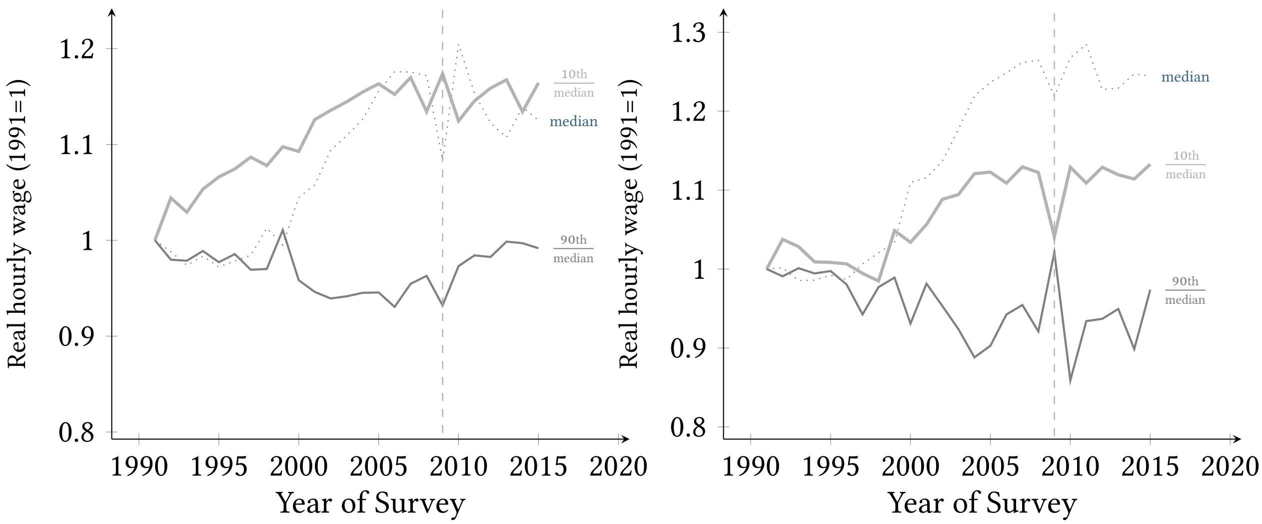


(a) High-skilled

Figure A.1: Wage heterogeneity by skill group: Percentiles ratio of real hourly wage (1991=1)

[37] An analysis to show the likelihood of getting a graduate job by father's education and/or social class using data from the British Cohort Study 1970 is available upon request.

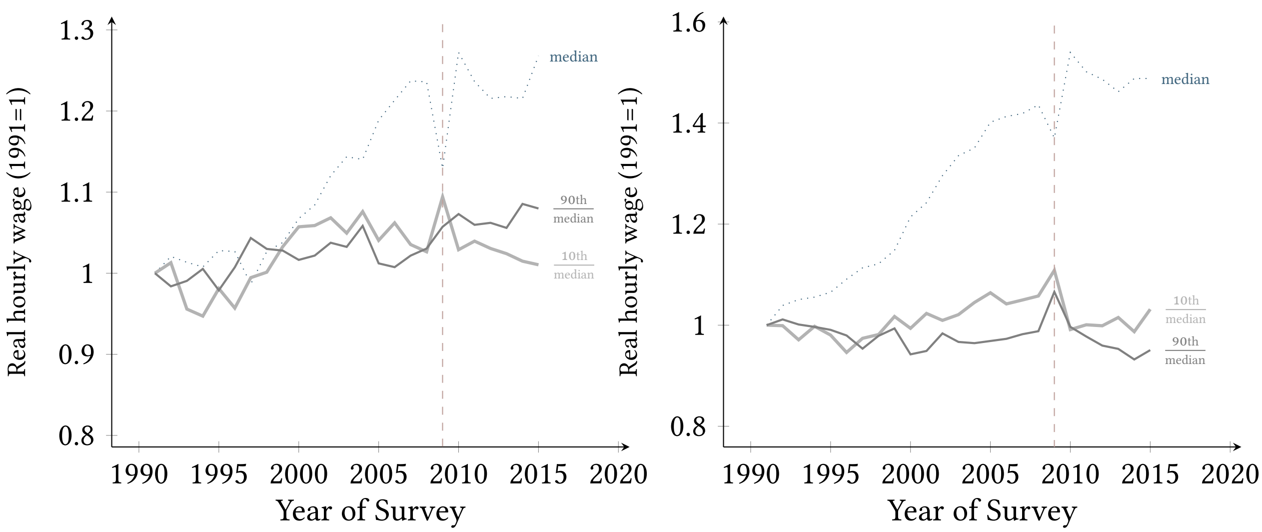
[38] On the contrary, low-skilled individuals may come from a less privileged parental background. Their access to good jobs is limited, but also their wage heterogeneity is smaller.



(b) Middle-skilled **(c)** Low-skilled

Figure A.1: Wage heterogeneity by skill group: Percentiles ratio of real hourly wage (1991=1) (cont.)

Note: Real (CPI Index Deflator; base year 2015) hourly wage of employees aged 23-59. This graph highlights the wage dispersion in the UK. 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



(a) Men **(b)** Women

Figure A.2: Wage heterogeneity by gender: Percentiles ratio of real hourly wage (1991=1)

Note: Real (CPI Index Deflator; base year 2015) hourly wage of employees aged 23-59.
Source: Own elaboration based on BHPS/UKHLS

B Productivity dispersion

Different firms present different productivity levels. To better understand the differentiation between low-, middle- and high- productivity firms, I look at the top and bottom 10% and median of the firm-level labour distribution in the UK. Between 1998 and 2019, the rate of growth of productivity has been 15.42% for the firms at the top (90th percentile) and 30% for those at the bottom (10th percentile). For the firms in the middle, productivity increased only by 3.3%. The dispersion of productivity is the difference between the top (90th percentile) and the bottom (10th percentile). Between 1998 and 2019, the dispersion increased 14.6%. However, at the beginning of the timeseries the top part of the distribution dominates the bottom one. This is not the case after the Great Recession.

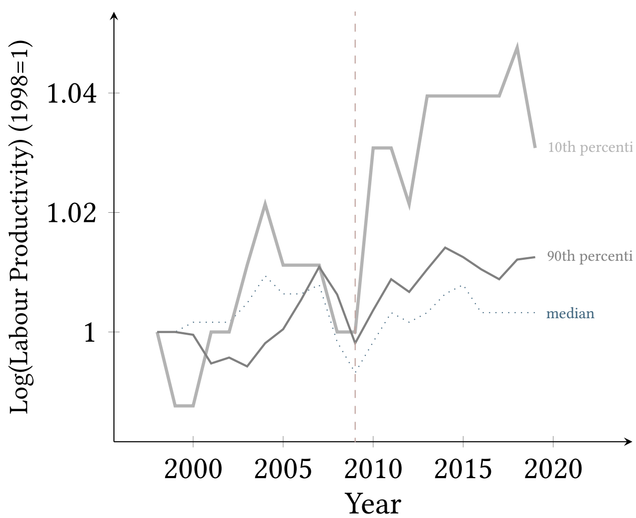


Figure B.1: Productivity heterogeneity in UK economy
Note: This graph shows the increasing dispersion of labour productivity between different firms in the UK 1998-2019. All productivity is indexed to be one in 1998. The lines show the growth in productivity at different parts of the distribution. After the Great Recession, the 'UK productivity puzzle' is observed.
Source: Own elaboration based on Annual Business Survey estimates (ONS, 2022)

C Continuous Firm Productivity

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

$$p = w + \frac{1 + \kappa \widehat{G(w)}}{2\kappa \widehat{g(w)}} \tag{9}$$

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 C.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 firms. Wages increase over these percentiles but smooth out beyond the 75th percentile. Figure C.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 C.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 C.4 looks at the predicted profit rate calculated as

$$\text{Profit Rate} = \frac{p - w}{p} \tag{10}$$

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.

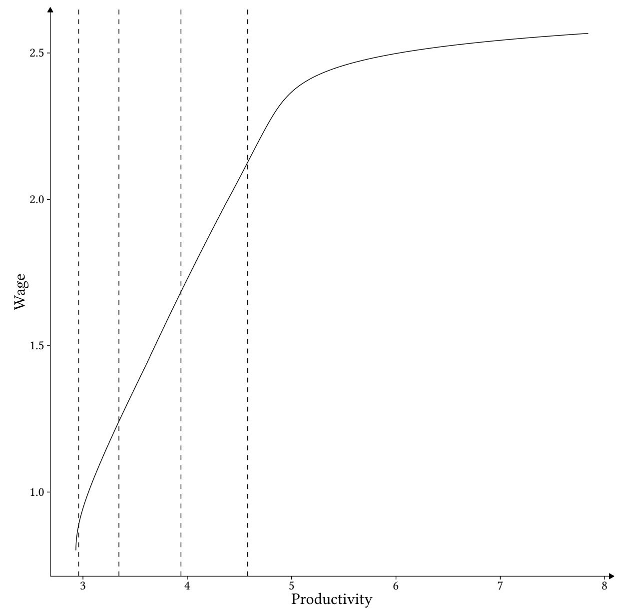


Figure C.1: Quantile-Quantile plot: Wage vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity. A positive relationship between wage and productivity is revealed. Wages increase at the beginning of the productivity distribution, but smooth out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

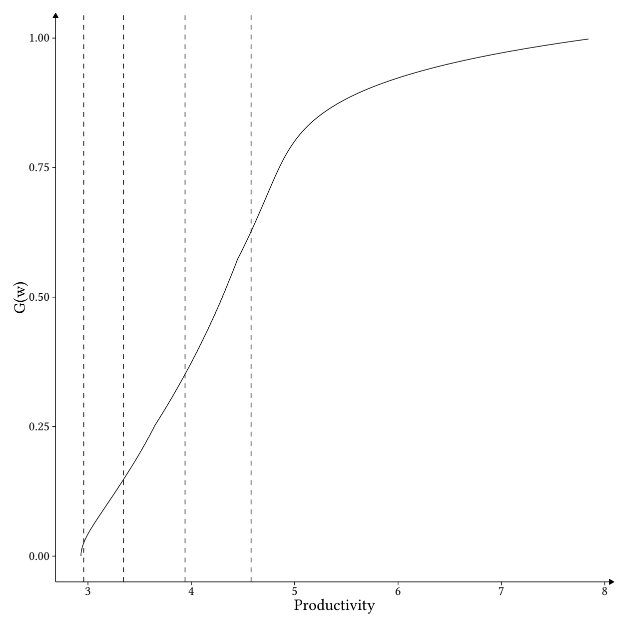


Figure C.2: Quantile-Quantile plot: $G(w)$ vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity. Concavity smooth out beyond the 75th percentile.
Source: Own elaboration

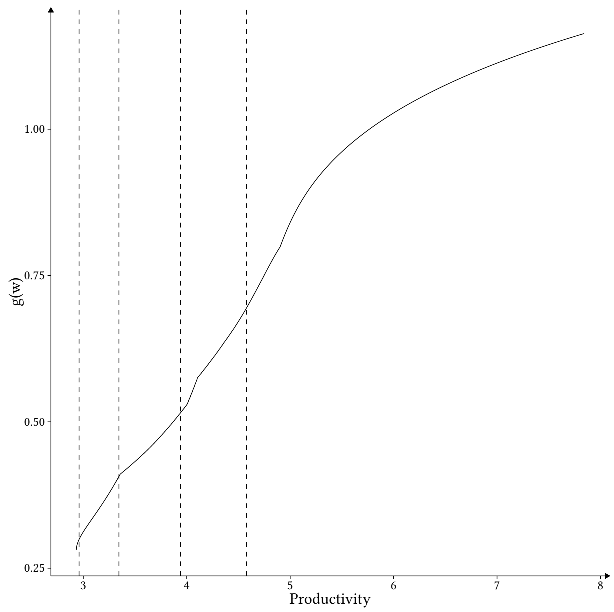


Figure C.3: Quantile-Quantile plot: $g(w)$ vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity.
Source: Own elaboration

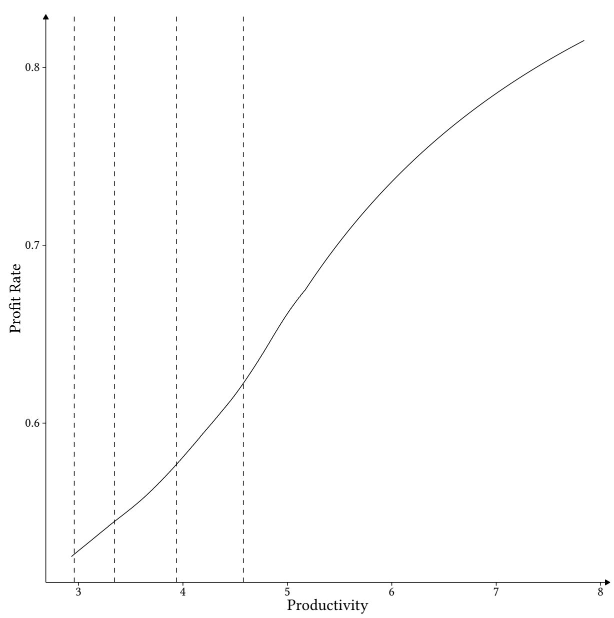


Figure C.4: Quantile-Quantile plot: Profit rate vs. Productivity
Note: Vertical dashed lines represent the 5th, 25th, 50th and 75th percentiles of productivity.
Source: Own elaboration

D Skills, education and occupations

This section presents how I group the different occupations based on skills and education levels.

Table D.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

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

E Measurement Robustness

To explore the robustness of my novel multidimensional index, I test how the magnitude of the 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 E.1 reports the incidence of mismatch annually. In column (1), the pure effect of the educational level on wages is observed. In column (2), controls for age and its square added. Finally, column (3) controls further for marital status. These estimates, in every column, 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 crisis. This way we can show that our measure is more resilient in cohort effects in the labour market.

Finally, scholars declare a negative relationship between the overeducation[39] and job sat-

[39] A comparison of the incidence of overeducation in the UK and this multidimensional measure constructed in

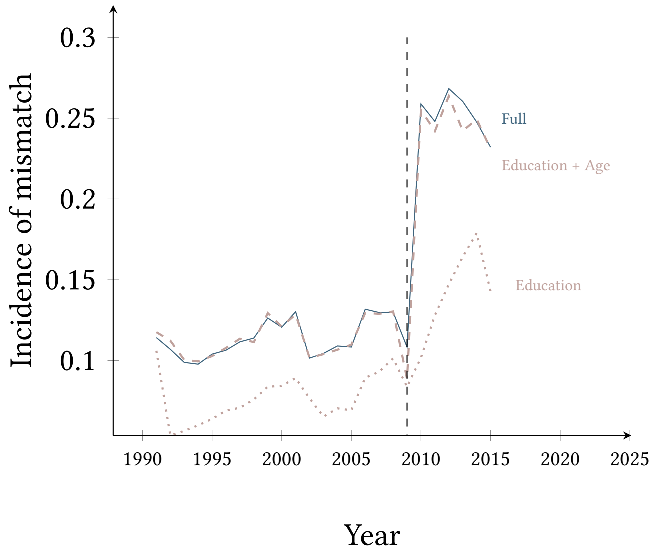


Figure E.1: Robustness Check: Alternative Specifications
Note: This figure presents alternative specifications for the measurement of mismatch. The dashed line shows the effect of education and it reports similar incidence to overeducation measures earlier met in the literature. Having controlled for 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

isfaction (e.g. Ueno and Krause (2018); Stokes et al. (2017); Kankaraš et al. (2016); Verhaest and Verhofstadt (2016); Green and Zhu (2010)). 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 E.2 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.

this paper is available upon request.

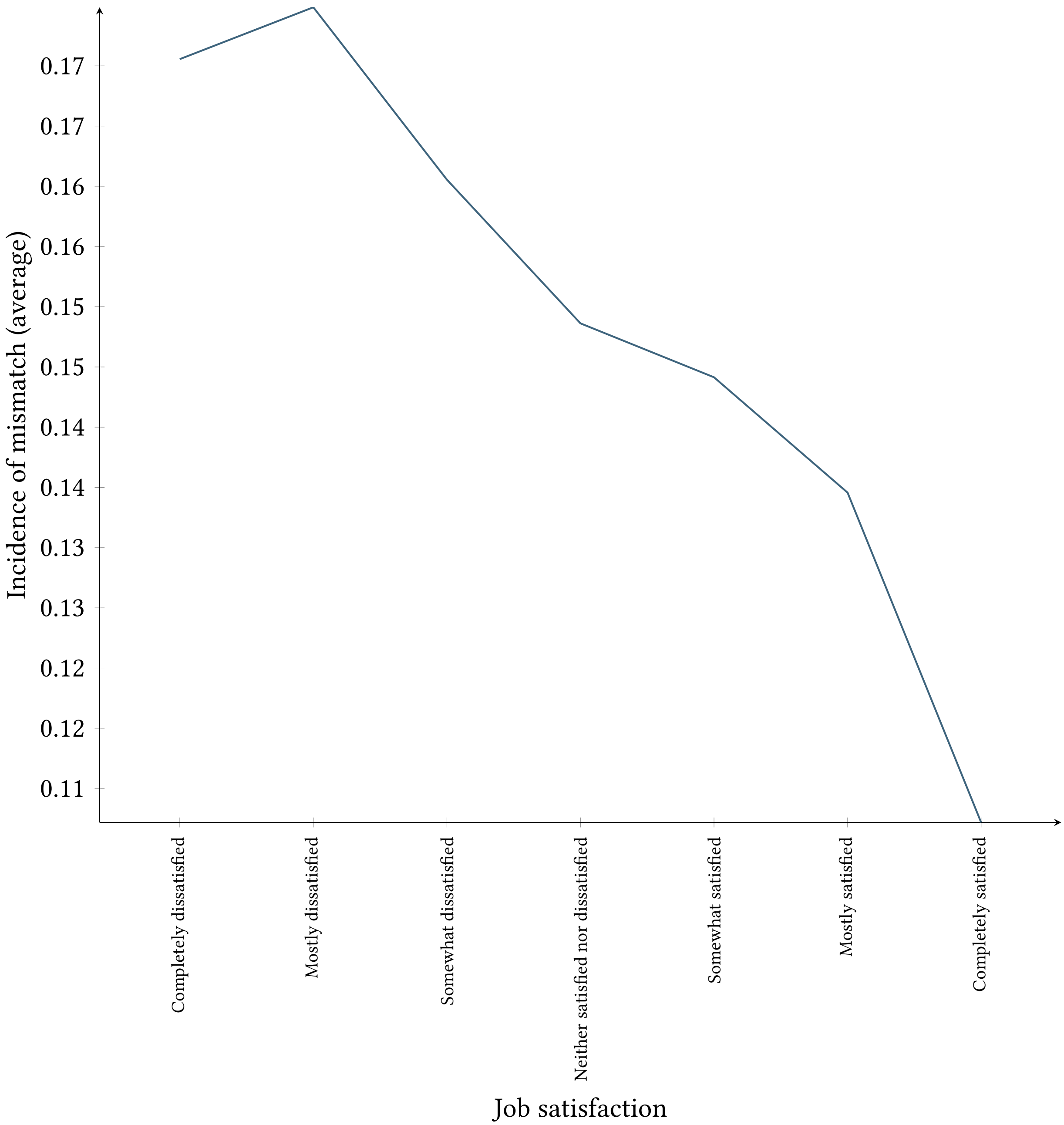


Figure E.2: Mismatch vs. job satisfaction
Note: The figure plots the average level of mismatch against the self-reported job satisfaction level.
Source: Own elaboration based on BHPS/UKHLS

F Test scores for skills

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

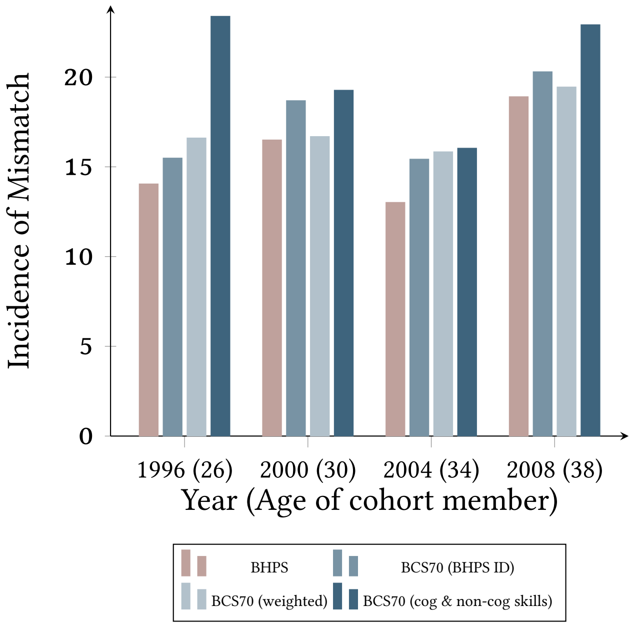
Age	Test
Birth	Mother Malaise
5	Mother Malaise Child Behavioural Measures (on Rutter Scale)
10	Child Behavioural Measures (on Rutter Scale)
16	Questions on: alcohol, drinking, smoking, sex, friends, shoplifting
26	Malaise score

Source: Own elaboration and Attanasio et al. (2020, table A1)

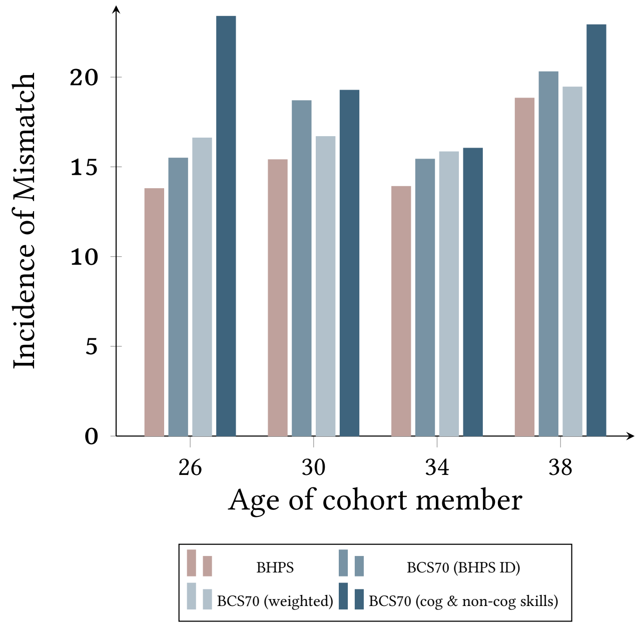
G Incidence of mismatch by gender

G.1 Women

This section replicates the three indices shown in Galanakis (2021) for women. The weighted index here is applied only for the restricted subsample. Available estimates exist for the re-



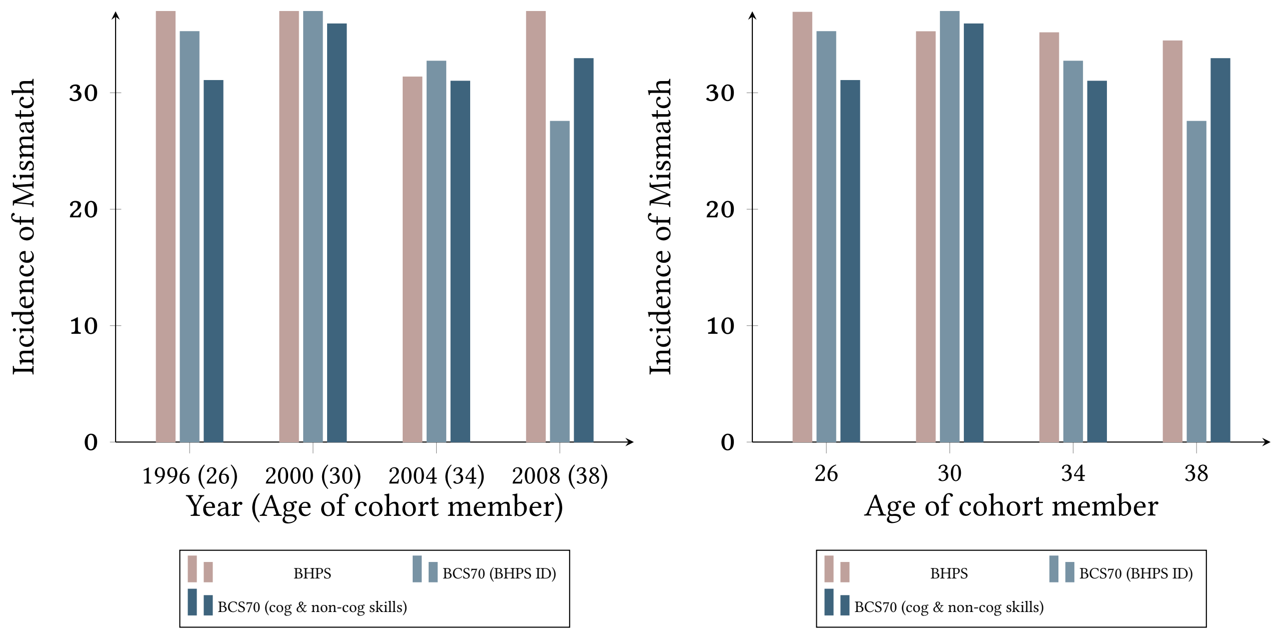
(a) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. 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 G.1: Incidence of mismatch: Women (restricted subsample)
Source: Own elaboration based on BHPS and BCS70

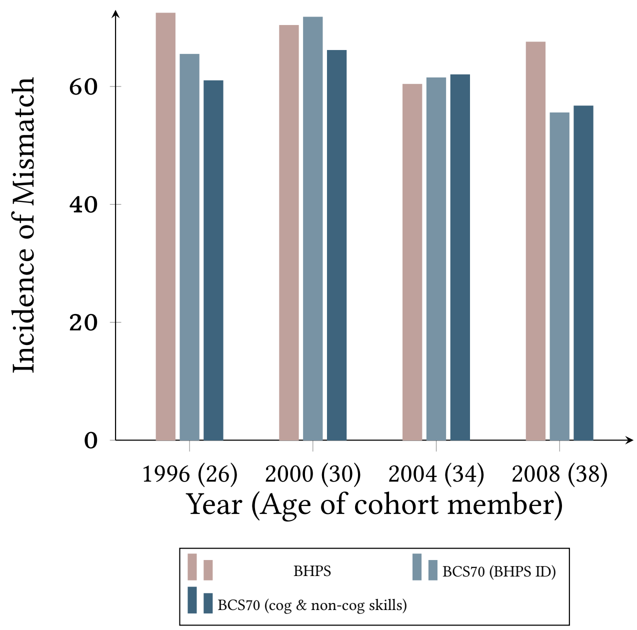
maining exercises, upon request.



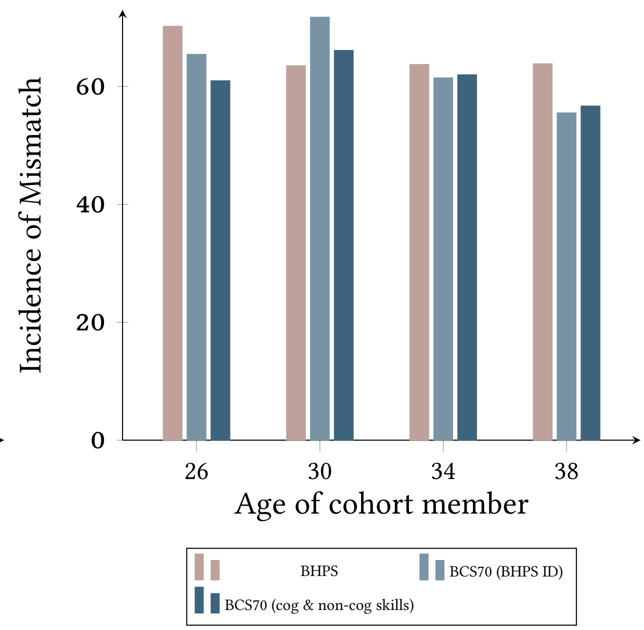
(a) Same year and same age in both samples
Note: BHPS reports the incidence for each particular year and only for those in the same age of the cohort member. BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. 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 G.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.

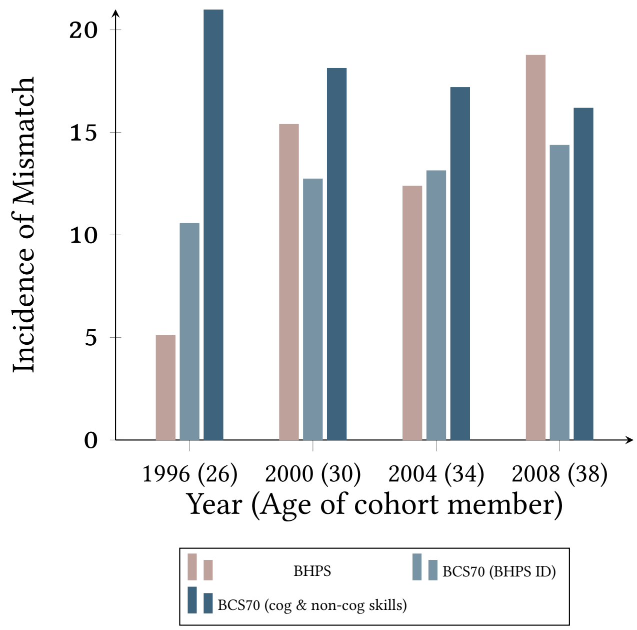


(b) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog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

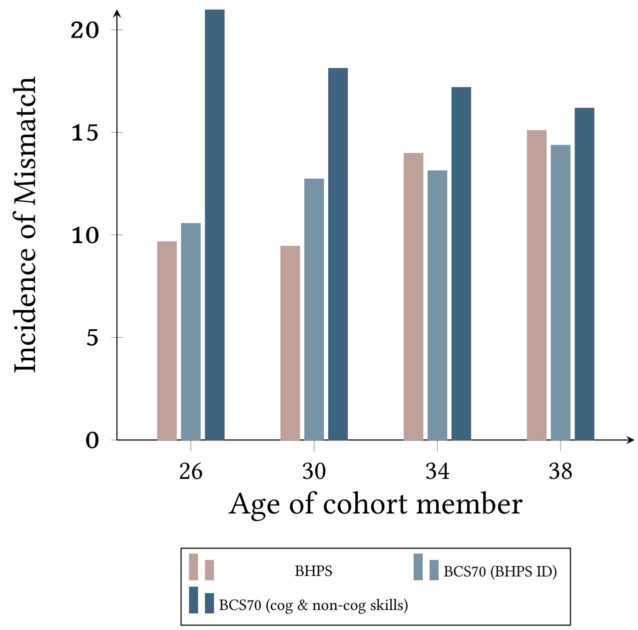
Figure G.3: Incidence of mismatch: Women (counterfactual)
Source: Own elaboration based on BHPS and BCS70

G.2 Men

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



(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.

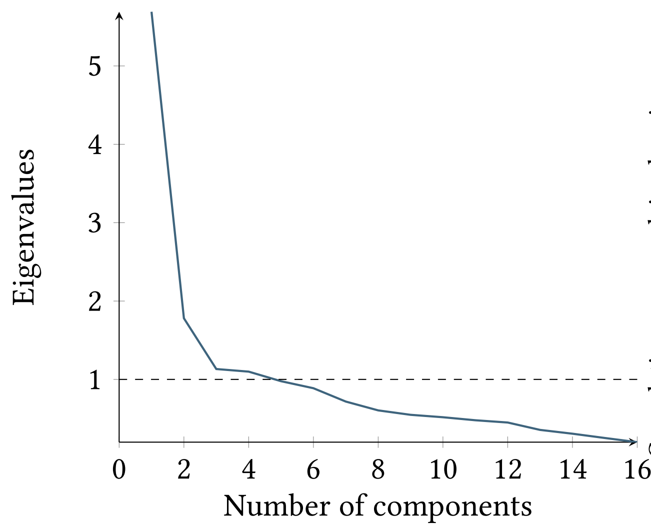


(b) Same age in both samples
Note: BHPS reports the incidence for those in the same age of the cohort member (panel average for each age). BCS70 (BHPS ID) follows the same identification as in BHPS and controls only for education. BCS70 (weighted) reports estimates with BHPS weights. Finally, BCS70 (cog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

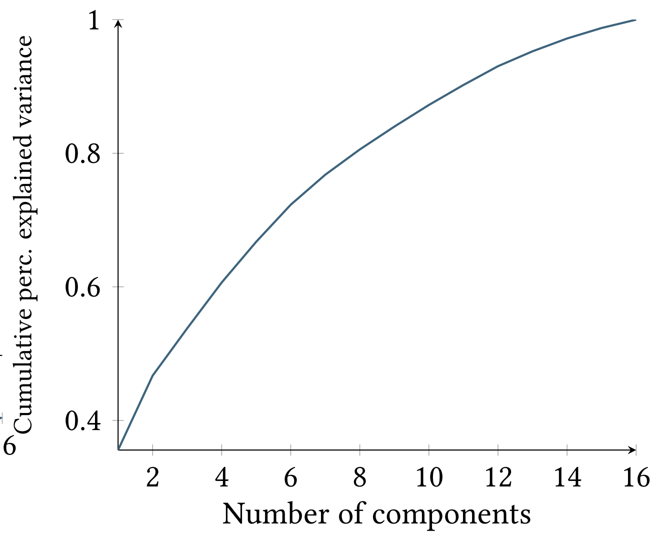
Figure G.4: Incidence of mismatch: Men (restricted subsample)
Source: Own elaboration based on BHPS and BCS70

H Principal Component Analysis by skills

H.1 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 4 components explain, cumulatively, 60.6% of the variation.

Figure H.1: Cognitive skills
Source: Own elaboration based on BCS70

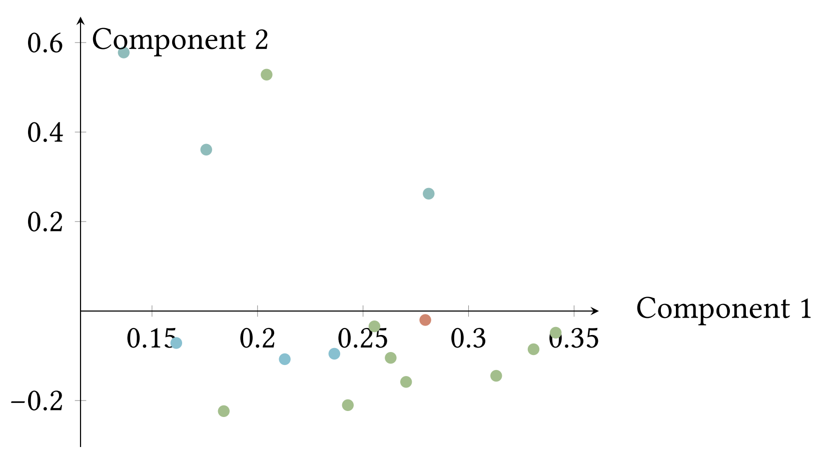
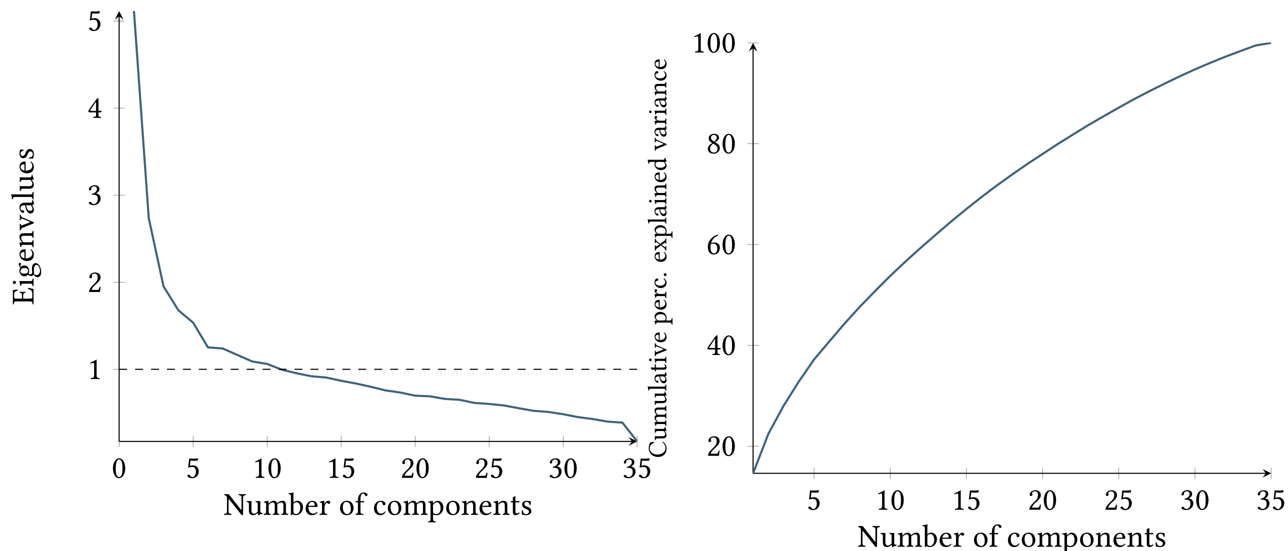


Figure H.2: Loading plot; cognitive skills only
Source: Own elaboration based on BCS70

H.2 Non-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 H.3: Non-cognitive skills
Source: Own elaboration based on BCS70

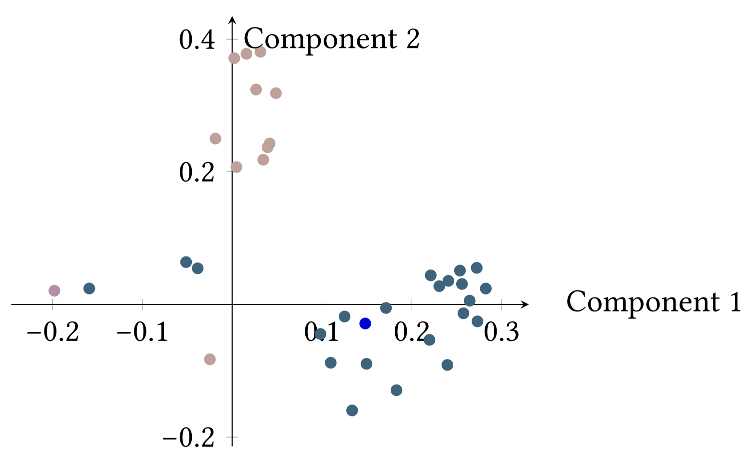


Figure H.4: Loading plot; non-cognitive skills only
Source: Own elaboration based on BCS70