Enabling Data Analytics for Actions Tackling Skills Shortages & Mismatch

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Table of Contents

LIST OF TABLES

ACRONYMS

Acronym	Explanation
ACS	American Community Survey
AES	Adult Education Survey
ALLS	Adult Literacy and Lifeskills Survey
ASVAB	Armed Forces Vocational Aptitude Battery
BIBB	Survey of the Working Population on Qualification and Working Conditions in Germany
BLS	Bureau of Labor Statistics
CEDEFOP	European Centre for the Development of Vocational Training
CEO	Chief executive officer
CHEERS	Children’s Environmental Exposure Research Study
DADS	French matched employer-employee data
DMP	Diamond, 1982; Mortensen and Pissarides, 1994
DOT	U.S. Dictionary of Occupational Titles
DSA	Direct self-assessment
ECHP	European Community Household Panel
ECVT	Encuesta de Calidad de Vida en el Trabajo
EHA	Graduate Survey of the Swiss Federal Statistical Office
ERINI	Priority Skills Unit of the Economic Research Institute of Northern Ireland
ESJS	European Skills and Jobs Survey
EU LFS	European Labour Force Survey
EU-SILC	EU Statistics on Income and Living Conditions
GSOEP	German Socioeconomic Panel

HEGESCO	Higher Education as a Generator of Strategic Competences
HILDA	Household, Income and Labour Dynamics in Australia Survey
IBS	UK International Benchmarking Survey
ICT	Information and Communication Technology
INPS	Istituto Nazionale della Previdenza Sociale
ISA	Indirect self-assessment
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
ISTAT	National Statistical Italian Centre
JA	Job Analysis
JAQ	Job Allocation Quality
LISA	Longitudinal integration database for health insurance and labour market studies (Statistics Sweden)
LNU	Standard of Living Survey (Levnadsnivåundersökningarna)
MAAS	Maastricht Aging Study
NLS	National Longitudinal Survey
NLSY	National Longitudinal Survey of Youth
O*NET	Occupational Information Network
OECD	Organisation for Economic Co-operation and Development
PIAAC	Programme for the International Assessment of Adult Competencies
PSID	Panel Study of Income Dynamics
R&D	Research and Development
REFLEX	Flexible Professional in the Knowledge Society survey
SBC	Dutch Standard Occupation Classification
SES	Structure of Earnings Survey
SHP	Swiss Household Panel
SKP	Standard Classification of Occupations, Statistical Office of Slovenia
SME	Small and Medium-sized Enterprise
SUN2000	Swedish Standard Classification of Education
UI	Unemployment Insurance

EXECUTIVE SUMMARY

This report surveys (i) the theoretical models proposed in the literature to define skill mismatch, identify its determinants, its effects, and the economic policies that can affect it, and (ii) the measures and the data that have been used so far to assess the extent of mismatch, and the ways in which these measures have been used in empirical analyses of skill mismatch.

We start by focusing on the two main conceptual reasons why occupational mismatch can occur: search costs and imperfect information in the labor market. The heterogeneity of firms and workers and the decentralized nature of the labor market require unemployed workers to engage in a costly search process to identify the firm offering a sufficiently high wage for their services, and the magnitude of their search costs affect the quality of firm-worker matches, as well as the quality of the match between workers and jobs (or tasks) within firms. In addition, aside from search costs, the quality of matches is affected by the imperfect information that workers have about firm and job characteristics, and that firms have about workers' characteristics (Section 2).

We explain that occupational mismatch can take different forms, such as vertical and horizontal mismatch, and present the related definitions of skill gaps, skill shortages, and skill obsolescence (Section 3). Unsurprisingly, capturing empirically this variety of forms of mismatch requires different measures (Section 4). The measures used so far vary widely depending on the method used (objective, subjective or mixed), the benchmark used to judge a good match (expert evaluations, realized matches, direct or indirect self-assessment) and the characteristics for which data are available (educational or skills, unidimensional or multidimensional). The variety of data recently used to measure on occupational mismatch are listed and described in the Appendix to the survey, which also lists the main papers in which each data set has been used. Beside describing the vast array of measures used in research on occupational mismatch, we illustrate their actual use in a selected number of prominent studies, and also survey measures used to measure skill shortages, which are increasingly relevant in the current state of labor markets in Europe.

We also analyze the economic factors that magnify or diminish the impact that search costs and/or informational imperfections have on occupational mismatch (Section 5). We start by discussing how various labor market imperfections tend to amplify (or reduce) the effects of these two basic frictions, namely: (i) geographical constraints and relocation costs, (ii) firms' firing and hiring costs, (iii) financial constraints, (iv) non-meritocratic promotions, and (v) workers' migrant status. Next, we explore whether and how skill mismatch responds to macroeconomic fluctuations, and how it depends on structural factors such as education and technology, and how it is affected by structural shocks affecting the composition of the demand or supply of labor, such as the China shock, the COVID-19 pandemic, the transition to a decarbonized economy and the ongoing demographic decline.

Next, we turn to the effects of occupational mismatch on firm-level and worker-level outcomes: the available evidence shows that a better workforce allocation enables firms to increase their productivity, and workers to earn higher wages and develop more rewarding careers. By the same token, factors that break up successful firm-worker or job-worker matches tend to cause persistent disruptions for both firms and workers (Section 6).

Building on the analysis of the determinants and effects of occupational mismatch, we investigate which economic policies can affect it, and which policy effects have been documented empirically so far (Section 7). As the main labor market frictions that produce occupational mismatch are search costs and imperfect information, we first consider all the policies that aim to improve the information available to labor market participants and reduce search costs. In line with the frictions analyzed in Section 5 as possible contributors to skill mismatch, we also consider policies that reduce housing, firing, and hiring costs, those that facilitate on-the-job training, and more generally skill acquisition, and migration policies that address skill shortages.

Finally, we conclude by pointing to the most novel and promising recent advances in this area, as well as to the remaining areas of ignorance that require additional work and improved data, especially in light of the ongoing and impending structural changes in the economy likely to prompt massive firm restructurings and worker reallocations (Section 8).

1. INTRODUCTION

The labor market is unlike any other: not only labor services are intrinsically heterogeneous, as they vary depending on the characteristics of the workers that supply them, but their productivity depends on the characteristics of the firms where work is performed and on those of the tasks to which workers are allocated, and so does the satisfaction of the workers that supply these services. Therefore, the quality of worker-firm matches and that of worker-job matches are of quintessential importance to both firms' productive efficiency and workers' personal welfare. Then it is no surprise that measuring the quality of occupational matches (or mismatches) and understanding its determinants and consequences has attracted keen attention by both researchers and policy makers. This paper provides an up-to-date map of the vast body of research on this topic.

1.1 Purpose of the deliverable

The purpose of this report is to survey (i) the theoretical models proposed in the literature to define skill mismatch, identify its determinants, its effects, and the economic policies that can affect it, and (ii) the measures and the data that have been used so far to assess the extent of mismatch, and the ways in which these measures have been used in empirical analyses of skill mismatch.

1.2 Relation with other deliverables and tasks

This report is meant to provide the basis for the other deliverables in the project, both as a reference to identify previous work relevant to other deliverables and relationship with such work, and as a source of research questions and policy issues to be explored in the project. To this purpose, the survey not only highlights the achievements of existing research on skill mismatch and skill shortages, but also presents the research questions that are still under-researched and the policy issues that would deserve attention in other deliverables of the project.

1.3 Structure of the Document

We start by focusing on the two main conceptual reasons why occupational mismatch can occur: search costs and imperfect information in the labor market. As explained in Section 2, the heterogeneity of workers, firms and jobs, and the decentralized nature of the labor market require unemployed workers to engage in a costly search process to identify the firms offering a sufficiently high wage for their services. The magnitude of their search costs affects the quality of firm-worker matches, as well as the quality of the match between workers and jobs (or tasks) within firms. In addition, aside from search costs, the quality of matches is affected by the imperfect information that workers have about firm and job characteristics, and that firms have about workers' characteristics.

Section 3 explains that occupational mismatch can take different forms, such as vertical and horizontal mismatch, and presents the related definitions of skill gaps, skill shortages, and skill obsolescence. Unsurprisingly, to capture empirically this variety of forms of mismatch requires a variety of measures, which are surveyed systematically in Section 4. The measures that have been used so far vary widely depending on the method used (objective, subjective or mixed), the benchmark used to judge a good match (expert evaluations, realized matches, direct or indirect self-assessment) and the characteristics for which data are available (educational or skills, unidimensional or multidimensional). The variety of data recently used on occupational mismatch are listed and described in the Appendix to this survey, which also lists the main papers in which each data set has been used. Beside describing the vast array of measures used in research on occupational mismatch, Section 4 illustrates their actual use in a selected number of prominent studies, and also surveys measures used to measure skill shortages, which are increasingly relevant in the current state of labor markets in Europe.

Section 5 turns to an analysis of economic factors that tend to magnify or diminish the impact that search costs and/or informational imperfections have on occupational mismatch. Specifically, it starts by discussing how various labor market imperfections tend to amplify (or reduce) the effects of these two basic frictions, namely: (i) geographical constraints and relocation costs, (ii) firms' firing and hiring costs, (iii) financial constraints, (iv) non-meritocratic promotions, and (v) workers' migrant status. Next, it explores whether and how skill mismatch responds to macroeconomic fluctuations, and how it depends on structural factors such as education and technology, and how it is affected by structural shocks affecting the composition of the demand or supply of labor, such as the China shock, the COVID-19 pandemic, the transition to a decarbonized economy and the ongoing demographic decline.

Next, Section 6 examines the effects of occupational mismatch on firm-level and worker-level outcomes: based on the available evidence, it highlights that a better workforce allocation enables firms to increase their productivity, and workers to earn higher wages and develop more rewarding careers. By the same token, factors that break up successful firm-worker or job-worker matches tend to cause persistent disruptions for both firms and workers.

Section 7 looks at occupational mismatch from the policy angle, asking which policies have been shown to have an appreciable impact in reducing it. As the main labor market frictions that produce occupational mismatch are search costs and imperfect information, it considers first of all policies that aim to improve the information available to labor market participants and reduce search costs. In line with the frictions analyzed in Section 5 as possible contributors to skill mismatch, this section also considers policies that reduce housing, firing, and hiring costs, those that facilitate on-the-job training, and more generally skill acquisition, and migration policies that address skill shortages.

Finally, Section 8 provides some concluding remarks and points to the most novel and promising recent advances in this area, as well as to the remaining areas of ignorance that require additional work and improved data, especially in light of the ongoing and impending structural changes in the economy likely to require massive firm restructurings and worker reallocations.

2. Theoretical Framework

Skill mismatch arises when workers are not well-matched to employers or jobs. This occurs either because workers are over- or under-qualified for the position, or because they have a different skill set from what the job would require, for instance as described in its posting. Hence, to frame the mismatch problem we refer to the theories so far proposed to model this matching process. In these frameworks, the mismatch can arise from two different types of labor market frictions: *search costs*, i.e., workers' costs to acquire information about posted wages and job vacancies, as well as firms' costs to obtain information about job seekers, and *imperfect information* about workers' skills and job tasks. The sources of these frictions vary across models, and in some of them the mismatch can arise from a combination of frictions, which may reinforce each other. In what follows, we start from an overview of models based on the presence of search costs, and then focus on settings that allow for imperfect information about skills and tasks.

2.1 Search models and search costs

While standard general equilibrium theory assumes that buyers and sellers trade homogeneous commodities in centralized, frictionless markets, labor markets are decentralized, feature several frictions, and are much more complex, especially because of the heterogeneity of firms, workers, and jobs. As a result, employers and prospective employees face significant costs to identify and achieve the best possible match. In this section, we review the most important models of labor market search, distinguishing between *random search* models – where jobseekers are presented with vacancies randomly drawn from a certain distribution of jobs – and *directed search* ones – where jobseekers can direct their search toward specific vacancies. As we shall see, search costs can generate mismatch in each of these models.

2.1.1 Random search

The matching process of workers with employers and jobs has been modeled in several ways. In the simplest model (McCall, 1970), employers post jobs with certain set wages, and job seekers "sample" – in other words, apply to and are (eventually) offered – jobs sequentially from this given wage distribution. Each time jobseekers sample a job offer, they have to decide whether to stop their search and accept the job or continue searching. They take this decision by comparing the wage of the job they sampled against the income they could earn if they remained without a job (for instance, the unemployment insurance benefits) and the *continuation value* of not accepting that job – i.e., the wages of the other jobs they could be offered if they kept searching – which crucially depends on the wage distribution they are facing and on the probability of receiving other offers.

In the absence of frictions, workers make their decisions optimally and accept a job whenever the offered wage is higher than their reservation wage, which depends on their non-employment income and their continuation value. When searching is costly or workers are imperfectly informed about the wage distribution they face, jobseekers may be over-optimistic or over-pessimistic about the wage distribution or the probability of receiving a job offer, so that they may end up setting a reservation wage that is either too high or too low compared to the perfect information benchmark (Mueller et al., 2021). Search costs and biased beliefs about the wage distribution and the job offers arrival rates could result in workers being under-employed or extending the duration of unemployment. The latter is particularly problematic, given the "scarring effect" of prolonged unemployment on re-employment outcomes and wages (see, for instance, Jarosch, 2023). Rogerson (1987) formalizes the intuition that higher search costs result in lower reallocation of workers across sectors where their skills may be more efficiently used.

In the seminal model of Diamond, Mortensen and Pissarides (DMP), instead of being posted by employers, wages are determined by bargaining between employers and workers to split the "value" of their match (Diamond, 1982; Mortensen and Pissarides, 1994). As in McCall (1970), search is "undirected" or random, that is, jobseekers are not able to direct their search to different types of jobs or different parts of the wage distribution. The matching between job seekers and employers happens via a *matching function* – a reduced-form way to model search frictions arising from the mismatch between the supply and demand of workers with specific types of skills. The matching function takes as inputs the number of job seekers (labor supply) and number of vacancies (labor demand) in a certain market and is usually assumed to have constant returns to scale. Under this assumption, the matching function becomes a function of the *tightness of the labor market*, *i.e.*, the ratio of the number of vacancies to the number of jobseekers. Opening a vacancy is costly for firms, and in equilibrium the value of a vacancy for a firm is equal to zero – if not, more firms will enter the market and open vacancies, violating the equilibrium condition. Once a match is formed, the *match surplus* is split between workers and employers through Nash bargaining.

In this framework, there are two key externalities. First, as tightness increases, workers find jobs more easily (*thick-market externality*) since there are more vacancies available for the same number of job seekers (Pissarides, 1984). At the same time, firms find workers more slowly (*congestion externality*), as there are now fewer workers that could be a match for their vacancies. Whether the search equilibrium is (constrained) efficient depends on whether these two externalities cancel each other or one of them dominates. According to the *Hosios condition* (Hosios, 1990), efficiency obtains only if workers' bargaining power is equal to the elasticity of the matching function with respect to unemployment, which is only possible if the matching function has constant returns to scale. This condition does not hold in many circumstances, for instance when there is a *holdup problem*, that is, firms have to make sizable investments before finding their employees (Acemoglu and Shimer, 1999), or when there is *job rationing*, that is, when there is a shortage of jobs even in the absence of matching frictions because of structural factors[1] (see Michaillat, 2012; Landais et al., 2018).

In the models discussed so far, employment relationships either last forever (in the McCall model) or are exogenously destroyed, and only then the newly unemployed search for a different job (in the DMP framework). A key innovation of Burdett and Mortensen (1998) is to allow workers to search while they are employed and to make job-to-job transitions. As in the McCall model, search is random: workers apply randomly for jobs, but they sample continuously from the distribution of

[1] This happens, for instance, when wages are too high compared to workers' productivity. In this scenario the least productive workers remain unemployed because it is not profitable for firms to hire them, even when hiring costs are zero (Michaillat, 2012).

vacancies and associated posted wages. In this model, workers accept any job offer that is simply higher than their non-employment value (if they are not currently working) or their current wage (if they are already employed). In this setting, the reservation wage does not depend on the continuation value of not accepting an offer because workers can keep searching and continuously move from one employer to the other even after they accepted a job. There is a strong correlation between wages and employer size: firms paying higher wages can recruit more workers and are larger. Inefficiencies can arise if firms have different productivity, as monopsony power could prevent workers from being assigned to more productive firms. Furthermore, the presence of search costs, combined with imperfect information about posted wages and future job offers, may bias workers' search and job acceptance decisions (Conlon et al., 2018), generating and reinforcing mismatch.

Postel-Vinay and Robin (2002) and Cahuc et al. (2006) offer more complex and richer random search models with on-the-job search. In Postel-Vinay and Robin (2002) firms offer wages to workers (wage posting) conditional on their characteristics and can respond to outside job offers received by their employees (counteroffers). Workers differ in their level of unobserved "competence" and firms also differ in their productivity. In equilibrium, wage dispersion is driven by heterogeneity in workers' and firms' productivities but also by matching frictions. Cahuc et al. (2006) revisit DMP's Nash bargaining framework allowing for on-the-job search. In their model, firms not only bargain with their employees but also compete for workers with other employers. Wages are mainly driven by three forces: (i) productivity; (ii) competition between employers; (iii) workers' bargaining power. By estimating their model based on French administrative data, they find that between-employer competition matters a lot in the determination of wages, while workers' bargaining power is less relevant, especially for intermediate- and low-skilled workers. This suggests that, by raising workers' rents from successful matches, employers' competition for labor may encourage workers' search effort and result in better job-skill matches.

Finally, another recent strand of the literature studies how sorting between workers and firms interacts with firm size: Eeckhout and Kircher (2018) show that there is a tradeoff between hiring more versus better workers, but this tradeoff can be solved by good management. They derive conditions for sorting that capture this tradeoff, and also show how their model can be augmented to account for labor market frictions.

2.1.2 Directed search

An alternative to random search is *directed search*, where jobseekers can direct their search toward vacancies offering different wages (Acemoglu and Shimer, 1999; Wright et al., 2021, for a recent review of directed search and competitive search). Contrary to DMP, the focus is on search for a specific vacancy, rather than on overall vacancies in the economy. In directed search models, labor market frictions are combined with a guiding role for prices. In this setting, frictions arise also from the lack of coordination in the search decision (Galenianos and Kircher, 2009). Workers know about the wages offered for various jobs and rationally anticipate the probability of getting those jobs, which depends on how many other workers are applying for the same jobs. They make their application decisions based on this information and maximize their utility. Firms post wages to maximize profits, anticipating the probability that their vacancies will be filled and the actual wage distribution they will face.

Shi (2002) illustrates how a directed search model can generate inequality among identical unskilled workers, even if they perform the same task and have the same productivity. Albrecht et al. (2006) construct a model where workers observe the wages posted and apply for their preferred jobs. On the firm side, the posted wage is set taking into account its effects on the pool of applicants. They show that, if workers make a finite number of applications, some workers will not be able to find a job, and the wages for some workers will be lower than the competitive level. In this case, the equilibrium will be inefficient and characterized by excessive vacancies. Complementary to this study, Galenianos and Kircher (2009) highlight that inefficiencies arise from firms' wages affecting only the number of received applications and not where workers additionally apply. Menzio and Shi (2011) develop a model of directed search on the job, where workers' transitions between employment and unemployment and across different employers depend on the heterogeneity in the quality of the existing firm-worker matches. They show that productivity shocks generate large fluctuations in workers' transitions, unemployment and vacancies if the quality of firm-worker matches is observed after the match is created.

2.1.3 Multidimensional skills

Another important aspect of the matching process concerns how to model skills. Should we think of skills as a single attribute (*e.g.,* “competence”) or as a set of skill dimensions? And if skills are multidimensional, are they separable or to be considered as an indivisible bundle?

Many studies look at skills as a one-dimensional item.[2] On the one hand, this approach makes skills, and therefore mismatch, relatively easy to measure, and has the benefit of decreasing the dimensionality of the problem. On the other hand, it limits the capacity to grasp and model the complexity of skills. The recent literature has increasingly focused on a multidimensional approach.

Lise and Postel-Vinay (2020) are the first to present a search and matching model where workers have multidimensional skills (namely, cognitive, manual, and interpersonal skills) and sort across firms with multidimensional job requirements. In their model, workers accumulate skills when they use them, and decumulate them when they do not. Upon estimating their model using data from O*NET and the NLSY79, they find that manual skills have modest returns and are easily accumulated and decumulated, while cognitive skills have much higher returns, but take more time to accumulate. Instead, interpersonal skills have only slightly higher returns than manual ones, and do not vary over employees’ working lives. They also find that the cost of skill mismatch (namely, the sum of the resulting firm output and worker utility loss) differs depending on the type of mismatch: it is highest for cognitive skills, and twice as high for workers who are underqualified in cognitive skills than for overqualified ones. They highlight the shortcomings of relying on a single skill dimension when studying the contributions of initial conditions vs. career shocks in determining lifetime output.

Choné and Kramarz (2021) also study a setting where skills are assumed to be multidimensional. They focus on how labor market outcomes change depending on whether skills can be “sold” separately on the labor market or not. When the former is the case, the implicit price of each skill

[2] We further discuss this aspect in Sections 3 and 4.

can vary across firms, and firms' size is increasing in productivity. When skills can be unpacked the matching equilibrium is more polarized and the wage schedule flattened.

2.2 Imperfect information

Besides search costs, *imperfect information* is the other major friction that can generate mismatch. On one hand, workers may lack knowledge of some attributes of the job offered. On the other, firms may not be able to accurately observe workers' skills. Furthermore, workers themselves may be uncertain about their skills and about the extent to which their skills fit a certain job.

Gibbons et al. (2005) develop a model where workers' skills determine their allocation to different sectors and their wages. In this setting, mismatch arises because both workers and firms are initially uncertain about some of the workers' skills. Over time, labor market participants learn about these unobserved skills and workers move from job to job and reallocate across sectors. Consistently, Topel and Ward (1992) show that many job switches occur over the first few years of workers' careers, and that job changes are associated with significant wage gains, signaling a possible improvement in matches.

Jovanovic (1979) pioneered learning as the main mechanism behind job turnover. Even when skills can be observed, a worker's productivity in a given job may not be known ex ante. As workers' tenure increases, their productivity becomes easier to observe, leading to turnover (for some workers) and better matches. Consistently with this learning mechanism, Fredriksson et al. (2018) find that mismatch, measured using Swedish administrative data, tends to decrease with experience: match quality is higher among experienced workers, particularly those who have worked in the same firm before. Work experience also affects the impact of match quality on wages and separations: for inexperienced workers, it is unrelated to entry wages, but it strongly correlated with greater separations and lower wage growth. By contrast, experienced workers receive a wage penalty if mismatched, but their wages and separations respond less to match quality. Hence, for the inexperienced the evidence suggests greater initial uncertainty and more learning than for the experienced. Similarly, using a different measure of match quality, Coraggio et al. (2024) find that mismatch decreases with experience, especially initially, and that wages increase in match quality.

Building on Menzio and Shi (2010, 2011), Baley et al. (2022) develop a directed search model where workers differ along multiple skill dimensions and sort into jobs with heterogeneous skill requirements, and workers and firms have incomplete information about workers' skills.[3] Mismatch arises from incomplete information in equilibrium. When they search, workers make a career choice, which determines the type of skill they seek to deploy, and its level of complexity. Over time, workers and firms update their beliefs about workers' skills using a noisy learning technology, where learning is more accurate for the skills used in production, similar to Lise and Postel-Vinay (2020). In equilibrium, workers reallocate both up and down the task complexity ladder, within a given career – using the same skills but with varying task complexity -- and across career paths – using different skills. They estimate this model using worker-level data from the 1979 National Longitudinal Survey of Youth (NLSY79) and data on occupation requirements by O*NET. They find that two opposing forces are at play over the business cycle: a *cleansing* effect and a *sullying* effect. On the one hand, under-qualified workers are more likely to be fired in recessions (*cleansing*), reducing mismatch in ongoing work relationships. On the other hand, in recessions, it is more likely that overqualified workers get hired for lower-complexity jobs, increasing the mismatch in new hires (*sullying*). In their framework they uncover an important interaction between job mobility and mismatch: transitions within a given career path tend to reduce mismatch – workers re-sort across job rungs as they revise their beliefs about their skills – while transitions into new career paths tend to increase mismatch, as workers have less accurate beliefs about the skills they have not been previously using.

Guvenen et al. (2020) develop a dynamic model of occupational choice and human capital accumulation with multidimensional skills and Bayesian learning about one's ability to learn skills. They show that in this context mismatch not only leads to lower wage level and wage growth in workers' current job, but it also produces a *scarring effect* that lowers wages in subsequent occupations.

[3] They provide direct evidence that workers are imperfectly informed about their skills by showing that workers' forecast errors about their future occupations can be systematically predicted by a measure of workers' ability realized at the time forecasts are formed.

Incomplete information and uncertainty about workers' skills may give firms an informational advantage over their employees, as firms end up being better informed about their own employees than about those of other firms. This *asymmetric information between firms* may prevent employees from switching to other employers, and thus enable firms to "underpromote" their employees. This idea was first formalized by Waldman (1984), who showed that if workers' promotion is the only available public signal about employees' quality, then firms have some incentive not to promote deserving workers to avoid exposing them to poaching by competitors, so as to contain their retention costs. Hence, in equilibrium, not every senior worker is assigned to a job that maximizes his/her output. More recently, Waldman and Zax (2020) show that this may also distort the mix of human capital investments financed by firms. To reduce the effects of the inefficient promotion policy, firms may be biased towards investing in firm-specific human capital. As a result, there will be underinvestment in general human capital.

To some extent, workers may overcome this underinvestment problem by investing in education themselves. In fact, if education is costly and its cost decreases with ability, workers can rely on their investment in education to be a costly signal of their quality, as shown by Ordine and Rose (2009), and thereby overcome asymmetric information problems. However, overeducation may be socially inefficient in the presence of costly search, due to the presence of externalities: in choosing how much to invest in education, individuals consider their own earnings and employment perspectives but do not internalize the detrimental impact that their schooling decisions have on the others' job opportunities. This effect results from the compositional effect of the decision to invest in education by the marginal individual, as shown by Charlot and Decreuse (2005). When workers are heterogeneous and can acquire education at a fixed cost, only those with high enough ability choose to do so and can take high-productivity jobs. If education expands, i.e. more people get educated, then the marginal individual acquiring education is less able than other educated individuals but more able than non-educated ones: hence, his/her investment in education lowers the average ability of both the educated and the uneducated workers. This induces firms to reduce vacancies for both types of workers and thus triggers a decline in the probability of employment. Via this mechanism, workers' decision to acquire education may lead to over-investment in general human capital.

3. Forms of Mismatch

Skills mismatch is a multi-faceted concept. Its complexity is reflected not only by the theoretical frameworks used to study it, as illustrated in Section 2, but also by the variety of measures that can be used to quantify the mismatch.

Following the Eurostat categorization,[4] skills mismatch can be described by focusing on the mismatch between the level of skills acquired by the worker and that required to perform a specific job or task (*vertical mismatch*). Skill mismatch can also arise from the discrepancy between the field of study in which workers specialize and the type of skills required to perform a particular job or task (*horizontal mismatch*). Moreover, as already noted in Section 2, skills can be seen as a multidimensional object, involving a bundle of cognitive and non-cognitive capacities, so that mismatch can occur from misalignment between any of these skills and the relevant job requirements (e.g., Lise and Postel-Vinay, 2020; Guvenen et al. 2020). This multidimensional approach has the clear advantage of providing a more accurate measurement of mismatch and a better understanding of the wage disparities and dynamics that mismatch can generate. However, it raises the issue of how to measure the set of skills of workers and whether these can be unpacked and traded separately in the labor markets or not (Choné and Kramartz, 2021). We will discuss these topics in greater detail in Section 4.

Skills mismatch is also related to concepts such as skill gaps, skill shortages, and skill obsolescence. Skill gaps arise when workers lack the skills required to perform a certain job, and thus refer to existing matches. They are relatively under-researched (McGuinness and Ortiz, 2016). Skill shortages are instead related to the difficulty of filling job positions. Although skill shortages

[4] McGuinness et al. (2018) and Brunello and Wruuck (2021) provide recent overviews of the literature on mismatch and skill shortages.

tend to be quite frequent based on self-reported data, this finding is often not confirmed by data based on vacancies and actual hiring procedures (Weaver and Osterman, 2017; Cedefop, 2015). Skill obsolescence refers to the process by which workers' skills become less sought after by firms. This phenomenon can be related to either physical obsolescence, due, for example, to skill depreciation due to aging, or to technological shocks that make some skills redundant in production (e.g. Autor et al., 2003; Hudomiet and Willis, 2022).

Section 4 will discuss these phenomena and their measurement in greater detail: they have led to the construction of different measures, often based on different data. Indeed, different economic issues regarding skill mismatch often require relying on different measures, and also determine whether it is more useful to aggregate the available information at the worker level or at the firm level. Aggregating it at the individual worker level is suited to understanding how suited a worker's skills are to those required to perform a given job. For example, when thinking of skill obsolescence, the natural level of aggregation is the worker level. Aggregating mismatch measures at the firm level is instead better suited to capture skill shortages or skill gaps.

In what follows, we overview vertical and horizontal mismatch, but defer to Section 4 the discussion of their measurement.

3.1 Vertical mismatch

Vertical mismatch refers to a quantitative aspect of skills accumulation and employment: it relates to the fact that a worker may possess a level of skills that is different from that required for the worker's current job. The mismatch, in this case, can be in two directions: a worker may have acquired more skills than the job requires (*overskilling*), or a lower level of skills than the job requires (*under-skilling*).

Since the early works on mismatch (e.g., Freeman, 1976; Duncan and Hoffman, 1981; Oosterbeck, 2000), skill level has been measured by the level of education, and accordingly the concepts of over- and under-skilling have often been translated into over- and under-education, depending on whether workers have a higher or lower level of education than their job would require. The problem with measuring vertical mismatch based on education is twofold. On the worker's side, it can be too coarse a measure to capture the actual mismatch with their job. Moreover, it only reflects the skills acquired through formal education, overlooking any learning process based on work experience (McGuinness and Wooden, 2009). On the firm's side, job entry requirements may not be a good proxy of which skills are needed to perform a job productively.

Indeed, more recent literature has exploited measures of vertical mismatch based on more detailed skills assessments (e.g., Desjardins and Rubenson, 2011; Flisi et al. 2017), and has relied on the broader concepts of *over-matching* and *under-matching*, which are based both on education and skills. The relevant literature focuses more on over-matching than on under-matching (e.g. Leuven and Oosterbeek, 2011; McGuinness, 2006): it finds that over-matched workers tend to have a wage penalty compared to well-matched workers with the same level of education or skills. At the same time, over-matched workers have higher wages than workers in the same jobs with lower levels of education or skills (McGuinness et al., 2018 for a recent overview). The literature on *under-matching* is smaller and the evidence on whether it generates wage differentials is mixed, although there is evidence that under-matching harms firm productivity (Kampelmann and Rycx, 2012).

3.2 Horizontal mismatch

Horizontal mismatch focuses on the contents, rather than the levels, of the skills acquired by the worker and on how they fit with the requirements of their job. In this case, if mismatch is measured on the basis of education, it reflects holding a job that is unrelated to the worker's field of education. As for vertical mismatch, the discrepancy between workers and jobs is often measured through the workers' subject of specialization during formal education, which may overlook the relevance of the on-the-job specialization process.

With respect to good matches, workers who are horizontally mismatched tend to have lower wages, are less satisfied with their jobs, and tend to regret their academic choices: Somers et al. (2019) provide a comprehensive literature review on horizontal mismatch and its consequences.

4. Measuring Mismatch

Occupational mismatch arises when a worker's skills differ from those required to productively perform the tasks she is assigned to, i.e., the set of tasks that define his/her job. As explained in Section 3, it can take different forms, and the literature has developed different types of measures depending on the forms of mismatch studied.

A key distinction across measures of occupational skill mismatch is in the definition of the benchmark for the goodness of fit between a worker's skills and the job she holds: different benchmarks produce different measures of mismatch. Indeed, the first step in measuring mismatch is defining what is a "good match". To do so, one needs to measure not only the skills of a worker, but also those required to productively perform a given job. The different approaches used in the literature can be divided into three broad groups: (i) **objective** methods, (ii) **subjective** methods, and (iii) **mixed** methods. Objective and subjective methods are defined by the source of information used to identify skill requirements for jobs and skill mismatch. Subjective methods rely on workers' assessment (WA) of their job and skills through surveys, where employees are asked whether their level and type of education fits their current job, or the job's education requirements. In contrast, objective methods do not rely on employees' self-assessment but rather infer the type of education or skills required to perform a job on the basis of job analysis (JA) by expert evaluations or of the realized distribution of worker-job matches drawn from observational data. Finally, mixed methods use a combination of both subjective and objective methods, depending on data availability.

Another relevant distinction to classify measures of occupational mismatch is that between (i) those based on workers' educational attainment and jobs' educational requirements, and (ii) those based on the direct measurement of workers' skills and those required for their job. Indeed, occupational mismatch has long been conceptualized and measured as an educational mismatch, where the educational attainment of the individuals is used as a way to summarize the set of skills they are endowed with. These measures overlook several important features of mismatch: (i) the dynamics of skill mismatch, e.g., the possibility that workers' skills evolve as a result of the experience acquired on the job, (ii) the fact that some skills are not attained via education (McGuinness and Wooden, 2009), and (iii) the evolution of the mapping from educational attainment to skills, due to changes in the educational system (Flisi et al., 2017). Nonetheless, measures of education mismatch have been widely used in economics, owing to their almost universal availability and the frequent lack of reliable data on individuals' skills.

The more recent literature has not only highlighted the need to measure skills directly rather than on the basis of educational attainment, but also shown the feasibility of such measures, based on new data. For instance, using data from the PIAAC survey, Flisi et al. (2017) build indicators of over-education and overskilling for 17 European countries and show that education and skill mismatch measure two different phenomena, with only a small percentage of mismatched individuals being mismatched both in terms of educational attainment and in terms of their skills. They document that there is a substantial portion of the population that is educationally over-qualified, yet not over-skilled: their education level exceeds what is required by their job, but their skills are just enough to cope with it. Conversely, another substantial portion of the population is formed by people who are over-skilled but not over-educated: while they feature the proper educational qualification, they own more skills than required for the job they perform. In Europe, the former situation tends to prevail in countries such as Estonia, Ireland, Italy and Spain, while the latter in countries such as Finland and the Netherlands. Accordingly, Flisi et al. (2017) suggest these cross-country differences may arise from differences in the educational systems of these countries, namely, their standardization (i.e., the uniformity of curricula and teaching methods across the country) and stratification (i.e., the internal differentiation of the system, in terms of specific tracks and extent to which students can move from one to the others). Typically, Southern European countries and Ireland feature a low level of tracking and quite standardized curricula, while Northern European countries typically have stratified educational systems, where vocational tracks provide specific skills and clear occupational profiles that are informative for employers: this may explain why the former countries suffer more from overeducation than the latter, which however may induce early specialization of workers leading to more over-skilling.

In what follows we survey the measures of occupational mismatch used in the literature. To guide the exposition, we follow the classification of existing methods presented in Table 1. First of all, we classify mismatch measures into those computed with objective methods and those based on subjective methods. Then, we further classify objective measures based on the benchmark used to define a "good match," namely, expert evaluations or realized matches, and divide subjective measures into those based on direct self-assessment and those based on indirect methods. Finally, for each type of measure, we briefly discuss studies that focus on one-dimensional skill mismatch, using education and/or generic skill as the key variable, and those that focus on multi-dimensional mismatch and rely on skill data. Furthermore, we briefly discuss studies based on mixed methods.

Table 1: Forms and measures of occupational mismatch

Method	Benchmark	Type of measure	Variable used
Objective	Expert evaluations	One-dimensional	Education
			Skill
		Multi-dimensional	Skills
	Realized matches	One-dimensional	Education
			Skill
		Multi-dimensional	Skills
Subjective	Direct self-assessment (DSA)	One-dimensional	Education
			Skill
		Multi-dimensional	Skills
	Indirect self-assessment (ISA)	One-dimensional	Education
			Skill
		Multi-dimensional	Skills

4.1 Objective methods

As highlighted by Table 1, depending on the source of information used to define skill mismatch, objective methods can be broadly divided into two sub-groups: (i) objective methods based on expert evaluations; (ii) objective methods based on comparisons with moments of the realized distribution of matches.

4.1.1 Objective methods based on expert evaluations

Measures of education or skill mismatch in this group rely on information provided by professional job analysts that define the "required" level of education, such as the U.S. Dictionary of Occupational Titles (DOT) and/or the skills required for a certain job, such as those listed in the Occupational Information Network project (O*NET). Measures of employee-job mismatch are then computed as the distance between the job requirements and the employee's education (Rumberger, 1987) or skills (e.g., Lise and Postel-Vinay, 2020).

4.1.2 Expert evaluations and multidimensional skill mismatch

To analyze the effect of occupational mismatch on workers' entry wages and career trajectories, Fredriksson et al. (2018) develop a measure of multidimensional skill mismatch at the job level based on four cognitive and four non-cognitive skills, drawn from military draft scores. Mismatches are measured as the sum of the absolute distances between a worker's skill and the average skill level possessed by tenured workers in the same 3-digit occupation and the same firm.

Lise and Postel-Vinay (2020) develop a model of on-the-job search in which workers differ in terms of three different types of skills, i.e., cognitive, manual, and interpersonal skills, and sort themselves into occupations with different skill requirements. They argue that it is important to allow for multi-dimensional skills, rather than subsuming all differences in a single scalar index of "skill" for at least three reasons: (i) different jobs require different levels of manual, cognitive, or interpersonal skills;

(ii) unused skills may deteriorate and used skills may be accumulated over time; and (iii) practitioners seem to give importance to different types of skills.

To obtain measures of skill mismatch along these three dimensions, they combine information on skill requirements drawn from the O*NET database with information on workers' skills from the National Longitudinal Survey of Youth (NLSY) database. In particular, from the over 200 descriptors of skill requirements contained in the O*NET they keep the first three principal components and recombine them so as to satisfy the following three exclusion restrictions: (i) the mathematics score only reflects cognitive skill requirements; (ii) the mechanical knowledge score only reflects manual skill requirements; (iii) the social perceptiveness score only reflects interpersonal skill requirements. Thus, they interpret the three skill requirement indices as cognitive, manual, and interpersonal. To measure instead the skills initially owned by a worker, they use the ten Armed Forces Vocational Aptitude Battery (ASVAB) scores that are directly available from the NLSY sample; individual scores on the Rotter locus-of-control scale and the Rosenberg self-esteem scale tests; three measures of criminal and antisocial behavior; two measures of health (BMI and weight); and an O*NET-based measure of cognitive, manual, and interpersonal skills attached to the level of education attained by each NLSY sample member. As exclusion restriction they assume that (i) the ASVAB mathematics knowledge score only reflects cognitive skills; (ii) the ASVAB automotive and shop information score only reflects manual skills; (iii) the Rosenberg self-esteem score only reflects interpersonal skills. Skill mismatch is then computed as the difference between the skill requirement of a job and the skills possessed by a worker (allowed to change over time starting from their initial level, as a result of accumulation or loss due to their use or disuse).

They find that the returns to skills differ across skill types, with manual skills only having moderate returns, interpersonal skills having slightly higher returns, and cognitive skills having much higher returns. However, manual skills adjust quickly as they are easy to develop on the job (and depreciate when left unused). Cognitive skills are much slower to adjust: they are essentially fixed over a worker's career. Furthermore, the cost of skill mismatch is an order of magnitude larger for cognitive skills than for manual or interpersonal skills, and is asymmetric: underqualification is more than twice as costly in terms of lost surplus than overqualification.

Finally, Lise and Postel-Vinay (2020) compare their model of multidimensional skill mismatch to a version of the model with only one skill and find that, when decomposing lifetime output, the one-skill model overestimates the importance of unobserved heterogeneity by a factor of two and underestimates the contribution of career shocks relative to initially observed skills by one-half.

Guvenen et al. (2020) develop a model of multidimensional skill mismatch based on information frictions, and similarly to Lise and Postel-Vinay (2020), propose an empirical measure of multidimensional mismatch that combines information on the skill requirements of a job from the O*NET project with data on the skills possessed by workers from the NLSY79 database. They show that occupational mismatches depress wage growth, determine scarring effects, and predict occupational switching behavior.

Baley et al. (2022) also measure multidimensional skill mismatch using the skill requirements described in the O*NET project together with individual information drawn from the NLSY79. Differently from Guvenen et al. (2020) and Lise and Postel-Vinay (2020), they use principal component analysis to reduce the types of skills to four, i.e., mathematics, verbal, social, and technical, rather than to three. Mismatches are measured as a linear combination of the absolute distance between each of the four skills possessed by the worker and the corresponding level required by the job, with more weight given to the skills that are estimated to be more valuable in the labor market. They find that in recessions underqualified workers are fired, and the mismatch among new hires goes up, primarily due to an increase in overqualification among workers hired for low-complexity jobs.

These types of measures have some drawbacks. First, the skill requirements of a job can only vary across job titles, not across firms (or classes of firms). In addition, the description of skill requirements of jobs based on expert evaluations is costly to implement and may become obsolete very quickly: indeed, skill requirements and workforce skills evolve in response to technological advancements, economic shifts, and changes in industry demand. Finally, there is a problem of discretion due to human judgement calls: what exactly determines the expertise of a professional job analyst? In principle, one may want to base the description of the skill requirements of a given job on the skills requested by firms in the description of their job vacancies. Is the knowledge possessed by job analysts comparable to this benchmark? An alternative is to measure skill requirements based on previous choices made by firms themselves: the next subsection surveys measures based on comparisons between the skills (or education) possessed by individuals and those typically possessed by people in the same occupation.

4.1.3 Objective methods based on the realized match distribution

Objective methods relying on the realized distribution of matches use observed employee-job allocations to explicitly or implicitly define the skill contents of jobs and/or skill mismatch. For example, Verdugo and Verdugo (1989) compare the workers' education level with the mean level of education attained by workers in the same occupation group. A mismatch is identified when the individual's education level deviates from the mean by more than one (or two) standard deviation. Kiker et al. (1997) propose a variation of the measure of education mismatch in Verdugo and Verdugo (1989) in which the mean level of education attained by workers in the same 3-digit occupation is replaced by the modal value. A clear limitation of these methods is that they do not take into account changes in the composition of the workforce across cohorts and are sensitive to the level of discrepancy (and the moment) chosen by the researcher.

4.1.4 Realized matches and multidimensional skill mismatch

A recent and notable example of a mismatch measure based on realized matches is that proposed by Fredriksson et al. (2018). The authors combine the objective method with the prediction of labor economics models that a good match has a high probability of lasting over time. Hence, they define the benchmark level of skills required to perform a job (defined as an occupation in a given firm) as the average one possessed by tenured workers in that job. This method has the clear advantages of being theory-driven, easy to implement with administrative data, and firm-specific, as it allows the same occupation to require different skills across firms. However, it can only be used to measure mismatch at the entry-level.

Multidimensional skill mismatch has been shown to matter also in explaining the costs of job displacement. In particular, Neffke et al. (2024) show that job switches by displaced workers result in changes in their earnings whose sign, magnitude and persistence depend on the type of skill mismatch that these workers experience in such job switches. In particular, separations are not invariably followed by earnings losses: if they are associated with skill redundancies, they are followed by permanent earnings losses for displaced workers; if instead they are associated with skill shortages, they are followed by gains in terms of earnings, which quickly return to the trajectories that displaced workers would have experienced absent displacement.

Neffke et al. (2024) estimate mismatches using data from the Survey of the Working Population on Qualification and Working Conditions in Germany (BIBB survey) and define them as differences in skill requirements between two occupations. First, starting from individual-level data, the authors aggregate the answers to 46 different survey questions on knowledge requirements to the level of occupations. Next, they use factor analysis to reduce the dimensionality of the descriptions of the skills used in each occupation to five broad skill factors. They further use 14 questions that aim to understand unfavorable working conditions and reduce them to a single factor, interpreted as the disutility associated with a given occupation. The authors then build their measure of skill redundancy (shortage) for a job-to-job transition by displaced workers using a weighted[5] combination of the distance between each of the five factors in the origin and destination occupations, interacted with an indicator for positive (negative) differences. Notably, these measures capture both vertical and horizontal mismatches and allow for mismatch in a job-job transition to depend on the direction of the change in occupation of displaced workers, rather than just on the pair of occupations involved in the change. Owing to this innovative feature, this methodology can distinguish between different types of skill mismatch associated with displaced

[5] The weights are obtained by estimating a regression of years of schooling onto the five skill factors and the disutility factor, so as to assign more weight to factors that require more years of schooling to be acquired.

workers' job switches, namely, between those associated with skill redundancies and those associated with skill shortages, as noted above.

Finally, a new strand of the literature on skill mismatch measurement relies on machine learning to extract the most information from the distribution of observed matches. Indeed, algorithms based on machine-learning techniques can be developed to match job requirements with worker skills using administrative data or a combination of survey and administrative data. Algorithms may also be applied to the data collected by skill-based matching online platforms, which facilitate the matching of job seekers with suitable employment opportunities based on their skill profiles, allowing for real-time assessment of skill matches (Athey, 2019).

An example of this approach is provided by Coraggio et al. (2022), who combine Swedish administrative worker and firm data with machine learning to estimate a mapping between workers' curricular characteristics and jobs. More specifically, the idea on which this method is based is to "learn" the ideal mapping between workers' observable characteristics and jobs by looking at the realized distribution of matches among the most productive firms and extend this mapping to other firms, so as to measure mismatches as discrepancies between the predicted and the actual assignment of workers' characteristics to jobs. The reliability of this method rests on two main assumptions: (i) the most productive firms constitute a valid benchmark to learn the (constrained) optimal assignment of skills to tasks; and (ii) a worker's curriculum can synthesize the relevant skills possessed by the worker and their evolution over time (via the past job history).

4.2 Subjective methods

Subjective methods rely on information provided by workers. They can be based on Direct Self-Assessment (DSA) or Indirect Self-Assessment (ISA). DSA methods consist of directly asking workers' opinions regarding whether their job is in line with their level and type of education. ISA methods instead ask workers about the education requirements of their current job. Key studies in the literature adopting the DSA approach include Chevalier (2003) and Verhaest and Omey (2006).

Examples of studies based on ISA methods are instead Duncan and Hoffman (1981), Hartog and Oosterbeek (1988), Sicherman (1991), Sloane et al. (1999), Battu et al. (2000), Allen and van der Velden (2001), Green and Zhu (2010), Frei and Sousa-Poza (2012), and Baert et al. (2013).

Other studies focus on disentangling the effects of formal education mismatch and skill mismatch, resulting in a multi-dimensional decomposition of job-employee mismatches. Data on formal education can be used to measure both vertical mismatches, i.e., the extent to which the employee's education level is differs from that required by her current job, and horizontal mismatches, namely, the distance between the employee's area of education (e.g. subject-specific degree) and that required by the current job. Typically, vertical mismatches are easier to measure than horizontal ones, at least using survey data, as the latter require more specialized questions than the former.

4.2.1 Subjective methods and unidimensional skill mismatch

Skill mismatches are commonly measured in terms of under- or over-utilization (under- or overskilling) or skill shortage (Allen and Van der Velden, 2001; Di Pietro and Urwin, 2006; Mavromaras et al., 2007; Mavromaras and McGuinness, 2012). The former type of skill measurement often relies on survey data, whereby employees report their own perceived lack of skills or degree of utilization of their skills in their current job. For both education and skills, a mismatch is defined by comparing employees' qualifications with formal job requirements (e.g. expert evaluations) or estimated job requirements (e.g. aggregating employees' assessments). In this context, there are measures of general skill mismatch, and measures of skill-specific mismatch (Desjardins and Rubenson, 2011; McGowan and Andrews, 2015a, 2015b).

Measures of skill shortages are often collected from firm surveys either directly, when enterprises are directly asked about experiencing such shortages, or indirectly, using data on vacancies (Neumark et al., 2013; Healy et al., 2015). While measurements of under- and over-skilling are typically used to investigate employee-job mismatch and its impact on labor market outcomes, measures of skill shortages tend to be used in relation to firm performance and to identify the drivers of the skill shortage itself.

In general, subjective measures of skill mismatch are appealing as they are easily observable, specific to the job of the respondent, and up-to-date. However, they may suffer from measurement error (e.g., overstatement of the skills necessary to perform a job) and, of course, may be heavily influenced by employers and workers' individual perceptions and biases. In contrast to objective methods, however, the subjective perspective may capture innate or general skills that may not be otherwise observable from realized matches and employees' biographical data, which instead may better convey information on skills in specific areas or domains. The distinction between general and specific skills has proved to be empirically relevant for labor market outcomes such as earnings and job satisfaction (Sánchez-Sánchez and McGuinness, 2015).

An important distinction in measuring employee-job mismatch is that between formal education mismatch and skill mismatch. Skill-specific mismatch is typically measured using survey data, where employees report the extent to which they perceive their own "skills" and/or "knowledge" to be adequate to their current job. Most of the works reviewed here adopt the subjective approach to skill mismatch, with the vast majority using ISA methods: they are mainly based on surveys, and skill mismatch is defined on the basis of employees' assessments. Here are some examples of questions used in surveys to measure skill mismatch:

- "My current job offers me sufficient scope to use my knowledge and skills" (skill mismatch);
- "I would perform better in my current job if I possessed additional knowledge and skills" (skill shortage);[6]
- "The extent to which they [employees] have used the knowledge and the skills acquired at university in their current job";[7]

[6] Survey data collected for the project "Higher Education and Graduate Employment in Europe"; see Allen and Van der Velden (2001). Responses are on a 5-level scale.

[7] ISTAT (National Statistical Italian Centre) survey in 2001 on individuals who graduated from all Italian universities in 1998 (Di Pietro and Urwin, 2006).

- "I use many of my abilities in my current job";[8]
- "Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?";[9]
- "Have you had formal training or education that has given you skills needed for your present type of work?" (yes or no).[10]

Allen and Van der Velden (2001) authored one of the early works that consider multiple dimensions of employee-job mismatches, investigating skill mismatch separately from educational mismatch. The authors use data collected for the project "Higher Education and Graduate Employment in Europe", focusing on Dutch survey data of employees' self-reported data on perceived job requirements to build measures of educational mismatch and skill mismatch. In particular, employees are asked questions on perceived educational requirements for their current job and on the extent by which they are lacking or using their "knowledge and skills". This allows the authors to disentangle the effect of educational mismatch and skill mismatch, in the forms of skill under-utilization or skill-deficit, as reported by the employees.

Using a similar methodology, Di Pietro and Urwin (2006) explore the differences in educational and skill mismatch in the Italian labor market, using an employee survey from the Italian National Statistical Institute (ISTAT). For educational mismatch, the authors consider both vertical and horizontal mismatch: to measure vertical mismatch, they compare the employee's degree with both the degree formally required for the job (if any) and with the perceived adequacy of the employee's degree; for horizontal mismatch, they rely on responses by employees in graduate jobs about the presence of formal requirements of a degree in a specific field. As in Allen and Van der Velden (2001),

[8] Household, Income and Labour Dynamics in Australia (HILDA) Survey; e.g. see Mavromaras et al. (2007)). Responses on a 7-level scale.

[9] Spanish waves (1994–2001) of the European Community Household Panel (ECHP). See Budría and Moro-Egido (2008).

[10] See footnote 8.

skill mismatch is measured using answers by employees about “the extent to which they have used the knowledge and the skills acquired at university in their current job”.

Both of these studies show that, while there is a correlation between educational mismatch and skill mismatch or deficiency, one does not imply the other. Moreover, both dimensions are important to account for the variation in labor market outcomes (such as wages and job retention), and they capture different relevant drivers of the job-employee mismatch. Moreover, while measures of mismatch based on formal education are static, measures of skill mismatch can better capture the dynamic nature of some worker characteristics: while formal education is measured at a fixed point in time in employees’ careers, skills can be measured at different times, potentially capturing labor market experience and additional training. However, measuring employees’ skills is more difficult, typically resulting in noisier measurement, which is also reflected in the generally weaker impact of skill mismatches on labor market outcomes, compared to educational mismatch.

In a series of papers using the Australian “Household, Income and Labour Dynamics in Australia (HILDA) Survey” data (Mavromaras et al., 2007, 2009; McGuinness and Wooden, 2009; Mavromaras and McGuinness, 2012), the authors use a measure of skill mismatch based on “over- skilling”. The latter is defined by the employee’s perceived usage of her skill in the current job, namely, the survey respondents express their agreement (on a scale from 1 to 7) to the statement: “I use many of my abilities in my current job”. This is used to define a measure of skill mismatch, dividing the employees into well-matched, moderately over-skilled, and severely over-skilled. Mavromaras et al. (2007, 2009) show that over-skilling is poorly correlated with educational mismatch, is persistent in the Australian labor market, and its impact on wages greatly depends on the employee’s level of formal education. McGuinness and Wooden (2009) focus on more extreme skill mismatches, defining similar over-skilling categories, but consider as moderately and severely over-skilled only the employees who do not report to be employed in an extremely complex or difficult job. It is also worth mentioning that the authors use a measure of “required upskilling” reported by the employees, based on the extent to which the current job requires the employee to learn new skills; this may be seen as a proxy for skill shortage. Finally, Mavromaras and McGuinness (2012) use the same data and definition of “overskilling”, but add a panel dimension that allows to investigate the dynamics of employees’ “overskilling”. This also shows that skill-based measures can capture changes that occur throughout an employee's career (e.g., on-the-job learning, additional non-formal training), which is not possible with measures based on formal education.

4.2.2 Subjective methods and multidimensional skill mismatch

In the surveys mentioned above, the definition of "skills" is rather broad, typically referring to general skills. However, in some cases it is also possible to define and study skill-specific mismatch, which arises when the worker's proficiency in a specific skill (e.g. specific competencies, like writing ability, ability to work in a group, etc.) does not match that required by the job.

The data required to define skill-specific mismatch are not always easily available, but some large surveys are providing it. Most of these surveys happen to collect data for many countries, enabling the possibility of comparative studies. Allen and De Weert (2007) extend the methodology in Allen and Van der Velden (2001), by expanding their analysis to five countries[11] represented in the 1998 Children's Environmental Exposure Research Study (CHEERS), using employee survey data. It is worth mentioning how their measure of skill shortage is constructed: absent any direct question on the matter in the survey, the authors identify 18 competencies on which employees had to report a measure on a five-point scale of both their own skill at graduation time and of the required skill in their current job. While this potentially provides a rich multi-dimensional description of workers' skill profiles, the discrepancies in the reported skill levels were used in an aggregate measure of skill shortage. Measures of skill under-utilization and vertical educational mismatch are defined similarly to the earlier work. Overall, the analysis confirms that, even if correlated, the two types of mismatch carry different information, with one not always implying the other: both have an impact on hourly wages, job satisfaction, and intention to quit, although the results are weaker for skill mismatches.

[11] The countries are: Spain, Germany, the Netherlands, the UK and Japan.

Desjardins and Rubenson (2011) is one of the first studies analyzing skill-specific mismatches, namely literacy and numeracy skills. The authors can measure both the skill level of the employees and the skill requirements of the jobs, by using the 2003-2007 Adult Literacy and Lifeskills Survey (ALLS), where respondents from different countries were asked questions about engagement in literacy and numeracy-related tasks at work; the data set also contains direct measures of employees' literacy and numeracy skill levels. Based on this information, a mismatch is defined by comparing job requirements and employee's level, for a specific skill. While the analysis does not fully exploit the multidimensional nature of skill mismatch, focusing on literacy mismatch, the derived measures of mismatch allow isolating specific skills.

The survey conducted under the Programme for the International Assessment of Adult Competencies (PIAAC) is another rich source of internationally comparable data regarding workers' skills. Similarly to the ALLS data, this survey assessed skills in literacy, numeracy, and problem-solving in technology-rich environments and includes, among others, information on educational attainment and how skills are used at work and in other contexts. Using this data set, Flisi et al. (2014) were able to replicate 21 measures of educational and skill mismatch from the literature (many of which are cited above) for 17 European countries.[12] The PIAAC data is also used in McGowan and Andrews (2015b, 2015a), where educational and skill mismatch are based on information from both the supply and demand sides. In particular, skill requirements for jobs are computed using the proficiency scores of workers who report themselves as well-matched. More recently, this data set has also used by Bandiera et al. (2024) to measure and compare the quality of skill matches in 28 countries, using a representative sample of over 120,000 individuals.

The Flexible Professional in the Knowledge Society (REFLEX) survey is another important source of data, containing skill-specific information for several countries. McGuinness and Sloane (2011) use it by focusing on graduate employees and define measures of over- and under-education relative to

[12] Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, Germany, Ireland, Italy, Netherlands, Norway, Poland, Slovak Republic, Spain, Sweden and United Kingdom.

the education level that employees perceive to be required to perform their current job, and a measure of over- or under-utilization of skills, based on responses rating skill and knowledge usage in current job, on a 5-level scale. Allen et al. (2013) rely on the same data, together with the Higher Education as a Generator of Strategic Competences (HEGESCO) data, extending the analysis to over 20 countries. They build measures of educational mismatch and skill mismatch analogously to McGuinness and Sloane (2011), with the important distinction that to harmonize formal education measurements across different countries, they focus on years of education; skill mismatch is formulated in terms of over-skilling. Sánchez-Sánchez and McGuinness (2015) also use REFLEX data to study educational mismatch (over/under-education) and skill mismatch (over/under-skilling) for 13 European countries.[13] They define these measures as in other studies, but leverage the richness of the REFLEX data by considering information on specific skills: the survey asked specific questions with respect to skill acquisition and usage in 19 key competency areas related to job performance. This information is used to derive a measure of over-skilling in each area, comparing the skill level of employees with the assessed requirements for the current job. The authors report that over-skilling in specific areas is poorly correlated with over-education and general over-skilling, and that the impact of over-education and over-skilling on wages and job satisfaction is not affected by controlling for mismatches in specific skills. Overall, this suggests that specific skills might fail to capture some other innate or general ability of employees and that both types of skill measures, general and specific, are relevant in the description of job-worker mismatches.

[13] Italy, Spain, France, Austria, Germany, the Netherlands, UK, Finland, Norway, Chez Republic, Portugal, Belgium and Estonia.

4.3 Mixed methods

Many mixed methods have also been used in the literature, whereby objective and subjective methods are combined, depending on data availability. For example, Chevalier (2003) and Chevalier and Lindley (2009) mix the JA method with the subjective approach (DSA/ISA) to obtain a more refined measure of overeducation. The authors use the JA method to determine whether an individual is overqualified, and then use a subjective question capturing individuals' "satisfaction regarding the match between education and job" to divide overqualified individuals between those who are apparently overqualified (being nonetheless satisfied with their match) and those who are genuinely overqualified (being also dissatisfied with their match).

A different approach related to wages is suggested by Nauze-Fichet and Tomasini (2002). A person is classified as overqualified if two-thirds of the individuals at the level of education immediately below that person are better paid. Indeed, all else being equal, education should enhance individuals' work productivity and thus raise their expected wage rate. Thus, individuals who are paid significantly less than the wage corresponding to their level of education are considered overqualified.

While all the above-mentioned contributions rely a subjective approach, there are also works that combine subjective and objective methods. For example, Béduwé and Giret (2011) use the French "Generation 98 survey" data to build and test separate indicators for horizontal educational mismatch, vertical educational mismatch, and skill mismatch, showing that only the latter two have a significant impact on wages. Their definition of educational mismatch uses objective methods (i.e., expert evaluations of the formal requirements of the job) rather than employees' self-reported assessments, while the skill mismatch is based on respondents' perception of over/under-utilization of their skills for their current job.

Depending on data availability, it is not always possible to completely separate educational mismatch from skill mismatch, so that in the literature there are mismatch measures that mix the two, combining measures of mismatch closely related to formal education with employees' skills to define a broader indicator that captures both types of mismatch. For example, Budría and Moro-Egido (2008) define a broad measure of skill mismatch using the Spanish waves (1994–2001) of the

European Community Household Panel (ECHP) survey data: respondents were asked two yes-or-no questions about the perceived adequateness of their qualifications and formal training for the current job, where both answers define educational mismatches, to be intended in a broader sense as the resulting measure encompasses both skill and formal education mismatches. Similarly, Green and Zhu (2010) use U.K. survey data[14] to build measures of overqualification and over-skilling using self-reported data, and use them to define a composite measure of job-employee mismatch.

4.4 Measuring skill shortages

We conclude this section with some information on measures of skill shortage. As we have seen, these measures have also been used in studies measuring skill mismatch. However, they need a separate mention because, in contrast to measures of skill mismatch, these measures are more often centered on the employers' perspective. Indeed, measures of skill shortage are commonly built using firm surveys, and are often used to test their impact on firms' performances (e.g. productivity). The usual DSA and ISA distinction also applies here. DSA measures are based on survey questions asking firms to rate difficulties in hiring and/or filling vacancies for certain occupations. ISA measures are constructed using information on unfilled vacancies or combining answers regarding the relevance of specific skills and barriers in their adoption. Forth (2006) focuses on Information and Communication Technologies (ICT) skill shortage. They combine data from the UK International Benchmarking Survey (IBS), with firms' financial data. The authors define ICT skills using a direct question, asking firms to assess whether or not their workforce had a sufficient understanding of ICT technologies. This measure is also validated with another one, combining firms' assessments on the relevance of ICT skills and barriers to ICT adoption.

[14] The authors use multiple sources of data: 2006 UK Skills Survey, Employment in Britain in 1992, the 1997 Skills Survey, and the 2001 Skills Survey.

Bennett and McGuinness (2009) construct two measures of skill shortage using vacancy data collected by the Priority Skills Unit of the Economic Research Institute of Northern Ireland (ERINI) and consisting of three separate surveys of high-tech firms in the engineering and information technology sectors. The first measure of skill shortage refers to hard-to-fill vacancies, directly reported by the firms, which were asked to indicate the degree of difficulty associated with recruiting staff within a set of occupational categories. The second measure tries to eliminate the subjectivity bias of the first one, being constructed using vacancies reported by firms as being unfilled in the 12 months preceding the survey. The authors show that, while the two measures are highly correlated, some determinants are unique to one or the other, thus indicating a certain amount of heterogeneity in the type of shortage being captured. However, both types of shortages are shown to hamper firm productivity.

Neumark et al. (2013) provide an objective measure of skill shortages in the U.S. economy, defined as the difference between projected supply and demand for skills, which are essentially defined on educational attainments, and are computed based on data from the Bureau of Labor Statistics (BLS), and the 2008 American Community Survey (ACS). The demand side is derived either by aggregating information directly available in the BLS data or from observed data on degree attainment within occupation categories, resting on the assumption that observed employment provides a good measure of workforce skills needs.

Instead, Healy et al. (2015) define a subjective measure of skill shortage using the Australian Bureau of Statistics' Business Longitudinal Database, which is a survey of small and medium-sized enterprises. The measure of skill shortage is a DSA measure, based on yes-or-no answers to the question: "Did this business have skill shortages during the year to 30 June 2005?" The data also contain information on the perceived determinants of skill shortage and how the firm responded to it, enabling the authors to investigate the severity of the skill shortage and its persistence over the years, which are both shown to vary across different types of skill shortage.

5. Determinants of Mismatch

As shown in Section 2, the mismatch between workers' skill sets and firms' skill requirements can arise from two main labor market frictions, namely, search costs and imperfect information, possibly in conjunction. In this section, we consider economic factors that can amplify or mitigate these frictions, and therefore can be regarded as determinants of skill mismatch.

Specifically, in Section 5.1 we discuss various market imperfections that may amplify the effects of these two basic frictions, namely, (i) geographical constraints and relocation costs, (ii) firms' firing and hiring costs, (iii) financial constraints, (iv) non-meritocratic promotion policies, and (v) workers' migrant status. Next, in Section 5.2, we explore whether and how macroeconomic fluctuations affect skill mismatch. Finally, in Section 5.3 we discuss structural factors affecting skill mismatch, such as education and technology, and structural shocks affecting the composition of the demand or supply of labor, such as the China shock, the COVID-19 pandemic, the transition to a low-carbon economy and the ongoing demographic decline.

5.1 Market imperfections

5.1.1 Geographical constraints and relocation costs

The distance between employers and prospective employees is a natural proxy for search costs: workers are less likely to engage in search activity for more distant job opportunities.[15] Employees can reduce this distance by relocating closer to suitable jobs, but this requires bearing the cost of a new house rental or purchase. Therefore, housing costs create an obstacle to workers' mobility in their search for suitable jobs, discouraging workers from filling vacancies in distant locations, and

[15] Distance may also increase the cost of relocating, especially when relocation also involves migration: Freeman et al. (2024) document that distance is a deterrent to migration, especially when it combines with language differences.

possibly preventing suitable worker-job matches that would occur with costless (or less costly) mobility. Indeed, using job application data from the U.S., Marinescu and Rathelot (2018) document that workers dislike applying to distant jobs.

By the same token, increases in house prices and rents can force workers to relocate to areas where housing is more affordable and thus may break productive job-worker matches. For instance, Cerqueiro et al. (2024) examine the labor reallocation triggered by a reform that abolished rent control in Portugal: both low-income and high-income workers relocated to the city outskirts, but the former ended up accepting worse jobs and lower wages in firms located close to their new residence, while high-income workers remained unaffected. The introduction of work-from-home arrangements and improvements in public transportation should have the opposite effects, i.e., reduce the effect of geographical frictions and relocation costs on skill mismatch.

While this evidence suggests that housing market frictions generate job mismatch particularly for low-income or low-wealth workers, they can also be problematic for homeowners, who are typically wealthier than renters: in fact, if the housing market is illiquid, homeowners face larger relocation costs than renters, and move less frequently. Moreover, the housing market tends to be less liquid in locations where the demand for labor is depressed. Bernstein and Struvyen (2022) find support for the "housing lock hypothesis" first theorized by Stein (1995). Using Dutch administrative data, they show that declines in home equity result in lower job mobility. Consistently, Brown and Matsa (2020) find that, during the Great Recession, job seekers in areas with depressed housing markets applied for fewer jobs that required relocation.

These findings are in line with the model by Head and Lloyd-Ellis (2012), which analyzes geographical mobility, unemployment, and homeownership in a setting with endogenous construction and search frictions in the labor and housing market. They show that the decision of homeowners to accept job offers in other locations depends on how quickly they can sell their houses, which in turn depends on local labor market conditions. Consequently, they tend to accept job offers in other locations less frequently than renters and to be more often unemployed – a prediction consistent with the finding by McGowan and Andrews (2015) that skill mismatch is lower in countries where residential mobility is not impeded by high transaction costs on real estate and stringent planning regulations. Another implication of the model is that these effects on skill mismatch should also be greater in thin labor markets, consistent with the finding by Büchel and Van Ham (2003) that the smaller the local labor market (in terms of the traveling time to the nearest agglomeration), the higher the risk of overeducation.

The effect of geographical constraints on mismatch may be amplified by workers' borrowing constraints: Van Doornik et al. (2024) show that liquidity constraints increase geographical mismatch. In the Brazilian context, they find that expanded access to credit for investment in individual mobility has substantial returns, as it enables workers to invest in individual mobility, search for jobs farther from home, and thus achieve higher formal employment rates and salaries. Their evidence highlights one channel through which workers' credit constraints can increase their mismatch. Conversely, the effect of geographical constraints on mismatch may be reduced by business groups' ability to relocate jobs to locations close to workers who demand lower wages and/or have better fit with their positions: using German data, Gong et al. (2024) show that business groups and conglomerates that operate in multiple locations arbitrage local labor markets, by relocating jobs to locations where they pay lower labor costs and/or can hire workers whose skills have a better fit with their positions.

5.1.2 Firing and hiring costs

High firing and hiring costs discourage firms from firing mismatched workers and replacing them with new hires, so that they can be expected to increase the persistence of mismatch. Autor et al. (2007) show that higher firing costs leads to lower productivity, by exploiting the adoption of wrongful discharge protection in several US states between the 1970s and 1990s. Their finding could be interpreted as a symptom that higher firing costs impair workers' reallocation towards better matches. Caggese et al. (2019) show that the firing cost differential between short-tenure and long-tenure workers may lead financially constrained firms to "fire the wrong workers" in response to a drop in demand, i.e., disproportionally fire short-tenure workers, even though these hold greater promise in terms of future productivity.

Maida and Tealdi (2021) analyze the impact of two reforms that increased the flexibility of the Italian labor market: the 2001 labor market reform that liberalized the utilization of short-term contracts in

Italy, and the 2003 reform, which modified apprenticeship contracts in terms of eligibility, duration, minimum wage, and training content. They find that the short-term contract reform significantly increased the relative flow of workers hired on short-term contracts, translating into a significant reduction in the relative flow of over-educated workers. Along the same lines, Berton et al. (2017) study the impact of the so-called Fornero Law, which in 2012 reduced firing costs of employees with long-term contracts in Italy, and report that this resulted in an increase in good matches, defined as those for which the worker's educational attainment equals the median educational attainment of her reference professional group.

At the cross-country level, McGowan and Andrews (2015) find that employment protection legislation is negatively associated with match quality. Similarly, Brunello et al. (2007) argue that labor mobility is significantly lower in Europe than in the United States, partly due to higher employment protection legislation, and that suboptimally low mobility can increase skill mismatch. Of course, differences in labor mobility between Europe and the United States may also reflect workers' preferences, i.e., stem from cultural factors and social norms.

5.1.3 Financial constraints

As mentioned above, Caggese et al. (2019) show that firms' financial constraints may interact with hiring and firing costs to amplify skill mismatch, as firms may end up "firing (or hiring) the wrong workers." Using administrative Swedish data, they show that financially constrained firms react to negative demand shocks by disproportionally firing short-tenure workers, as firing costs increase in tenure. This points towards a potential distortion due to financial constraints. Financially constrained firms are also more likely to hire workers with short-term contracts, reducing the incentives for on-the-job learning and, thus, skill acquisition (Caggese and Cunat, 2008).

Credit constraints may also affect workers, preventing them from investing in the acquisition of the "right skill set" given the available job vacancies, and thus may contribute to skill mismatch (as workers end up filling positions for which they are not qualified) and/or skill shortage (as some of the vacancies posted by firms remain unfilled).[16] In principle, this problem should only arise for general (i.e., portable) skills, because firms have the incentive to finance on-the-job training costs for workers to acquire firm-specific (i.e., non-portable) skills.

However, in practice firms often provide general training to their employees, covering part or all of the direct cost of the relevant courses (Manchester, 2010). A substantial body of theoretical literature shows that this can be rationalized by information asymmetries. The pioneering work of Katz and Ziderman (1990) showed that, when firms have private information on the true value of training, adverse selection deters their competitors from poaching trained workers, as they would tend to attract the least successfully trained ones. Hence, firms providing general training can retain workers at a low wage, and recoup the cost of training: adverse selection enables firm-sponsored general training in equilibrium, transforming general training into *de facto* specific training. Acemoglu and Pischke (1998, 1999) extend this argument, contending that employers possess better information about employee productivity (not only about the value of training) than other firms. Again, this information asymmetry confers monopsony power to employers, enabling them to partially recoup their investment in general training, even in the absence of search frictions. Informational frictions may reduce skill mismatch, rather than increasing it.

Even though – as this literature illustrates – firms should have the incentive to provide both firm-specific and general training, workers' credit constraints may still affect their skill accumulation. Based on credit report data linked to administrative employment histories, Herkenhoff et al. (2023) show that a relaxation of financial constraints in the form of an increase in credit limits induces workers to search longer for jobs and that the resulting improved access to credit reduces mismatch, based on evidence on earnings and sorting. Similar conclusions are reached by Hi and Le Maire (2023) who study the effect of a Danish mortgage reform relaxing credit constraints for homeowners.

[16] As mentioned in Subsection 5.1.1, workers' financial constraints may also exacerbate relocation costs: the inability to obtain a mortgage loan to buy a house in a new location, for instance, reduces the mobility of workers and thus limits their ability to search for jobs more suited to their skill set, consistently with the evidence by Van Doornik et al. (2024).

5.1.4 Non-meritocratic promotion policies

Matching workers to the right jobs is part of managers' tasks. Hence, mismatch should be negatively correlated with the quality of managers and their human resource practices. A recent strand of research has measured the quality of managerial practices via standardized surveys addressed to managers and has shown the resulting indicators to be robustly and positively correlated with productivity and with employees' human capital (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013, 2019). Bloom et al. (2019) find that structured management practices and wages are positively correlated in a cross-section of countries. Relatedly, Bloom et al. (2013) present causal evidence that the provision of consulting on managerial practices leads to dramatic improvements in productivity in a sample of Indian textile firms (see also Cornwell et al., 2021, and Ichniovski et al., 1997).

However, this research has not specifically analyzed the relationship between managerial quality and skill mismatch. Coraggio et al. (2024) address this issue by showing that better managers improve the skill match quality of their subordinates. They estimate a measure of job allocation quality (JAQ) by applying a machine-learning algorithm to Swedish employer-employee administrative data and show that the JAQ of rank-and-file workers correlates with the job experience and the JAQ of their firms' managers. They also study managerial turnover events, and find that turnover events that improve the quality of the managerial team are followed by increases in the rank-and-file workers' JAQ, while those that reduce the quality of the managerial team are followed by the opposite outcome.

These results square with the evidence on the importance of managers in allocating human capital within the firm and in shaping workers' careers (Minni, 2023; Pastorino, 2023). Research on German data illustrates that better managerial practices correlate positively with the skills of the hired workers (suggesting assortative matching dynamics at play) as well as with higher productivity and wages, even after controlling for workers' characteristics (Bender et al., 2018).

Have all firms the same incentive to appoint managers who rely on best practices and promote workers according to merit? As we just illustrated, the literature on managers and workers' quality suggests that good managers are largely beneficial, hence one could be inclined to think that all firms would try to appoint the best possible people to managerial positions. However, if entrepreneurs may prefer non-meritocratic promotion policies if these yield private benefits to them in the form of power over the firm, and they have a strong enough taste for power: promoting a low-skill rather than a high-skill employee enables the entrepreneur to retain real authority over the firm, without the risk of flawed decisions being challenged or disclosed by a competent manager. Even though failing to promote on the basis of merit has a cost in terms of forgone managerial efficiency and profitability, this cost is shared among all the firm's financiers, while the benefit accrues to the entrepreneur alone. Pagano and Picariello (2022) show that the extraction of the private benefits of control associated with non-meritocratic promotions is more likely to occur in countries with low corporate governance standards, which may in turn reflect deep-rooted institutional and cultural features of these countries (La Porta et al., 2000; Licht, 2024). The authors show that a questionnaire-based index of firm meritocracy correlates positively across countries with an index measuring the protection of minority investors against abuses by controlling shareholders, for a sample of 55 countries. Their model shows that non-meritocratic promotion policies not only generate skill mismatch, productivity losses and wage losses, but also reduce workers' ex-ante incentives to invest in human capital, and thus the fraction of high-skill workers in the population. These predictions are consistent with the evidence by Bandiera et al (2024), who show that GDP per capita is higher in more meritocratic countries, defined as those where workers are matched to jobs based on their skills rather than on idiosyncratic characteristics unrelated to productivity.

The tendency towards non-meritocratic promotions is also related to the pervasiveness of family firms, which may itself be related to cultural and social norms regarding the centrality of the family in societal organization. In family firms, the preference for dynastic managerial appointments leads to inefficient selection of managers, forgoing sizeable productivity gains (Burkart, Panunzi and Shleifer, 2003, Burkart and Panunzi, 2006, Bennedsen et al., 2007, Lippi and Schivardi, 2014, Lemos and Scur, 2020, Bandiera et al., 2018). This results in fewer career opportunities for non-family employees: in family firms, favoritism toward family members tends to be associated with lower promotion rates of employees who are not part of the controlling family, and effectively face a “glass ceiling” in their careers (Di Porto et al., 2024).

Deviations from meritocratic promotions may also occur as a result of gender or racial discrimination, as shown by research on the efficiency costs of favoritism and racial or gender-based discrimination at the workplace, which may also stem from cultural factors and social norms shaping entrepreneurs' and managers' preferences. These may induce them to engage in discriminatory policies at the cost of forgoing incremental profits from meritocratic personnel policies. Becker (1957), Prendergast and Topel (1996), and Friebel and Raith (2004) analyze the impact of supervisors' discretion on promotions and favoritism in organizations. However, regulatory changes that enhance the protection of external financiers (whether shareholders or creditors) should discipline firms and induce them to more meritocratic appointments and promotions, hence to less workplace discrimination. Consistently with this prediction, Gao et al. (2022) find that a change in U.S. regulation that reinforced creditor protection in some states, improving their firms' access to financing, significantly narrowed the earnings gap between minority and white workers, especially for mid- and high-skill workers and for firms with worse diversity practices ex-ante, and increased the frequency of minority workers' promotions and reassignments to technology-oriented occupations.

A potentially fruitful avenue for future research is to investigate whether changes in managerial practices triggered by corporate events such as restructurings (e.g., mergers, acquisitions, and private equity interventions), switches to non-family firm status (e.g., sale of family firms to companies run by professional managers) or firm bankruptcies significantly affect skill mismatch, and in which direction.

5.1.5 Migration-related frictions

The skill set of immigrants can be expected to be less well-matched to jobs available in their host country than that of native workers, as typically they undertook their educational curriculum before migrating and therefore without knowing the job opportunities that would be available in the host country, unlike natives. Indeed, the evidence points to skill mismatch being more common among migrants compared to native workers.

Most of the papers on this issue measure mismatch as the discrepancy between the required level of education for a particular job and the worker's educational attainment level, and conclude that migrant workers typically feature greater over-education than natives. Using microdata from the Adult Education Survey (AES) provided by Eurostat, Nieto et al. (2013) find that the probability of over-education of migrants exceeds that of natives by 44.4 percentage points and that their probability of horizontal mismatch is 18 percentage points higher than for natives. Moreover, migrants from non-EU countries are more likely to be mismatched, controlling for individual characteristics, while immigrants from EU countries do not differ significantly from natives in their mismatch probability. Based on the cross-country analysis with data from an annual survey data from 86 countries in 2008–2013, Visintin et al. (2015) also find that the differential skill mismatch between natives and migrants depends on both the country of origin and that of destination, as certain combinations of countries imply greater frictions than others, for example due to educational requirements, labor market regulations, and language barriers: migrants who work in Europe and Asia are more likely than native workers to be over-educated, whereas the opposite applies to migrants in Africa and Latin America. Jestl et al. (2015) document that migrants employed in the manufacturing and tradable services sector of EU countries feature greater job-skill mismatch than native workers, and find that in general migrants tend to be more over-educated than natives especially if they hold jobs that typically feature a low share of people with higher educational attainment levels. Moreover, the share of relative over-educated migrants (i.e., those holding jobs for which they are better qualified compared to natives) is much smaller than that of relative under-educated migrants.

However, it is not clear to what extent these results stem from migrants' inability to deploy their actual skills due to cultural factors such as language barriers and host countries' regulations that tend to delay or prevent the recognition of their educational qualifications, or instead reflect the fact that their formal qualifications are of intrinsically lower quality than those in the host countries, so that their apparent over-education is not a substantive one. Measures of mismatch that are not based on educational qualifications but on direct measures of workers' cognitive skills reveal that migrant workers are generally under-skilled for their jobs compared to native workers. McGowan and Andrews (2015a), who base their mismatch indicator on the skills measured by the OECD PIAAC, find that, while migrants are more likely to feature skill mismatch than their native counterparts in most OECD countries, they are less likely to be over-skilled and more likely to be under-skilled than natives. Sorting out the puzzle of migrants' over-qualification coexisting with their under-skilling relative to natives is an interesting research question.

5.2 Macroeconomic fluctuations

Job mismatch is higher in recessions than in expansions: using the National Longitudinal Survey of Youth data on tenure and wages, Bowlus (1995) finds that mismatches are more frequent in recessions, resulting in shorter job tenure for new hires, and that the labor market recognizes the greater level of mismatching in recessions and compensates for it via lower wages. Summerfield and Theodossiou (2017) provide evidence that unfavorable economic conditions at graduation decrease the likelihood of a good job-worker match, not only on impact but also subsequently over the relevant worker's career. They measure mismatch in terms of over-education by both industry and occupation, and use data from the German Socio-Economic Panel and region-level unemployment rates from 1994 to 2012. They report that 1 percentage point increase in regional unemployment raises the probability of over-education by 1.6–1.7 percentage points for university graduates. Labor market entry conditions affect workers for up to 9 years after graduation.

The idea that recessions generate persistent rises in skill mismatch is consistent with the search model calibrated by Baley et al. (2022) on the U.S. economy: they estimate that displacement triggers 19% earnings losses 5 years after displacement and 10% earnings losses 10 years after displacement. This finding is also consistent with microeconomic evidence produced by Neffke et al. (2024), based on the work histories of individuals in Germany between 1975 and 2010. As mentioned in Subsection 4.1.4, not only they document that plant closures have lasting adverse effects on the earning trajectories of workers displaced from their jobs, but also that these effects vary with the skill mismatch that workers experience after displacement. Comparing the earnings of displaced workers with similar non-displaced workers, they find that displaced workers with redundant skills feature permanently lower earnings, while the earnings of those with skill in short supply recover quickly. These findings dovetail with much evidence that the impact of recessions (and booms) on starting wages is persistent, and also affect the career progression of workers (Kahn, 2010; Oreopoulos et al., 2012; Oyer, 2008; Schoar and Zuo, 2017). This suggests that job mismatch in the first few years of workers' careers affect their human capital accumulation, not just their current wage.[17]

Şahin et al. (2014) estimate to what extent mismatch contributed to the increase in unemployment in the United States during the Great Recession of 2008-09. They estimate mismatch to have risen sharply during the recession: "in mid-2006, the fraction of hires lost because of misallocation of unemployed workers across industries ranged from 2 to 3 percent per month, depending on the index used. In mid-2009, at the end of the recession, it had increased to roughly 7 to 8 percent per month" (pp. 3544-5), and then it gradually decreased back to the pre-recession level by 2012. To estimate the extent of mismatch in the economy, they build a multi-sector version of an otherwise standard aggregate search and matching model (Pissarides, 2000), which they calibrate to US data, and define a mismatch index by comparing the actual allocation of unemployed workers across sectors to a benchmark allocation selected by a planner facing no obstacles in moving idle labor across sectors, except for the within-market matching friction. Equipped with this mismatch index, they find that mismatch has a countercyclical pattern and that it can explain up to one third of the increase in the U.S. unemployment rate during the Great Recession.

Baley, Figuereido and Ulbricht (2022), who build and estimate a directed search model using U.S. data, offer a more nuanced picture of the impact of recessions on job mismatch. As mentioned in Subsection 2.2, they find that recessions have two opposite effects on job mismatch: more firings of very low-skill workers ("cleansing effect"), which reduce the mismatch of employed workers, raising their average labor productivity by 1.4%; and greater mismatch among new hires, due to an increase

[17] The persistence of the scarring effects of displacement is also consistent with evidence by Graham et al. (2023), who analyze matched employer-employee panel data from the U.S. Census, documenting a persistent 15% drop in wages following bankruptcy. This also applies to managers: Eckbo, Thorburn, and Wang (2016) report that only one-third of CEOs maintain executive employment after a bankruptcy filing, especially when their firm's previous profitability was below the industry average, and departing CEOs suffer large income and equity losses.

in over-qualification among workers hired for low-complexity jobs (“sullying effect”), which reduces the productivity of new hires by 0.9%.

5.3 Structural factors and shocks

Skill mismatch and skill shortages can be amplified by various long-term economy-wide **institutional or technological factors** as well as by their changes, i.e., by **structural shocks.**

5.3.1 Education

Mismatches can arise when educational curricula do not adequately align with the skills demanded by firms: as discussed in Section 4, many empirical studies measure skill mismatches as the difference between the actual level of education possessed by a worker and the level of education typically required for his/her job. Indeed, there is some evidence that schooling helps develop general skills in numeracy and literacy. Asai et al. (2020) test whether initial education affects the skills measured by the OECD PIAAC standardized test in adults about 45 years old, and find that this is the case for Belgium, the only country for which they have a sufficiently large sample for PIAAC scores: exploiting a Belgian reform that raised mandatory schooling from 8 to 12 years for people born after 1969, they find a causal effect of schooling on literacy skills of size comparable to the correlation between these two variables, and a somewhat lower effect on numeracy skills. However, several other studies show that educational mismatches and skill mismatches are weakly correlated at best (Allen and van der Velden, 2001; Flisi et al., 2017; Green and McIntosh, 2007; McGuinness and Sloane, 2011, Quintini, 2011, among others): there is considerable variation in skills within educational levels, possibly due to variation in individual ability and to on-the-job training received by workers after completing their formal education. Indeed, Levels et al. (2014) find that, when measures of PIAAC skills are added to educational qualifications as explanatory variables in wage equations, the explanatory power of education and of education-based mismatch measures drops considerably. Hence, it is unclear to which extent the skill mismatch of workers can be traced back to their formal education curricula: this is a research question surely worthy of further investigation.

5.3.2 Technology

Technological advances, such as automation, Artificial Intelligence (AI), and digitalization, create demand for new skills and render existing skills obsolete. Workers may struggle to keep pace with technological changes, leading to a mismatch between the skills they possess and those required by evolving job roles. This point can be formalized within the skill-biased technological change hypothesis (Goldin and Katz, 2008; Acemoglu and Autor, 2011; Goos et al., 2014), which highlights that labor supply follows a slower adjustment process than demand, thus creating inequality, skill mismatch, and likely skill shortages. The skills that technological innovations render obsolete depend on the type of innovation: while automation tends to destroy routine-intensive jobs, AI eliminates more abstract jobs by increasing the productivity of remaining workers but rendering many jobs redundant (Atalay et al., 2020). At the same time, innovations create other jobs in which labor has a comparative advantage, so the net effect on total labor demand is not clear, as discussed in Acemoglu and Restrepo (2019, 2022, and 2023). However, even if technological advances may not affect total labor demand, they are likely to require different skills, hence generating a mismatch, and thus creating the need for some form of retraining.

5.3.3 Shocks to labor demand and/or supply composition

The “China shock,” i.e., the increase in Chinese import competition between 1990 and 2007, is a major example of a large economy-wide structural shock to labor demand that led to skill mismatch in U.S. and European labor markets. The shock led to the disappearance of many routine jobs (the “hollowing out” or polarization of the job distribution) in the sectors most exposed to import competition and led to job loss for workers equipped with those skills, causing a persistent drop in employment and labor force participation in manufacturing (Autor and Dorn, 2013, and Autor et al., 2013).

The COVID-19 pandemic is another example of a large structural shock with highly heterogeneous effects on the demand for labor. Some firms, especially in high-tech industries, were able to adapt well to social distancing requirements, by resorting extensively to teleworking, while others, such as those in the food catering, travel, and hospitality sectors, could not do so, as the nature of their business requires close contact with customers and between employees: the pandemic unearthed a previously hidden economic watershed between resilient and non-resilient firms. As a result, workers whose tasks enabled them to telework were able to retain their jobs, while those who could not were placed on furlough schemes and in some cases lost their jobs. To some extent, the pandemic led to a persistent transformation of work habits and technologies, with teleworking becoming much more widespread than before: as of mid-2023, full days worked at home accounted for 28% of paid workdays among U.S. workers, i.e., 4 times the 2019 rate (Barrero et al., 2023). This suggests a persistent change in the skill requirements of firms, but the workforce appears to have adapted to this structural shock: Pizzinelli and Shibata (2023), who apply the framework of Şahin et al. (2014) to the U.S. and the U.K. to measure mismatch during and after the pandemic, find that mismatch rose sharply at the onset of the pandemic, but by late 2021 returned to previous levels. This suggests that workers quickly acquired the skills required to telework.

Currently, the decarbonization of the economy, the incipient buildup of European defense and the demographic decline are all low-frequency factors bound to affect the composition of both the demand for labor and that of the supply of labor. On the one hand, decarbonization is bound to generate massive job losses in fossil fuel industries such as coal and oil production, while new jobs are being created in environmentally friendly activities: "in the UK alone, 250,000 have already been created, according to the Climate Change Committee, and the government's green task force has pledged to increase that to 2mn by 2030… [they] now make up a third of postings in the UK, according to social network LinkedIn" (Muir, 2024). Of course, this will require workers to acquire new skills: "according to the Institute of the Motor Industry data, only 39,000 of 168,600 vehicle technicians in the UK are qualified to maintain electric vehicles. In the US, just 1.4 percent of mechanics are EV certified" (ibidem). The rapid growth of defense companies, due to the increasing spending by European countries on military equipment, is likely to require workers with new skills and thus generate mismatch.

On the other hand, an aging workforce may lead to shortages of skilled workers in certain industries. European firms already complain that skill shortages are a severe constraint on their growth, especially in high-tech industries. ManpowerGroup, a global workforce solutions company, found that 75% of the employers in 21 European countries could not find the skills they required, against 42% in 2018. The Eurobarometer survey, carried out in late 2023, revealed that 54% of small and medium-sized enterprises (SMEs) in the EU considered finding employees with the right skills (especially technically trained staff) as one of the top three most serious problems for their company. These survey responses dovetail with empirical evidence that shows that skill shortages hamper firm performance. As mentioned in Section 4.4, using Irish vacancy data, Bennett and McGuinness (2009) find that skill shortage has a negative impact on firm productivity. More recently, using a large French administrative dataset with detailed information on job vacancies over 2010-17, Le Barbanchon et al. (2023a) find that hiring difficulties adversely affect firms' employment, capital, sales, and profits, especially in labor-intensive and in expanding sectors, and when skill shortages refer to non-routine cognitive, high-skill, high-wage, and specialized occupations.

In principle, firms should be able to overcome labor shortages by offering more attractive wages to potential job applicants. This raises the issue of whether firms that report difficulties in filling their vacancies are not simply offering lower wages that are too low. Friedrich and Zator (2024) explore this issue by using administrative data from Germany, and confirm that firms reporting skill shortages initially underpay their workers, increase wages later, and by doing so reduce their skill shortage problem. This begs the question of why they fail to increase wages earlier: the authors argue that this is due to firms' inability to compute market-clearing wages, due to their limited information.

To some extent, immigration can reduce skill shortages, especially for countries that can attract high-skill immigrants: using granular data about migration and employment of male football (soccer) players, Freeman et al. (2024) show that the role of distance becomes largely insignificant for migrants at the top of the skill distribution, and also language differences tend to be less of an impediment to migration for those at the top of the skill distribution. Their results suggest strong assortative matching, with players more likely to move between teams with similar average skill. Such assortative matching may also help immigrants overcome their tendency to be more mismatched to available jobs than natives. Orefice and Peri (2023) also document positive assortative matching for immigrants: immigration in a local labor market, by increasing the variance of workers' abilities, should prompt high-quality firms to screen for the quality of workers, and thus may improve assortative matching between firms and workers. They test this prediction using French matched employer-employee (DADS) data over the period 1995-2005 and find that a supply-driven increase of immigrant workers in a district triggers stronger positive assortative matching, and is associated with higher average productivity and firm profits.

6. Effects of Mismatch

Reducing occupational mismatch, i.e., improving the quality of job allocation, can in principle benefit both firms and workers: a better workforce allocation should enable firms to increase productivity, while workers should enjoy both a monetary gain, as at least part of their increased productivity should translate into higher wages, and greater work satisfaction, as being assigned to a more suitable job should enable them to develop a more rewarding career. Indeed, this is precisely what the evidence suggests.

6.1 Productivity

When workers are mismatched with their jobs, productivity declines, as tasks tend not to be performed optimally. This results in lower output, efficiency, and profitability for businesses. Coraggio et al. (2024) show that firm-level productivity (whether measured by the logarithm of value added or by the logarithm of sales per employee) correlates with indicators of job allocation quality (JAQ) produced with machine-learning techniques using Swedish employer-employee data, controlling for a host of firm-level variables generally associated with productivity (industry, capital, and labor, ownership) and for the workers' characteristics used to predict JAQ. They also show that improvements in management quality are associated with better worker-job matches (as already mentioned in Section 5.1.4).

This dovetails with evidence presented by Minni (2023), who shows that top-performing managers can reallocate workers to more suitable roles, leading to large productivity and wage gains, and by Fenizia (2022), who studies the impact of managers in the administrative public sector exploiting their rotation across sites, and finds that a one standard deviation increase in managerial talent raises office productivity by 10%, so that assigning better managers to the largest and most productive offices would increase output by at least 6.9%.

By the same token, talent misallocation due to discrimination can significantly impair aggregate labor productivity: Hsieh et al. (2019) estimate that between 20% and 40% of the growth in U.S. productivity can be explained by changes in the allocation of talent, primarily due to the improvement in occupational outcomes of female and black workers.[18] As already mentioned, Bandiera et al. (2024) bring cross-country evidence to bear on the contribution that the quality of worker-job matching can give to achieving technically feasible productivity gains: using internationally comparable data on worker skills and job skill requirements for over 120,000 individuals across 28 countries, they document that workers' skills better match their jobs' skill requirements in higher-income countries, and that 36% of the gains from adopting frontier technology are obtained via enhanced skill-based sorting.

McGowan and Andrews (2015a) also provide cross-country industry-level evidence on the relationship between labor productivity and both skill and qualification mismatch for 19 OECD countries. They rely not only on skill mismatch indicators aggregated from micro-data drawn from the OECD PIAAC database, but also on educational mismatch indicators, which is important because they often differ considerably from each other, as already noticed. They find that greater

[18] More broadly, the relationship between productivity losses and the misallocation of talent fits in the macroeconomic literature initiated by Hopenhayn and Rogerson (1993), who showed that if firing costs prevent firms from fully adjusting their labor force in response to shocks, some firms will hold an inefficiently large number of workers, whereas others will have too few of them, resulting in total factor productivity (TFP) losses. Subsequent contributions on misallocation abstracted from the source of the distortions ("wedges"), and treated them as primitives. Hsieh and Klenow (2009), who provide a methodology to calculate TFP losses from the wedges identified in firm-level data, estimated that misallocation can explain half of the TFP gap between China or India and the United States. See Hopenhayn (2014) for a review of this literature.

skill and qualification mismatch is associated with lower labor productivity and that over-skilling and under-qualification account for most of the correlation. Next, they decompose aggregate productivity into the unweighted average of the firm productivity distribution, which they refer to as "within-firm productivity", and the sample covariance between firm size and productivity, which captures the extent to which more productive firms have larger relative size (the so-called Olley-Pakes covariance term), which can be seen as a measure of "allocative efficiency". They find allocative efficiency to be negatively related to both over-skilling and under-qualification, while unweighted average productivity is negatively correlated only with under-qualification. They rationalize the result that greater over-skilling is significantly associated with lower allocative efficiency as reflecting the greater difficulties met by more productive firms in hiring skilled workers when these are already employed by less productive firms.

6.2 Wages and careers

There is ample evidence that skill mismatch decreases both current and future wage growth, especially if it occurs at early stage in workers' careers (see Section 5.2). Using data from the NLSY79, Guvenen et al. (2020) find that mismatch reduces wages and increases the likelihood of occupational switching: a one-standard-deviation increase in either math or verbal mismatch results in a 5 percent relative increase in the likelihood of switching occupations. Similar results regarding the effects of cognitive mismatch are reported by Fredriksson et al. (2018), using Swedish data. These results are confirmed by DeLoach et al. (2022) using the NLSY97 cohort, who additionally find that non-cognitive mismatch based on the 'Big Five' personality traits typically correlated with labor market outcomes (conscientiousness, agreeableness, emotional stability, extraversion, and openness) also increases the likelihood of changing occupations.

Coraggio et al. (2024) also find that the goodness of worker-job matches, measured at the individual worker level, rises significantly (from 35% to 57%) for a 50-year working life, the largest gain occurring in the first 5 years, where the goodness of worker-job matches rises by about 12 percentage points: this accords with the intuition that learning is faster for junior workers and that their reallocation to more suitable jobs is easier than for senior employees (Farber and Gibbons, 1996). Moreover, workers allocated to their most suitable job earn significantly more than mismatched workers with the same characteristics or with the same job: a worker allocated to her most suitable job is estimated to earn 2.4% more than a mismatched worker with the same characteristics or with the same job. Finally, well-matched workers are 1.2 percentage points less likely to switch to a new employer than mismatched workers with the same characteristics, and a worker who goes from being mismatched to being well-matched is 2.7 percentage points less likely to switch to a new employer.

An open research question is to what extent the productivity increase arising from a better skill match translates into higher wages or into greater firm profits. Presumably, this depends on the degree of monopsony power of firms in the labor market: for instance, if firms have great market power in the labor market, overqualified workers may accept jobs below their skill level, leading to lower wages than that corresponding to their qualification. According to Coraggio et al. (2024), firm-level gains in match quality are strongly associated with increases in wages but more tenuously associated with increases in firm profitability. However, this may be a reflection of the fact that their estimates refer to the Swedish labor market, where trade unions and employment protection regulations confer substantial bargaining power to employees.

6.3 Unemployment and underemployment

Skill mismatch can contribute to higher rates of unemployment and underemployment, particularly among marginalized groups such as youth, women, and minority populations. When it is hard for unemployed workers to find job opportunities that match their skills and qualifications, they will tend to search longer, leading to prolonged periods of unemployment, or may eventually settle for jobs that have a low fit with their skills, leading to underutilization of skills. Moreover, if achieving good matches requires time and effort to overcome information and search frictions, the dissolution of good matches can have persistent "scarring effects", as displaced workers suffer large and persistent earnings losses, as shown by the research reviewed in Section 2.2 and 5.2.

7. Policies Affecting Mismatch

Section 2 pointed out that the main labor market frictions that produce occupational mismatch are search costs and imperfect information. Hence, the most obvious policies to reduce skill mismatch are those that can improve the information available to labor market participants and reduce search costs. Other policies that may mitigate mismatch are those that reduce housing frictions, firing and hiring costs, those that facilitate on-the-job training and more generally skill acquisition, and migration policies that address skill shortages, namely, policies addressing labor market frictions that contribute to mismatch (Subsection 5.1).

7.1 Improving labor market information and reducing search costs

Enhancing the availability and accessibility of labor market information can facilitate matching between job seekers and employers. Job portals, career guidance services, and labor market analytics can provide valuable insights into skill demand and supply dynamics, reducing information asymmetries and frictional unemployment. Exploiting the great potential of AI in the automated provision of labor market information to job seekers may be an even more fruitful avenue to reduce search costs and improve job-finding rates, as shown by three recent studies that performed large-scale experiments providing automated and custom-designed search advice to job seekers.

Behagel et al. (2022) analyze the employment effects of directing job seekers' applications toward firms likely to recruit, building upon an internet platform developed by the French public employment service. Their randomization design, with about 1.2 million job seekers and 100,000 establishments, enables them to measure the effects of the recommender system, which induces a 2% increase in job-finding rates among women, due to increased search effort as well as to greater ability to target the firms recommended to them. They also find that these effects translate into an increase in aggregate job-finding rates.

Along the same lines, Altmann et al. (2022) conduct a large-scale randomized controlled trial based on the universe of unemployment benefit recipients in Denmark, to study how online job search advice affects the job search strategies and labor market outcomes of unemployed workers, providing job seekers with vacancy information and occupational recommendations through an online dashboard. A randomization procedure shows that online advice is highly effective when the share of treated workers is sufficiently low: in regions where less than 50% of job seekers are treated, treated job seekers increase their working hours and earnings by 8.5–9.5% in the year after the treatment. However, for higher treatment intensities, there are substantial negative spillovers on other treated job seekers, due to greater competition between applicants.

Similarly, Le Barbanchon et al. (2023b) design a machine-learning job recommender system that uses job seekers' click history to generate personalized job recommendations and deploy it on the largest online job board in Sweden, setting up a two-sided randomized experiment to evaluate its impact on job search and employment outcomes. They find that treated jobseekers are more likely to apply for the recommended jobs, and have 0.6% higher employment in the subsequent 6 months. Recommending a vacancy to a jobseeker increases the probability to work at the recommended workplace by 5%, and by even more for less-educated and unemployed workers.

Workers' search costs may not only be lowered by improving labor market information and tailoring it to individual jobseekers' needs, but also by reducing the physical costs of engaging in job search. Banerjee and Sequeira (2023) show that reducing transport costs for job seekers can improve search outcomes, by performing a field experiment in South Africa: they provide job search subsidies to a subset of randomly selected job-seekers and analyze their search activity through the main bus rapid transit network connecting the township to the city center, and find that the transport subsidy leads job seekers to search more intensively and to adjust their beliefs in line with their search experience.

7.2 Housing policies

As shown in Subsection 5.1.1, the lock-in effect of housing can be affected by high transaction costs of housing sales and stringent rental regulations, which, together with the high price of housing, constrains residential mobility and can generate mismatch, especially in the presence of thin labor and housing markets. Hence, policies that directly reduce rental costs by lowering taxes for landlords that adopt rent control prices ("affitto concordato" in Italy) may improve labor market search. Policies aimed at encouraging mobility to neighborhoods with better job opportunities, such as those studied by Chetty et al. (2016), may also play an important role in reducing mismatch. McGowan and Andrews (2015b) provide cross-country evidence that skill mismatch is lower in countries with housing policies that do not impede residential mobility, i.e., have comparatively low transaction costs on buying property and less stringent planning regulations.

7.3 Labor market flexibility

Employment protection legislation can have the unintended effect of reducing the reallocation of workers across jobs, resulting in a potential persistence of skill mismatch, as argued in Subsection 5.1.2. Davis and Haltiwanger (2014) document that the American labor market has become less fluid since 1990, as worker reallocation rates have declined, and show that the "good-faith exception," a policy aimed at protecting workers from wrongful discharges, had the effect of reducing job reallocation rates. The evidence for Italian reforms analyzed by Maida and Tealdi (2021) and Berton et al. (2017) is also consistent with the prediction that reducing firing costs tends to reduce skill mismatch. Minimum wage policies may also have unintended "lock-in" effects: Dube et al. (2013) and Brochu and Green (2013) find that minimum wage hikes reduce worker reallocation rates in the United States and Canada, respectively. The cross-country evidence by McGowan and Andrews (2015b) also indicates that greater flexibility in wage negotiations is associated with a better matching of skills to jobs.

Implementing policies that support flexible labor market arrangements, such as job sharing, telecommuting, and flexible work hours, can help accommodate diverse skill sets and preferences among workers. Flexible work arrangements can enable individuals to leverage their skills more effectively while balancing work-life commitments. However, a drawback of flexible work arrangements is that workers may feel less committed to developing skills suitable to their job. Moreover, for such jobs, employers may be less willing to invest in workers' human capital (Felstead et al., 2000). There can also be significant gender differences in the reasons for taking on such arrangements: Garnero et al. (2014) analyze administrative employer-employee data from Belgium and suggest that, while part-time work is often used by males to free up time for training, women often downgrade to more flexible jobs to accommodate domestic needs.

7.4 Enhancing education and training

If credit constraints prevent workers from investing in their skill development and education, as argued in Subsection 5.1.3, vocational training programs that align with the needs of industries can help bridge the gap between the skills demanded by employers and those possessed by workers. Curriculum reforms, apprenticeship programs, and partnerships between educational institutions and industries can facilitate the development of relevant skills and knowledge among students and workers. The meta-analysis of active labor market policies provided by Card et al. (2018) summarizes the estimated effects found by over 200 recent studies of active labor market programs. They find that their effect on the probability of employment is on average close to zero in the short run, but tends to become positive 2–3 years after completion of the program, with larger average effects for programs that emphasize human capital accumulation, for females and long-term unemployed workers, and more frequent positive impacts in recessions. The cross-country evidence by McGowan and Andrews (2015b) also suggests that higher participation in lifelong learning is also associated with better matching of skills to jobs.

The effects of active labor market policies vary considerably across programs. In particular, encouraging continuous skill development and upskilling among the workforce helps ensuring that workers remain adaptable to changing job requirements and technological advancements. Training programs may be especially useful for low-skill and displaced workers: informational frictions and credit constraints may prevent unskilled or poorer workers from accessing such training programs, leading to potential “poverty traps”, which warrants public interventions to promote their training. Indeed, Escudero (2018) finds that active labor market policies improved employment outcomes in OECD countries from 1985 to 2010, especially for low-skill employees. Similarly, Hersch (1991) provides evidence that the provision of on-the-job training is negatively correlated with overqualification. Jacobson et al. (2005a) show that providing retraining through community colleges substantially increases the earnings of displaced workers, and Jacobson et al. (2005b) notice that displaced workers who self-select into these programs are likely to be those that have the highest expected returns from retraining. However, subsidizing retraining programs too generously inevitably reduces their average expected social benefit, as they will also attract workers less suited for retraining.

On the whole, the benefits of on-the-job training for workers’ careers are large: Ma et al. (2024) show that on-the-job training is a major reason why workers in richer countries enjoy faster rates of lifetime wage growth than workers in poorer countries. Using cross-country firm and worker-level data, they show that firm-provided training is a key determinant of workers’ human capital, and based on a general equilibrium search model they estimate firm-provided training to account for 38% of cross-country variation in wage growth. One channel through which such positive wage effects are likely to operate is the reduction in skill mismatch that on-the-job training can achieve, especially in the first years of workers’ careers, which tend to coincide with particularly steep wage increases, as shown by Coraggio et al. (2024), among others.

The benefits of on-the-job training for workers’ careers are also likely to depend on how homogeneous or stratified is the formal training provided by a country’s educational system: as explained in Section 4 with reference to the findings by Flisi et al. (2017), some educational systems tend to feature uniform curricula and teaching methods (e.g., in Southern European countries and Ireland), while others feature specific tracks and mobility across them (typically, in Northern European countries). In the first case, which tends to be associated with over-education and under-skilling, workers are more likely to benefit from the specialized upskilling resulting from on-the-job training than in the second case, where workers tend to feature under-education and over-skilling.

7.5 Migration policies

Liberal migration policies can help address skill shortages due to insufficient native population, especially if these policies are coupled with selective tax breaks for immigrants with the skill sets that are in short supply in the domestic economy. Preferential tax treatments for high-skill immigrants have been implemented in several European countries, such as the Netherlands, Denmark, Finland, Sweden, France, Spain, Portugal, and Italy (Bassetto and Ippedico, 2023). The empirical evidence on the welfare effects of these tax policies is limited, although Bassetto and Ippedico (2023) find a positive fiscal effect in the Italian context. Reliance on tax exemptions to attract high-skill immigrants raises however the potential issue of “beggar-thy-neighbor” effects, which effectively translates into conferring rents to high-skill immigrants without necessarily increasing their aggregate inflow. Moreover, as these policies target high-skill individuals who are likely to be in the top percentiles of the wage distribution, they also present significant equity concerns. Following extensive policy debates, the generosity of the tax exemptions has recently been reduced in the Netherlands and in Italy.

7.6 Unemployment insurance policies

Introducing unemployment insurance (UI) schemes of “moderate” generosity can increase workers’ search intensity for job opportunities and thus reduce skill mismatch. Diamond (1981) was the first to formally show that a positive unemployment rate can be efficient if it induces workers to be more selective in their job application decisions. Policymakers can influence the length of job searches by providing more generous unemployment benefits to displaced workers. The benefits of these policies must be traded off against the output losses that can be induced by excessive unemployment, suggesting that there is a socially efficient level of UI.

Diamond's model neglected heterogeneity in workers' and firms' characteristics. Marimon and Zilibotti (1999), who present a model with two-sided heterogeneity, show that UI helps workers to find jobs that better match their skills. As a result, a technological shock that increases potential mismatch will result in higher productivity but lower employment (due to a longer search) in economies with more generous UI benefits.

While most models predict that UI improves the quality of job matches, Nekoei and Weber (2017) point out that extending UI benefits can be expected to have two opposite effects on wages: a positive effect due to longer job search, and thus better match quality, but also a negative effect due to the depletion of human capital. Indeed, empirical studies report contrasting findings on this point. Card et al. (2007), Lalive (2007), and Van Ours and Vodopivec (2008) find insignificant effects of UI on wages, while Schmieder et al. (2016) find a negative effect, results that are at odds with the hypothesis that UI extensions should lead to better matches and, thus, higher wages. However, these studies infer the effect of UI on mismatch indirectly, by examining its effect on earnings of workers who transition to employment. Farooq et al. (2020) explicitly decompose the channels through which UI affects wages by exploiting a series of temporary UI extensions adopted in the US during the Great Recession. They measure match quality as the residual from an AKM-type regression (Abowd et al., 1999), following Woodcock (2015) and Lachowska et al. (2020), and find that a 53-week increase in UI duration, close to the average extension adopted between 2008 and 2009, increases match quality by 4.1%. They also show that UI extensions improve employer quality but with little effect on sorting.

Beside affecting skill match quality by encouraging job search, the generosity of the UI system can affect workers' incentive to acquire the skills required for talent-intensive jobs, which tend to feature higher productivity and earnings than other jobs. As in these jobs workers' quality is typically revealed by their performance, they tend to also feature high layoff risk. Pagano and Picariello (2023) show that, if firms compete for talent, they cannot insure workers against this risk, so that the more risk-averse workers will choose less quality-revealing jobs, which lowers expected productivity and salaries. Their model predicts that public UI corrects this inefficiency, encouraging workers to acquire the skills required for talent- sensitive jobs and thus resulting in greater employment in talent- intensive industries. The authors show that this prediction is consistent with the distribution of U.S. employment across occupations and states.

7.7 Bankruptcy laws

Reforming bankruptcy laws may improve firms' allocative efficiency, by limiting the survival of zombie firms that prevent labor reallocation. Andrews and Cingano (2014) explore bankruptcy laws that can make it harder for firms with lower productivity to exit the market and free up misallocated labor. Relatedly, Li and Ponticelli (2022) find that the staggered introduction of Chinese specialized courts leads to the reallocation of employment out of zombie firms. Davydenko and Franks (2008) show how bankruptcy laws also affect bank lending practices, and thus impact access to credit, which may, in turn, affect skill mismatch.

7.8 Industrial policies

Acemoglu et al. (2018) present a model where firms have different potential to innovate: "high-type" firms generate innovation and grow over time, whereas "low-type" firms innovate less and are more likely to exit. The source of the skill mismatch in this model is the positive externality generated by investment in research and development. As firms do not internalize positive spillovers generated by R&D, the demand for skilled labor will be too low, and some skilled workers will be employed in operation activities rather than in R&D, and in low-type firms. The authors show that a tax on incumbent firms will encourage the exit of less productive firms and lead to the reallocation of skilled labor to more productive ones. Estimating the model on the basis of US Census microdata, they find that the optimal tax rate on continuous operations is large, in the order of 70 percent. Conversely, the most common industrial policies, i.e., R&D subsidies, are ineffective in achieving the social optimum, as they cannot discriminate between different types of firms. Indeed, Golsbee (1998) notices that R&D subsidies, rather than reallocating highly skilled individuals to more productive firms, may simply end up increasing the wages of incumbent skilled workers, given their highly inelastic labor supply.

8. Conclusions

We conclude this survey by singling out the most promising recent developments in research on occupational mismatch, as well as the areas which still require additional research, either because they are comparatively under-researched or because are most relevant for policy.

As already stressed in several points of this survey, frontier research on skill mismatch considers workers' skills as a multidimensional object, and therefore exploits data sets where both workers' skill sets and jobs' skill requirements are multidimensional. This requires researchers to address the issue of how to aggregate these skills and how to measure the distance between those required by employers and those possessed by employees. A natural development of this approach is to join occupational mismatch measures with merged employer-employee administrative data sets. Lately, the latter have themselves started to be exploited to produce measures of mismatch based on realized matches, exploiting machine learning techniques, and to analyze how they differ across firms and workers, not only cross-sectionally but also over time. This is likely to be a lively area of research in the near future, as administrative data sets lend themselves to analyzing how mismatch reacts to macroeconomic and microeconomic shocks and to policy interventions.

Relatedly, the application of machine learning to administrative data has been shown to have high promise as the basis for a new type of policy interventions, namely, the provision of individually tailored information to employees in their job search process. As mentioned in Section 7, the first studies in this area have been shown to have a measurable policy payoff in the context of large-scale experiments. This is an area where European researchers and policy-makers may capitalize on a wealth of national administrative data, in many cases much more detailed and comprehensive than those available in the United States. The main limitation is that coverage and variable availability in these national data sets tend to vary considerably from country to country. Moreover, in some countries these data sets have non-negligible access costs, both to protect the privacy of respondents and because of the sheer complexity and magnitude of the databases.

While research on skill mismatch is already massive, as shown by the present survey, all existing work on this issue suffers from an important limitation: it analyzes skill mismatch at the level of individual workers, without taking into account that typically workers operate as part of teams, and that the productivity of each team member depends on the skills of other team members, not only on his/her own skills. Hence, the quality of a worker allocation to a job depends on the job allocation quality of his/her coworkers: if the productivity spillover effects within workers teams are significant, one should try to measure the skill match quality of the whole team, rather than only that of its individual components. Of course, pursuing this objective requires addressing two difficult issues: first, identifying the boundaries of coworker teams within a firm, which requires data that are typically not easily available; second, taking into account the endogenous nature of teams and the assortative matching that presumably occurs in their formation, which in turn affects their productivity. So far, only few studies have addressed these difficult issues, by focusing on specific instances where teams are clearly defined.[19] However, there is evidence that the human capital embedded in teams is valuable, especially in high-tech firms: for instance, in the U.S. teams of inventors who operate in companies that go bankrupt become less stable and produce fewer and less impactful patents (Baghai et al, 2024).

Another area that would deserve far more attention by researchers is the impact of economic policies and structural shocks on skill mismatch and skill shortages. This is a particularly serious shortcoming in view of the large structural shocks that are already affecting our economies, such as (i) the digital transition and particularly the likely spread of AI methods in production and distribution, (ii) the climate transition and thus the phasing out of carbon intensive technologies and their replacement with more sustainable ones, and (iii) the large investments in military industries that are required by rising geopolitical tensions. All these structural changes in the economy are inevitably going to require new skills from workers, and lead to the obsolescence of existing ones, and are therefore likely to lead to a (hopefully temporary) increase in skill mismatch. At the same

[19] For instance, Ronchi and Silvestrini (2024) investigate the decision-making process and the quality of decision of collegial courts, exploiting the quasi-random allocation of both judges and cases to judicial panels, and document that mixed-gender teams rule more leniently on similar offenses. Instead, Allocca (2023) studies the relationship between the performance and structure of teams in the context of a research institution, Virgo, whose 200 scientific researchers carry out projects in self-formed teams who report their activities in a work diary, and finds that randomly formed teams perform worse than the observed self-formed teams, and teams with a more diverse membership perform better.

time, the rapid demographic decline, especially in Europe, Japan and Korea, but subsequently all over the world, is likely to make skill shortages increasingly widespread and problematic. Hence, addressing all of these issues is going to require additional research efforts in this area.

TRAILS

Enabling data analytics for actions tackling skills shortages & mismatch

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Appendix: Data Used to Measure Mismatch

Mismatch measures differ not only because they try to capture different forms mismatch (see Section 3) and rely on different methodologies to construct them (see Section 4), but also because they often draw on different data. This appendix lists and describes the main data sets used in the recent literature.

Survey data are the most used. They are the only datasets allowing for the use of subjective methods. Still, their information (about skills and educational attainments) can also be used to apply the objective method either in combination with other sources of data or by applying the realized-match procedure. The main survey data used in the literature are listed below, by geographical area.

A1. EU Data

- **European Community Household Panel (ECHP)**

The European Community Household Panel is a panel survey consisting of interviews held every year with a sample of households and individuals. The total duration of the ECHP was 8 years, running from 1994 to 2001 (8 waves). The countries involved were Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal, Sweden, and the United Kingdom.

"PE-Employment" is the section of interest. Examples of questions asked:

- PE016: Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?
- PE021: Have you had formal training or education that has given you skills needed for your present type of work?

Papers that use this dataset: Budria and Moro-Egido (2008), Congregado et al. (2016).

- **European Skills and Jobs Survey (ESJS):**

The Cedefop European skills and jobs survey (ESJS) is a periodic survey collecting information on the job-skill requirements, digitalization, skill mismatches and workplace learning of representative samples of European adult workers. The first wave was carried out in 2014, while the second in 2021. The data of the ESJS2 were collected among adults aged 25-64 who are in wage and salary employment (excluding those in self-employment and family workers), living in private households and whose usual place of residence is in a territory of each of the EU-27 Member States, Iceland and Norway for a total of 46 213 interviews.

Examples of questions included in the survey:

- Q50. What is the level of education usually needed nowadays to do a job like your main job?

- Q51. Considering your main subject or field of study at your highest level of education (business, engineering, health etc.), how relevant is it for doing your main job?

Papers that use this dataset: CEDEFOP (2015, 2016a, 2016b, 2018).

- **European Labour Force Survey (EU LFS):**

The EU-LFS is a harmonized survey conducted by Eurostat, providing confidential quarterly or annual data on employment, unemployment, and labor market participation of people aged 15 and over, as well as on persons outside the labor force from 1983 onward. The EU-LFS is currently conducted in the 28 member states of the European Union, two candidate countries and three countries of the European Free Trade Association (EFTA). The survey contains information on a representative sample of households in each country. Individuals are assigned a weight to represent the share of people with the same characteristics in the country. For each individual in a specific year, the EU-LFS provides information on age, nationality, skills, labor force status (employed, non-employed) and region of residence 12 months before and sector of employment 12 months before. The main strength of the EU-LFS is to use the same concepts and definitions in every country, follow

International Labour Organization guidelines using common classifications (NACE, ISCO, ISCED, NUTS), and record the same set of characteristics in each country. While not specifically focused on skill mismatch, the EU LFS includes information on educational attainment, occupation, and industry, which can be used to analyze patterns of skill utilization and underutilization. Researchers leverage EU LFS data to identify trends in skill demand and supply, assess labor market dynamics, and monitor progress towards policy objectives.

It gives information about the attained level of education but not about the required one, realized-match are the measures developed from this dataset. In addition, it provides information on employment status and ISCO codes at the 3-digit level.

- **EU Statistics on Income and Living Conditions (EU-SILC):**

The EU-SILC is a harmonized survey that provides timely and comparable data on income, poverty, social exclusion and living conditions in the European Union. The survey provides two types of annual data: cross-sectional data (2004-2022) over a given time period, and longitudinal data (2005-2021) on individual-level changes over time, observed periodically over a four-year period. The EU-SILC survey is conducted in the EU 27 member states, plus Switzerland, Iceland, Norway, Serbia and UK. There are two kinds of variables in EU-SILC: the primary and secondary variables. The primary (target) variables are collected every year, whereas secondary variables are collected every five years or less frequently in the so-called ad-hoc modules. Both primary and secondary variables are collected at two different levels, the household and the individual level. All components of EU-SILC, both for households and for individual persons in the target population, are based on a nationally representative probability sample of the population residing in private households within the country, irrespective of language, nationality or legal residence status.

EU-SILC survey provides comparable information on social exclusion, gross and disposable income, and housing conditions at the household level, along with information on labor status, employment characteristics of the main job, education, and health at the individual level. Income variables, at a detailed component level (e.g., employee's earnings, benefits, etc.) are also collected at the individual level. In addition, it provides information on ISCO codes of the current job at the 2-digit level. The survey does not contain any information about job educational requirements or the realized match, and thus additional sources of information from job analysts should be used to measure skill mismatch. Finally, the longitudinal dataset allows us to identify patterns of career mobility and wage mobility.

- **Structure of Earnings Survey (SES):**

This survey provides EU-wide harmonized structural data on gross earnings, hours paid, and annual days of paid holiday leave. These data are collected every four years, under EC regulations aimed at providing accurate and harmonized data on earnings in EU Member States, participating EFTA countries, as well as candidate and potential candidate countries for policymaking and research purposes. The SES provides detailed and comparable information that can be used to study the relationships between the level of hourly, monthly, and annual remuneration, personal characteristics of employees (sex, age, occupation, length of service, highest educational level attained, etc.) and their employer (economic activity, size and economic control of the enterprise). Unlike the other Structure of Earnings Survey tables, this dataset presents the main indicators of the several vintages of SES (SES2002 / SES2006 / SES2010 / SES2014 and SES2018) merged into one table.

The survey does not contain any information about job educational requirements or the realized match. It also provides information on ISCO codes of employees at the 3-digit level. These variables require additional sources of information from job analysts.

- **Cheers European Graduate Survey:**

This survey contains information about 3000 graduates, collected through a written questionnaire on the relationship between higher education and employment four years after graduation. Respondents answered questions on their socio-biographic background, study paths, the transition from higher education to employment, early career, links between study and employment, their job satisfaction, and their retrospective view on higher education.

The countries surveyed were: Austria, Czech Republic, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, United Kingdom.

Relevant questions:

E2: To what extent has your study (you graduated from 1994 or 1995) been useful for preparing you for your present work tasks?

F1: If you take into consideration your current work tasks altogether: To what extent do you use the knowledge and skills acquired in the course of study?

F2: How would you characterize the relationship between your field of study and your area of work?

F3a: To what extent is your employment and work appropriate to your level of education?

F3b: What is the most appropriate level of course of study/degree for your employment and work in comparison to that which you graduated from in 1994 or 1995?

Paper that uses this dataset: Allen and De Weert (2007).

- **Programme for the International Assessment of Adult Competencies (PIAAC):**

This international survey is conducted in over 40 countries as part of the Programme for the International Assessment of Adult Competencies (PIAAC). It measures adults' proficiency in key information-processing skills (literacy, numeracy, and problem-solving) and gathers information and data on how adults use their skills at home, at work, and in the wider community. The Survey consists of two parts:

1. The background questionnaire, which includes a range of information regarding the factors that influence the development and maintenance of skills such as education, social background, engagement with literacy and numeracy and ICTs, languages, as well as information on outcomes that may be related to skills.

2. The direct assessment of cognitive skills (literacy, numeracy and problem-solving), which evaluates the skills of adults in three fundamental domains.

The survey is administered every 10 years and has had two cycles so far. In the First Cycle, there were three rounds of data collection, between 2011-2018. In 2018, the Second Cycle of the Survey began, with results for this cycle to be published in 2024.

The first cycle involved countries are Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States, Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey, Ecuador, Hungary, Kazakhstan, Mexico, Peru.

For the Second Cycle, two additional components have been added to the background questionnaire: Socio-emotional Skills and Quality of Work Environment. These will aid in furthering our understanding of the respondents and enriching the questionnaire. Furthermore, a new Employer Survey will be available, investigating enterprises' skills needs, strategies to address skill gaps, and business factors affecting demand for skills.

Papers that use this dataset: Levels et al. (2014), McGowan and Andrews (2015), Flisi et al. (2014).

- **Flexible Professional in the Knowledge Society (REFLEX):**

The REFLEX project has been carried out in sixteen different countries: Austria, Belgium-Flanders, Czech Republic, Estonia, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. The report focused on the remaining 13 countries. A major part of the project consisted of a large-scale survey held among some 70 000 graduates from higher education in these countries. In each country, a representative sample has been drawn of graduates from ISCED 5A programs who got their degrees in the academic year 1999/2000.

Paper that uses this dataset: McGuinness and Sloane (2011).

A2. National-Level European Surveys

- **SPAIN**: **Encuesta de Calidad de Vida en el Trabajo (ECVT)**

It is a survey conducted every year from 2001 to 2010 on a sample of 9240 individuals. It investigates different aspects of job careers and education paths.

These are the two relevant questions for measuring mismatch:

1. What kind of education does a person need in order to perform your job?

2. Considering the job that you do, how long would it take someone with the required education, who begins the job, to do it correctly?

Paper that uses this dataset: Alba-Ramirez (1993).

- **GERMANY**: **German Socioeconomic Panel (GSOEP)**

The Socio-Economic Panel (SOEP) is a representative, multi-cohort survey that has been running since 1984 (up to 2021). Every year, individuals in households throughout Germany are surveyed by our survey institute on behalf of DIW Berlin. These respondents (19.032 obs.) provide information on topics such as their income, employment history, education, and health. Because the same people are surveyed every year, it is possible to track long-term psychological, economic, societal, and social developments. To keep pace with changes in society, random samples are added regularly and the survey is adapted accordingly.

Paper that uses this dataset: Büchel (2002).

- **THE NETHERLANDS**: **Maastricht Aging Study (MAAS)**

The Maastricht Aging Study (MAAS) was designed to specify the usual and pathological aging of cognitive function. In short, the main questions of MAAS are: who deteriorates when in which aspects of cognitive function, and what biomedical or psychosocial factors can be identified that may act as mediators in this process? The study comprises four independent panel studies in which data concerning health characteristics and neurocognitive status of 1,900 initially healthy individuals are collected for 12 years.

Paper that uses this dataset: De Grip et al. (2008).

- **SWITZERLAND: Graduate Survey (EHA)**

The survey's focus is the employment and educational situation of graduates of institutions of higher education one and five years after graduation.

Paper that uses this dataset: Diem (2015)

- **SWITZERLAND: Swiss Household Panel (SHP)**

Collecting data on households and individuals since 1999, the Swiss Household Panel (SHP) is an ongoing, unique, large-scale, nationally representative, longitudinal study in Switzerland. The data of the SHP provide a rich source of information to study social change in Switzerland over a significant period on a wide variety of topics. The SHP aims to provide both continuity and innovation in measurement and data collection, with the combination of retrospective and prospective longitudinal data in the most recent refreshment sample as one notable example of such an innovation.

Papers that use this dataset: Frei and Sousa-Poza (2012).

- **SWEDEN: Standard of Living Survey (Levnadsnivåundersökningarna, LNU)**

The original basis for LNU was a random sample of 1/1000 of the Swedish population between 15 and 75 years of age. LNU uses a multidimensional approach, covering individuals' command over resources in terms of family and social relations, material living conditions (income and wealth), health, education, working conditions, political life, leisure time activities, housing conditions, etc. The questions have, in all the different years, to a large extent been asked to the same persons, which means that a significant "panel" - consisting of about 1000 individuals - have been interviewed in all of the six survey occasions. In addition to the interview data, register information has been added, mainly in order to calculate household income.

Paper that uses this dataset: Korpi and Tåhlin (2009).

- **UNITED KINGDOM: UK Employer Skill Survey**

The UK Employer Skills Survey 2024, conducted by the Department for Education and other UK governments, involves over 20,000 employer interviews to assess skills challenges. It covers recruitment difficulties, skills gaps among employees, training practices, and employer awareness of skills initiatives.

A3. U.S. Surveys

- **Adult Literacy and Lifeskills Survey (ALLS):**

Conducted between 2003 and 2008, the Adult Literacy and Lifeskills (ALL) Survey measured the literacy and numeracy skills of a nationally representative sample of 16- to 65-year-olds in participating countries in two rounds: first, in 2003 and then again between 2006 and 2008.

The original seven countries/territories to participate in the first round were Bermuda, Canada, Italy, Norway, Nuevo Leon (Northern Mexico), Switzerland, and the United States. Four countries participated in the second round: Australia, Hungary, Netherlands, and New Zealand.

Paper that uses this dataset: Desjardins et al. (2011).

- **National Longitudinal Surveys (NLS):**

The National Longitudinal Surveys (NLS) are a set of surveys designed to gather information at multiple points in time on the labor market activities and other significant life events of several groups of men and women. Two cohorts of workers are followed: 1997 and 1979 through respectively

2021 and 2020. These data track individuals' educational attainment, employment trajectories, earnings, and skill acquisition. Researchers utilize these data to examine the relationship between individual characteristics (such as education) and employment outcomes, assess the impact of skill acquisition on career advancement, and identify patterns of skill utilization and underutilization.

Papers that use this dataset: Baley et al. (2022), Bowlus (1995), Guvenen et al. (2020), Lise and Postel-Vinay (2020).

- **Panel Study of Income Dynamics (PSID):**

The study began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Information on these individuals and their descendants has been collected continuously, including data covering employment, income, wealth, expenditures, health, marriage, childbearing, child development, philanthropy, education, and numerous other topics.

Papers that use this dataset: Daly et al. (2000), Duncan and Hoffman (1981).

- **American Community Survey (ACS):**

The American Community Survey (ACS) is an ongoing survey that provides vital information on a yearly basis about jobs and occupations, educational attainment, veterans, whether people own or rent their homes, and other topics

Paper that uses this dataset: Neumark et al. (2013).

A4. Job Analysts' Data Sets

Job analysts' data are used to compute objective mismatch measures. More precisely they are needed to assess skills or educational requirements for a specific job. The following are examples of this kind of dataset.

A4.1. EU Job Analysts' Data Sets

- **ARBI Code**

Developed by The Dutch Ministry of Social Affairs. ARBI code contains a classification into seven levels of job complexity, developed by the Dutch Ministry of Social Affairs.

Papers that use this dataset: De Grip et al. (2008), Hartog and Osterbeek (1988).

- **Standard Classification of Occupations (SKP 2008)**

Prepared by the Statistical Office of the Republic of Slovenia. The Standard Classification of Occupation 2008 (SKP-08) is the obligatory national standard used for classifying jobs and occupations into occupational groups in official and other administrative records and statistical surveys. It thus provides the consistency of data in monitoring of occupational structure of the active population and of the labor market demand. SKP-08 is based on and is comparable to the International Standard Classification of Occupational 2008 (ISCO-08).

Papers that use this dataset: Domadenik et al. (2013).

- **Swedish Standard Classification of Education (SUN2000)**

Prepared by the Statistic Sweden this dataset is the Swedish version of ISCO.

Papers that use this dataset: Nordin et al. (2010), Fredriksson et al. (2018).

- **Dutch Standard Occupation Classification (SBC)**

The classification of occupations used by Statistics Netherlands until 2012 is based on type of work. In the 1992 classification the level and field of the required skills are the main criteria.

A4.2. U.S. and International Job Analysts' Data Sets

- **Dictionary of Occupation Titles (DOT)**

The Dictionary of Occupational Titles (DOT) was created under the sponsorship by the Employment and Training Administration (ETA), and was last updated in 1991. The DOT was replaced by the O*Net, and ETA no longer supports the DOT.

Paper that uses this dataset: Hartog (1980).

- **International Standard Classification of Occupations (ISCO)**

The International Standard Classification of Occupations (ISCO) is a four-level hierarchically structured classification of occupation groups managed by the International Labour Organisation (ILO). The two latest versions of ISCO are ISCO-88 (dating from 1988) and ISCO-08 (dating from 2008).

Focusing on the latter, ISCO classifies jobs (defined as "a set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self-employment") into 436 unit groups (4-git codes). It aggregates them into 130 minor groups (3-digit), 43 sub-major groups (2-digit), and 10 major groups (1-digit), based on their similarity about skill level and specialization required for the jobs.

Skill level is a function of the complexity and range of tasks and duties to be performed in an occupation. Normally skill level is applied at the level of ISCO Major Groups, with the exception in Major Group 1(Managers) and Major Group 0 (Armed Forces Occupations), where the concept of skill level is applied primarily at the second hierarchical level.

There are four skill levels in ISCO-08, which also provides examples of:

- the typical or characteristic tasks performed at each skill level;
- the types of skill required (in broad terms); and
- the typical occupations classified at that skill level.

Skill specialization, instead, is defined in terms of

- the field of knowledge required;
- the tools and machinery used;
- the materials worked on or with; and
- the kinds of goods and services produced.

Within each major group, occupations are arranged into unit groups, minor groups, and sub-major groups, primarily based on aspects of skill specialization.

Researchers use the information contained in this dataset to obtain a benchmark of the required skill level for a job, to be compared to the actual worker's skill set collected from other datasets.

Paper that uses this dataset: Domadenik et al. (2013).

- **Standard Occupational Classification (SOC)**

It is used for career information, job matching and the development of government labor market policies. Within the context of the classification, jobs are classified in terms of their skill level and skill content similarly to ISCO.

- **International Standard Classification of Education (ISCED)**

ISCED is the reference international classification for organizing education programs and related qualifications by levels and fields. The classification was developed by UNESCO in the mid-1970s and was first revised in 1997 (ISCED-97). A further review of ISCED was undertaken between 2009 and 2011 involving extensive global consultations with countries, regional experts and international organizations. Finally, ISCED 2011 was adopted by the UNESCO General Conference in November 2011.

Compared to ISCED 1997 which had seven levels of education, ISCED 2011 has nine education levels, from level 0 to level 8 (tertiary education is more detailed):

- ISCED 0: Early childhood education ('less than primary' for educational attainment)

- ISCED 1: Primary education
- ISCED 2: Lower secondary education
- ISCED 3: Upper secondary education
- ISCED 4: Post-secondary non-tertiary education
- ISCED 5: Short-cycle tertiary education
- ISCED 6: Bachelor's or equivalent level
- ISCED 7: Master's or equivalent level
- ISCED 8: Doctoral or equivalent level

A useful property of this classification is that each ISCED education level translate into a ISCO skill level one-digit code. The table below summarize the conversion:

ISCO-08 skill level	ISCED-97 groups
4	6 Second stage of tertiary education (leading to an advanced research qualification)
4	5a First stage of tertiary education, 1st degree (medium duration)
3	5b First stage of tertiary education (short or medium duration)
2	4 Post-secondary, non-tertiary education
2	3 Upper secondary level of education
2	2 Lower secondary level of education
1	1 Primary level of education

Most researchers using this dataset collect information about workers' educational attainments and test whether they align with the required level as reported by the matched information from ISCO and ISCED.

Paper that uses this dataset: Domadenik et al. (2013).

- **Occupational Information Network (O*NET)**

It is a comprehensive database developed by the U.S. Department of Labor, containing detailed information on hundreds of occupations. It provides standardized data on job requirements, including skills, abilities, knowledge, and work activities. Researchers utilize O*NET data to assess the match between workers' skills and job requirements, identify skill gaps, and inform workforce development strategies.

Papers that use this dataset: Baley et al. (2022), Guvenen et al. (2020), Lise and Postel-Vinay (2020).

Recently the literature moved to a multidimensional approach to address mismatch issues. This approach needs detailed information about different kinds of skills. For this purpose, some researchers have found it very useful to resort to military tests that collect information about both cognitive and attitudinal skills. Fredriksson et al. (2018) and Lise and Postel-Vinay (2020) respectively exploit the Swedish War Archives and the Armed Services Vocational Aptitude Battery (ASWAB).

A5. Worker-Level National Administrative Data

Several national administrative data sets contain individual-level information about workers' education and skills attainments and occupation descriptions, such as:

- QUADROS DE PESSOAL, Portugal
- STATISTICAL REGISTER OF THE LABOUR-ACTIVE POPULATION ("SRDAP"), Slovenia
- EMPLOYMENT REGISTERS BY STATISTICS SWEDEN
- EMPLOYMENT OUTLOOK (OECD)
- VISIT-INPS, Italy
- LISA, Sweden

TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch