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MEASURING MISMATCH IN ETF PARTNER COUNTRIES

A METHODOLOGICAL NOTE

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1. INTRODUCTION AND OVERVIEW OF MISMATCH CONCEPTS

The skills needs of the labour market and the supply of skills coming from educational institutions are often said to be poorly matched. Mismatch is one of the explanations often given for high youth unemployment rates and labour market rigidities. But the exact extent of the mismatch is an unknown entity in the partner countries of the European Training Foundation (ETF). An innovation and learning project has therefore been launched to support ETF partner countries in improving their systems to achieve a better match between the supply and demand for skills in the short and medium term, thus enhancing the employability of youth and adults and improving economic competitiveness. The project aims to do this through clarifying the concepts of matching, and through providing an overview of the most promising methodologies to measure mismatch and forecast future skills needs. In this paper, we will discuss some of the key concepts briefly, before examining a number of methodologies through which mismatch may be measured quantitatively. The intention is to explore the possibilities for quantitatively measuring mismatch, and so qualitative methods will largely be ignored in this paper, although it should be stressed that several of the quantitative methods described here attempt to measure whether the quality of the skills live up to the requirements of the labour market.

An ETF position paper on mismatch will examine the basic mismatch concepts in greater detail. The first year of the ETF project saw country reports being drafted by national experts for the participating countries – Croatia, Egypt, Kyrgyzstan, Republic of Moldova, Montenegro, Serbia, Turkey and Ukraine – and an overview of these country reports will be published in a synthesis report. A more detailed analysis of the results on mismatch will also be published, along with a paper detailing the special conditions which must be taken into account when discussing mismatch in ETF partner countries. This paper will focus on the theoretical differences between the different methodologies, with the addition of an analysis and discussion of some results by means of a case study. These results will be expanded upon and accompanied with results from the other countries in the forthcoming paper on mismatch results. Recommendations for ETF partner countries must take the data availability into account. It is essential to assess what data are available for each methodology before making recommendations to countries, as no methodology can be more reliable than the underlying data.

A mixture of deficiencies in the labour market, such as wage inflexibilities, limited geographical mobility, unclear definitions of skills, matching frictions (such as, but not limited to, retraining or moving costs and incomplete insurance) and lack of information, are the main causes of a series of skill discrepancies. Social and political factors may also influence mismatch, i.e. a government may chose to support a particular industry and thereby cause a new demand for skilled labour in that industry. Discrimination in any form will also negatively affect the labour market's ability to match the supply and demand of skills. Such factors are invaluable explanatory variables when interpreting the results presented here. At an aggregate level, we can talk about **skills shortage or oversupply**[1], while at an individual level the problem is described as a **skills and qualifications mismatch**[2].

Skills are acquired through practice and through the fields of study engaged in by students. Different fields of studies may lead to similar skills sets, but it is more common for educational programmes at the same level of education to lead to different skills sets. The question of educational matching is occasionally phrased as a question of qualifications: how equitable is the match between the number of people with certain qualifications and the number of available jobs corresponding to those qualifications (Bartlett, 2007). Shortages and oversupply may refer to a shortage or an oversupply of either skills or qualifications as required by the labour market.

Mismatch can be measured along several axes. The first and perhaps most fundamental is the distinction between a **mismatch of skills** and a **mismatch of qualifications**. Qualifications are issued as the formal recognition of someone as possessing a given skills set. This does not imply that two individuals with the same qualifications possess the same skills or possess certain skills to the same extent. Qualifications thus remain approximations of the skills set of a person, and we can not assume that a qualification mismatch is equivalent to a skills mismatch, and vice versa. It is possible to be over-educated[3], but under-skilled, for example: in a situation where a person with tertiary education is working in a position that only requires secondary education, the tertiary graduate is considered overqualified, but it may well be the case that this person lacks some of the practical skills necessary to perform the job and thus is under-skilled. Since skills are not always formally recognised, it is also possible to have the inverse situation, where the actual skills of an

1 **Shortages** appear when the number of people holding certain qualifications (or skills) is less than the number of available jobs requiring those qualifications (or skills). The opposite situation, where there are more people available holding particular qualifications/skills than the number of vacancies requiring those qualifications/skills, is said to be characterised by **oversupply**. Mismatches are often discussed at the macro level, but this obscures the fact that there may be shortages in one sector and oversupply in another.

2 This describes the inadequacy of employees' skills or qualifications (both in terms of lack and excess) with respect to their current job.

3 This terminology can be criticised for overlooking the social benefits of education, and for ignoring the evidence showing high rates of return to investment in education and training, which implies that further education and training is beneficial. The terminology will be maintained in this paper as a technical definition, and should not be seen as an indication that the authors believe any individual can have received too much education or training.

employee are being fully used, but the employee does not have the level of education believed to be necessary for the job. Such a person can be characterised as under-qualified, if only the educational attainment is considered.

Presumably, in most cases, a prospective employer is likely to be more interested in the particular skills set of an individual than their actual educational attainment level. Logically, employers should therefore be more interested in skills than in qualifications. Skills mismatch is also the main interest of the ETF, and ideally we would wish to measure skills mismatches. However, skills can be difficult to measure and – in the absence of good, reliable data – education levels are often used as imperfect proxies for skills.

Under-education is when a person does not possess the education level required for a given position, whereas **under-skilled** is when a person does not possess the skills required for a given position. Similarly, **over-educated** is when a person has an education level beyond what is required for a given position, and **over-skilled** is when a person has more skills, or more advanced skills, than are required for a given position. Mismatch occurs when one or more of these phenomena is present. Not all of the methodologies discussed in this paper are able to distinguish between over- and under-education or between over- and under-skilled. We will therefore only use the terms when a methodology is clearly able to make this distinction. In all other instances, we will simply refer to mismatch.

Another axis is the distinction between **horizontal** and **vertical mismatch**. A vertical mismatch occurs when there is a discrepancy between the **levels** of education or skills which a person possesses, and the requirements of the job held by the person. A horizontal mismatch, on the other hand, occurs when there is a discrepancy between the **types** of skills (or fields of study) which a person has attained and the requirements of the job held by the person. Are the skills which the person has, the right skills for the job? And if not, can the skills which the person has be transformed or re-directed into the right skills for the job?

This is not entirely the same as the distinction between a **quantitative** and a **qualitative** mismatch used by some researchers (Fetsi, 2011), which can be seen as a third axis. The qualitative mismatch is similar to the horizontal mismatch. Does an individual have the required skills? The quantitative mismatch is a description of the fit between the number of people holding certain qualifications and the number of available jobs corresponding to those qualifications. It is therefore the same as qualification shortage or oversupply.

One common problem that the methods for measuring educational mismatch share is that different degrees of educational mismatch are treated as equal. A university graduate working in a job for which no skills are required is considered in the same way as a university graduate working in a job for which upper secondary education is required. Treating these two cases as if they were equivalent makes it harder, if not impossible, to recognise the relevance of different policies to address the mismatch. Another common mistake is assuming that mismatch is always a problem that must be eradicated. All economies will exhibit some elements of mismatch at any given moment, and most people will at some point in their careers experience a mismatch between their skills and abilities and the tasks which they are responsible for. At an individual level, mismatch must be solved through a combination of further training, change in responsibilities, or mobility, whereas, at the macro level, policymakers will be interested in following the general tendencies in mismatch, as described in this paper. Mismatch at the macro level should be monitored so that deteriorating matching conditions in the labour market may be met by relevant policy actions before the mismatch becomes endemic. The policy actions will obviously depend upon the exact nature of the mismatch seen.

It must be said that throughout the discussion above we have chosen to ignore the mobility dimension of mismatch. It is perfectly possible to have a situation where the number of available jobs requiring certain skills matches the number of unemployed persons holding those same skills, but vacancies are not filled because the jobseekers are not sufficiently mobile (for a variety of reasons) to fill the vacancies[4]. Policymakers at both the national and the local level must, of course, factor mobility in when assessing mismatches and pondering an appropriate policy response, and employers also have a role to play in overcoming mismatch caused by lack of mobility. A perfect match is not a realistic option for any society. The real challenge lies in minimising the problems of matching and in alleviating the effects of any mismatch.

Another element that has been ignored is the manner in which matching takes place in different types of economies. In centralised economies, manpower planning would adapt education and training provision in the light of an examination of short- and medium-term economic demands for skills, as well as taking into account projections for long-term skills needs. In perfect market economies, however, matching (or mismatching) would be influenced by the demand for qualifications, which in turn influences the choices of individuals regarding which course of study to undertake, and also the choices of training providers as to what programmes to offer. Wages is an important mechanism in reflecting and influencing matching, and some methodologies use wage information in an attempt to measure mismatch.

4 This is often called regional mismatch, and there are a number of papers on the topic. See e.g. Obadic (2006); Kosfeld (2007); Lincaru (2010); Boeri and Scarpetta (1996); and Manacorda and Petrongolo (2006); and for a recent perspective in the light of the current financial crisis, see Canon and Chen (2011). Yet another dimension concerns countries experiencing high levels of migration, where the skills of migrants need to be taken into account, along with levels of demand in the countries they are migrating to and from.

Finally, there are issues related to time, which will not be treated in this paper but nonetheless merit mention. The first of these is **skills obsolescence**. Educational attainment levels from initial education are commonly used to group workers into skills groups, but this kind of approach ignores the fact that skills need to be maintained. Over time the initial education becomes less and less relevant for the skills of the individual, as some skills are forgotten and new skills are acquired through various mechanisms, such as learning by doing, adult education and on-the-job training. Not all fields experience change at the same speed, nor at the same time, and arguably in some fields experience built up over a career may be more important than textbook knowledge. It is, therefore, important to have a measure of what skills workers actually possess, if not of the change in skills over time. In principle, skills obsolescence can be tested in four different ways. As will become apparent from Chapter 2 on Methodologies for measuring mismatch, the first three are similar to the ways in which mismatch can be measured:

- objectively, by testing the change over time of workers' skills;
- subjectively, by asking workers (or employers) whether they have experienced skills obsolescence;
- indirectly, by measuring individual productivity (e.g. by using wage levels); or
- with a proxy such as the rate of innovation which can be interpreted as a measure of the speed of obsolescence (Cedefop, 2010).

According to the research conducted by Cedefop, relatively few surveys include questions such as, 'how much of the occupational knowledge and skills that you acquired during your education can you still apply in your current work?', 'have your qualifications depreciated?' or 'to what extent are your qualifications suited to your current job?'. Consequently, there is not a lot of quantitative research into the extent of skills obsolescence.

Another aspect of **mismatch over time** (or **career mismatch** as we may also choose to call it) is that people may start out in their careers as over-educated, but count on their over-education as a mean to faster promotion – the classic example is police officers, where university-educated officers are often given access to faster promotion routes than secondary-educated officers, who have to spend longer patrolling the streets before being promoted to detective (McMillen et al., 2003). In this view, under-educated people can be understood as having entered the labour market earlier, taking a (relatively) low paying job for which they were exactly matched, and from that position working their way up and gaining promotion to positions for which their job experience qualifies them, but for which their educational qualifications alone would have been insufficient. Throughout most people's careers there is, therefore, most likely at least one moment when they are exactly matched with their job, and thus mismatch should be seen as a dynamic concept. Panel data would be useful to elucidate this phenomenon. An analysis that at several distinct points in time focuses on traditional static mismatch, cannot measure the mismatch of the individuals involved over time, but it can expose the overall extent of mismatch over time. We will not venture any further into this issue here, as our main focus in this paper is on collective mismatch and on current or relatively recent mismatch. Anyone interested in the mismatch of individuals should, however, pay attention to where in the individual's career path the measurement is taking place.

It is not altogether surprising that such a variety of ways to measure mismatch produces very different results. The different methodologies described in Chapter 2 can be grouped broadly into three categories: objective, subjective and empirical (or indirect). It is sufficient to note here that research results have shown male over-education to lie in a range from 16% under the empirical method, to 30% under the subjective method, and possibly to be as high as 50% under the objective method (McGoldrick and Robst, 1996). Different methods may identify different people as being over-educated, and some subjective measures correlate poorly. Verhaest and Omey (2006) compared five different measures of over-education and 'concluded that objective job evaluation and subjective data on the level of education required to do the job should always be preferred over the empirical method or to subjective measures of the education level required to get the job' (Cedefop, 2010, p. 61).

Chapter 2 will examine several methodologies for measuring mismatch. Each methodology will be presented and discussed in its own right. The chapter concludes with an overview of all the methodologies and their respective strengths and weaknesses. Particular attention is paid to the expected availability of data in ETF partner countries. The methodological section is followed by a case study. This is based on Turkish data, for the simple reason that we had access to more (and more reliable) data from Turkey than from any other ETF partner country. Thus, using Turkey as an example, we can compare most of the objective methodologies for the same period. A few conclusions and recommendations for future practical actions and activities in the area of mismatch conclude the paper.

2. METHODOLOGIES FOR MEASURING MISMATCH

In this chapter we will examine a number of different methods for measuring mismatch. In turn each methodology will be introduced and discussed. Each methodology has its strengths and weaknesses, and these must be clearly laid out in the context of ETF partner countries, so that the recommendations can assist partner countries in advancing their knowledge concerning mismatch. Detailed technical descriptions of the methodologies are included so that this chapter can also serve as a manual on how to calculate mismatch. Nonetheless, an effort will be made to introduce each method in as non-technical a manner as possible. Non-technically inclined readers may wish to go straight from the introductions to the descriptions of the data needed and the strengths and weaknesses of each methodology, skipping the technical elements.

2.1 COEFFICIENT OF VARIATION

The coefficient of variation is, strictly speaking, a statistical technique where it is essential to specify what variation is being measured. In other words, one should specify 'coefficient of variation of employment by education', for example. In practice, however, this is rarely done and we will simply use 'coefficient of variation' here, whilst reminding the reader that it is possible to use several different variables for calculations. The technique compares the distribution of skills within different groups, and the difference of these skills distributions between the different groups is expressed in just one number which measures the overall extent of mismatch (for an example see European Commission (2002)). For example, the skills of employed people can be compared to the skills possessed by unemployed people. The higher the number, the greater the difference between the skills possessed by people employed in the labour market and the skills possessed by people wishing to enter the labour market. The extent to which the distributions are different can therefore be seen as a measure of the ineffectiveness caused by the matching process of supply and demand of skills in the labour market.

The coefficient of variation (CVAR) can be expressed with the following formula:

$$CVAR = \sqrt{\sum_i \frac{\left[w_i \left(\frac{e_i}{p_i} - \frac{e_0}{p_0} \right)^2 \right]}{\left(\frac{e_0}{p_0} \right)}}$$

where w_i are employment weights, e_i are the employed people by educational attainment and p_i refers to the educational attainment of the working-age population, the unemployed or the non-participants. Note that

$$e_o = \sum_i e_i \text{ and } p_o = \sum_i p_i$$

In order to capture skills mismatch, the skills distribution of employed people may therefore be compared with the skills distribution of the potential labour supply, in an attempt to determine the amount of variation between the two distributions. Both skills distributions will be measured by education levels. The coefficient of variation method compares the degree of variation from one data series to another, even if the means are considerably different from each other; it is calculated as the ratio of the standard deviation to the mean and it is sometimes multiplied by 100 to be expressed as a percentage. In theory, educational attainment can be sorted into any number of groups, as long as these are supported by the underlying data structure – it must be possible to break down both distributions into the same groups. In practice, levels are habitually divided into three weighted groups labelled low, medium and high, and composed, respectively, of primary to lower secondary (in terms of the levels from the International Standard Classification of Education) – ISCED 1–2; upper secondary – ISCED 3–4; and tertiary – ISCED 5–6. This is typically done for the working-age population, or for the population aged 25 to 64. The latter age group ensures a more balanced measure, as only population groups expected to have left education are included. Mismatch may vary significantly for different age groups, as different cohorts over time have been exposed to various degrees of education. It would therefore be interesting to measure the coefficient of variation with data broken down by age.

Data needed

For the calculation of a coefficient of variation of employed people, the educational attainment of the population is required, together with that of the employed population measured by the same education levels. Coefficients of variation of employed people can also be compared with the educational attainment of unemployed or inactive people.

Such data are generally available from labour force surveys (LFS), even though problems related to comparability may arise. Difficulties are mainly associated with educational classifications which are not always consistent with ISCED levels. As long as the results are not supposed to be compared to results from other countries, but rather used to measure whether there is lesser or greater mismatch within a country over time, comparability issues due to non-standard classifications are not problematic. Other complications may derive from inconsistencies in age groups. It is not unheard of to have the educational attainment of the whole population expressed for different age groups (typically 15–64 or 15+), than for the employed population. The reason for this kind of discrepancy is that the data come from different sources which have different structures. Typically, the data for employed people come from LFS data, and the educational attainment data come from other sources, such as censuses or household surveys.

For ETF partner countries, data on employment and unemployment by education level are generally available, as most countries conduct LFS at least once a year, while information on the educational attainment of the population can be more limited, as the sources for this data are not always publicly available.

Strengths and weaknesses

From a mathematical perspective the coefficient of variation is preferable to standard deviations when comparing data sets with different units or widely different means, as it is dimensionless.

On the other hand, it is quite a simplistic measurement, and when the mean value is close to zero, the coefficient of variation will approach infinity and will thus be sensitive to small changes in the mean. Furthermore, it cannot be used to construct confidence intervals for the mean, while the standard deviation can.

All in all, given the difficulty in finding more detailed data, the coefficient of variation is a suitable choice for obtaining a first measuring of mismatch for many ETF partner countries. The direction of the mismatch, however, is not measured, so it is not possible with this technique to state, for example, whether the supply of highly educated people is too high compared to demand or there are too few low-skilled workers.

To compensate for such weaknesses, the coefficient of variation can be interpreted in tandem with the proportions of unemployed versus employed (or inactive versus active) in each education category (see the next methodology for more details).

2.2 PROPORTIONS OF UNEMPLOYED VERSUS EMPLOYED

This methodology does not aim to provide a single figure for the extent of the mismatch. Rather the location of the mismatch is indicated by comparing the number of unemployed people at a given education level with the corresponding number of employed people who have the same level of education. For example, if there are more unemployed at a given education level than there are employed with the same educational attainment, then we can say that there is an ‘excess supply’ of skills in that category, and in the opposite case we can say that there is a skills gap (or ‘excess demand’). By calculating this over time for all the education levels we can see changes as they are occurring and we can determine where the skills gaps are.

Data needed

It is essential to have data on both the unemployed and the employed populations according to the same educational categories. In principle, the employed population could also be compared to the inactive population, in which case the educational attainment levels of the latter would need to known.

Strengths and weaknesses

A major strength of this methodology is that it clearly indicates which education level(s) there is an excess or shortage of in the labour market. As with most objective measures, this methodology generalises at a macro level, which means that it does not indicate at the level of the individual whether mismatch exists or not.

2.3 VARIANCE OF RELATIVE UNEMPLOYMENT RATES

This statistical method (Lipsey, 1960) is an alternative to the coefficient of variation in the sense that where the coefficient of variation needs the distribution of two groups (e.g. of the employed and of the unemployed), the variance of relative unemployment rates relies on the characteristics of one group only. As for the coefficient of variation; the higher the value of the variance, the higher the level of mismatch. If detailed data is available it can be used to measure the degree of heterogeneity in the labour market across a number of dimensions, typically educational attainment, occupation and geographical region. Technically, it is expressed as

$$m_u = Var\left(\frac{u_i}{u}\right)$$

where u_i is the unemployment rate for group i, while u is the total unemployment rate.

Higher values designate more scattered unemployment rates in the particular groups than in the entire population, and therefore a bigger mismatch. It could be interesting to examine, for example, if mismatch might be more sensitive to geographical differences than to education level, or whether the kind of occupation which the unemployed seek to have may possibly generate as much mismatch as the place of employment. In principle, there is no limitation on the dimension chosen for examination, other than data being available.

Data needed

Data required for the calculation of this indicator are unemployment rates by education (or occupation or region) and total unemployment rates. Unemployment rates by education level are widely provided by labour force surveys, but the same may not be true for unemployment by region. Unemployment data by occupation is not normally gathered, but one could either substitute the occupation with field of study, under the assumption that the unemployed will strive to work within their field of study, or conduct special surveys where this question is added.

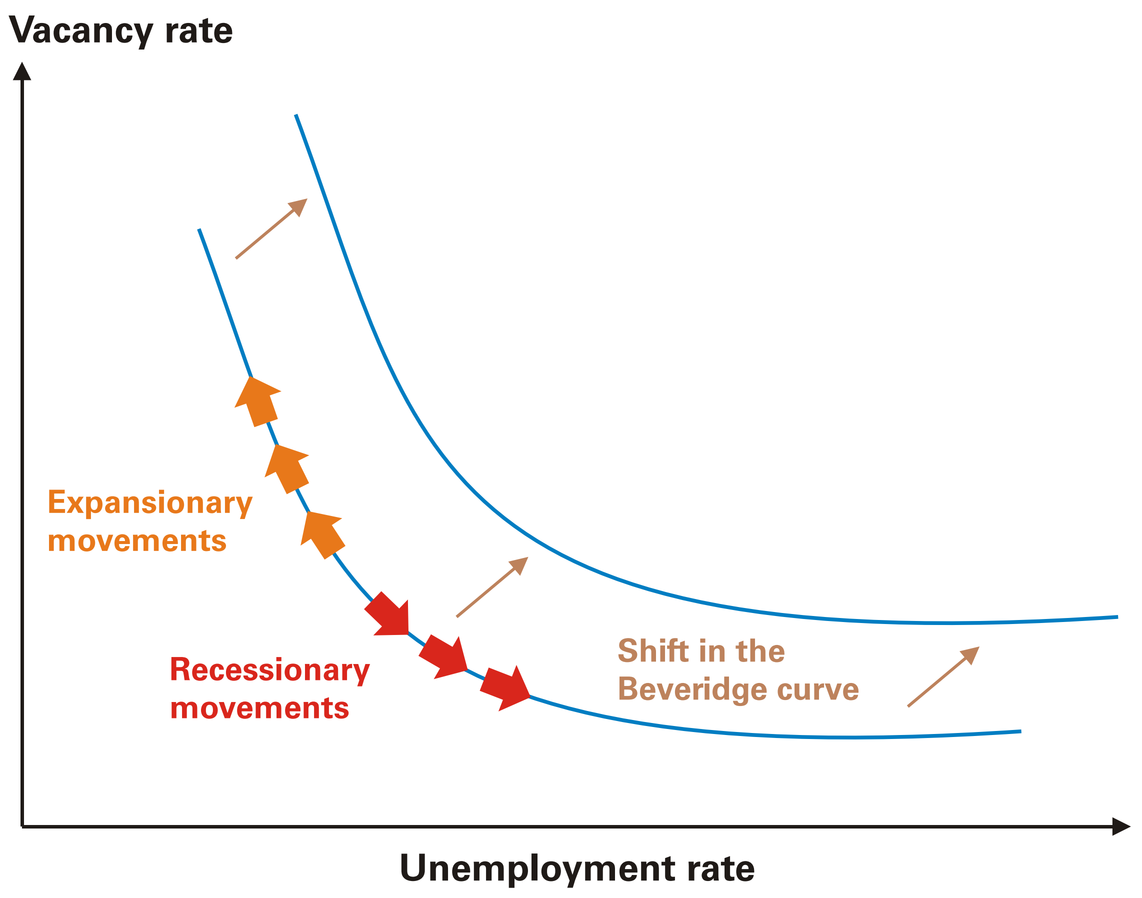
Strengths and weaknesses

The variance of relative unemployment rates is mathematically similar to the coefficient of variation, as the two measures are both calculated by squaring the differences from the mean; but while the coefficient of variation compares diverse clusters of the population (e.g. the educational structure of unemployed people versus that of the working-age population), the variance of relative unemployment compares groups of unemployed (e.g. by education level) with respect to the entire unemployed population. Therefore, this indicator can be used to support the results already obtained with the coefficient of variation, even if it does not add a lot more in terms of information. On the other hand, it can be used as a replacement of the coefficient of variation in cases where data by education level are available only for one category (e.g. unemployed) and not for both categories of interest (e.g. unemployed and working-age population or employed and unemployed).

2.4 BEVERIDGE CURVE

The Beveridge curve is the depiction of the relationship between the unemployment rate and the vacancy rate for several distinct points in time – for a given set of labour market matching institutions. It thus shows the dynamics of the matching process. More precisely, the Beveridge curve depicts all the vacancy and unemployment rate combinations resulting from the available data over a given period. The curve does not correspond to the actual 'path' of the data over time, as these movements may be the simultaneous result of both movements along the curve and shifts of the curve. The data does not allow for a disaggregation of these two possibilities. An example can be seen in **FIGURE 2.1**.

FIGURE 2.1 **BEVERIDGE CURVE**



The higher the level of vacant jobs, the lower the unemployment we would expect, as the probability of finding a job should increase. Since data are mapped for several points in time, movements in time can be used to describe the evolution of mismatch; an external shift of the Beveridge curve, where vacancies and unemployment are both increasing – shifts in the Beveridge curve as indicated in Figure 2.1 – can be interpreted as a decline in the matching process due to a more inflexible labour market, while the opposite situation may be a sign of enhancement in the functioning of labour market institutions. Movements along the Beveridge curve are seen as either expansionary or recessionary movements caused by the economy at large and not related to changes in the functioning of the labour market per se. Nonetheless, it is also true that an increase in unemployment could be due to workers leaving their employment and/or job losses, while an increase in vacancies could be explained by the creation of new working positions, or, again, by workers leaving their job. It is therefore not always easy to interpret what the data are really hiding; for a discussion see Bleakley and Fuhrer (1997), and Petrongolo and Pissarides (2001).

Data needed

As mentioned above, data on unemployment and vacancies rates are required in order to plot the Beveridge curve for a given country. Vacancy rates are calculated by dividing the total number of vacancies by the sum of the employed and the number of vacancies.

While data on unemployment rates are generally available from labour force surveys, vacancy data for ETF partner countries are often either not available, or not representative of the total number of vacancies in the economy which is being examined. Vacancies in the informal economy are not registered, and since the informal economy is significant in most of ETF partner countries, this is a serious concern. In many of ETF partner countries, jobs are not filled via public employment services and there may not be a requirement to register vacancies.

For ETF partner countries vacancy data are seen to be particularly scarce in Central Asia and in the Mediterranean region. All in all, it is probably only possible to plot the Beveridge curve for about a dozen out of 31 ETF partner countries.

Strengths and weaknesses

The Beveridge curve can be considered as a practical tool for summarising the outcomes of flows into and out of unemployment and vacancies, given the efficiency of the labour market matching process. On the other hand, such a tool must be handled carefully, as the comparison of unemployment and vacancy rates which the Beveridge curve proposes only gives an indirect measure of the efficiency changes within the labour market matching processes. Unemployment rates and vacancy rates are affected by other aspects than just labour market matching processes. It is the assumption that these other aspects are stable that allows us to see the relationship between unemployment and vacancy rates as driven by matching processes. Furthermore, the observed results are heavily dependent upon the reliability of the vacancy data, which differs greatly from country to country. Unreliable vacancy data undermines the Beveridge curve. With good vacancy data, on the other hand, it is possible to compare vacancy rates for specific occupations or qualifications and use these vacancy rates as the basis for a discussion of relative skills shortages (or excesses).

All things considered, the Beveridge curve should not be used alone as a measure of mismatch, especially in countries with poor vacancy data, but rather it should be read in tandem with other, more specific, indicators, which may or may not confirm the first general assessment stemming from an interpretation of the Beveridge curve.

2.5 SYSTEMATIC JOB EVALUATION

Systematic job evaluation is a method whereby the specific level of qualifications necessary to perform a given job is pre-determined through theoretical considerations: to do job A, it is necessary to have qualification X. In other words, it requires a pre-defined level and type of education to be considered as suitable for each particular job. Once this has been established, it is then possible to examine whether individuals have the right qualifications for their jobs. For each job or occupation the numbers of those with the right qualifications can be measured, and it is possible to calculate the share of, respectively, over- or under-qualified people[5]. Systematic job evaluation can be regarded as an objective measure since the assessment is done according to clear criteria, even if it does not allow more than one education level to be suitable for particular occupations. It also does not take into consideration that the suitable education level may change over time. It is not uncommon to see increases in the qualifications demanded for particular jobs. This means that someone who could have been perfectly matched earlier in their career, can cease to be perfectly matched, only because the qualifications regarded as necessary for the same job are now set at a much higher level.

Data needed

In order to carry out a systematic job evaluation, it is essential to have detailed micro-data on education and occupation. LFS or household surveys are normally suitable sources for obtaining such data, therefore ETF partner countries which conduct LFS should be able to conduct a systematic job evaluation, assuming that the questionnaires are sufficiently detailed when it comes to occupation. Each occupation must be linked explicitly to a qualification according to pre-defined criteria. There is no standard for such links, although some attempts have been made. See Wolbers (2003) for an example. The ETF has conducted surveys on transition from education to work in Serbia, Ukraine and, more recently, Syria. Those surveys theoretically all allow for the calculation of systematic job evaluation.

Strengths and weaknesses

This method provides a theoretical good fit, as occupations and education levels can be 'paired' and evaluated; the drawback is that the definition of which level of education or qualification should be considered as suitable for each particular job is a time-consuming process, and these levels have to be verified in each ETF partner country before an analysis can be done. Standards differ, and it cannot be taken for granted that individual countries share the same links between qualifications and occupations, as the content of qualifications are very heterogeneous. The occupations are in theory comparable across all countries, as all countries report data on occupations according to the ILO norms, but these norms do not harmonise job content, and the required skills may differ widely. In fact, there are no similar norms for qualifications, and adopting a uniform approach for all countries would be tantamount to an implicit acceptance that the education systems provide similar skills without regard to the actual curricula or national standards.

5 It should be stressed here that an over-qualified person is not necessarily any better at a given job than someone who is considered under-qualified. Over-qualified simply refers to someone having a qualification which is considered to be at a higher level than that which corresponds to the job in question.

2.6 WORKER SELF-ASSESSMENT

One subjective method for measuring mismatch is that of directly asking employees how their skills and educational competences are exploited in their job (Battu et al., 2000; Dorn and Sousa-Poza, 2005). Each individual worker is assumed to be well aware of their own skills, and must also be assumed to know how demanding their job is; therefore, this method should, in theory, be capable of providing an accurate evaluation of the extent of both education and skills mismatches at the individual level by aggregating the individual answers. Enterprise surveys can be used to derive the same kind of assessment of the suitability of employee skills compared with the requirements of a job. The crucial difference being that the enterprise surveys would reveal the assessment as made by the employer.

Data needed

Data has to be gathered through ad hoc surveys with questions on the suitability of the worker's educational background and skills. There are currently no commonly agreed standards for such formulations to be used. Mismatch has been measured through formulations such as these: What level of education is needed for your job? What is the highest level of education you have completed with a certificate? Does your work correspond to your education level? How well do the skills you have match the skills needed to do your current job? Comparability is therefore problematic, not only between countries with different surveys, but even within any given country over time, as questions can change from survey to survey.

Given the diversity and multitude of existing surveys – after all, not only national authorities conduct surveys, but also many international organisations and non-governmental organisations – it is possible, and even highly likely, that such questions have already been asked in previously conducted surveys in ETF partner countries, but no overview of such sources exists. To use existing surveys, it would be necessary to comb through the questionnaires used in past surveys within each country and determine if such a question had been posed. Once relevant questions are identified in a particular questionnaire, the raw data sets would then have to be requested and the data on mismatch extracted.

For ETF partner countries, data on worker self-assessment can be made available for Serbia, Ukraine and Syria through ETF transition surveys, and further data will be collected for Morocco, Armenia and Georgia in late 2011 and early 2012 as part of a round of ETF surveys on migration. For the remaining ETF partner countries, data are not known to exist.

Strengths and weaknesses

The advantage of running self-assessment surveys is that such a method allows for the collection of precise information referring to the topic that is being analysed; on the other hand, results are undeniably subjective and need to be interpreted carefully. Different formulations of the questions may cause significant differences in the replies, so comparability is an issue where the questions have not been formulated in a consistent manner. Another constraint is the high costs of running ad hoc surveys in several countries, especially if significantly large samples are to be taken into consideration for data representativeness.

On the whole, this method provides detailed knowledge for mismatch measurement, but it comes at a high cost, so if cost is the main constraint, other methods using existing data should be used. One way of minimising the costs while optimising outcomes is to include a few key questions in surveys devoted to other research areas. The inclusion of questions on the use of skills in the ETF migration surveys is one example of this.

2.7 MISMATCH BY OCCUPATION

This method is based on comparisons of the ratio of people with a given education level (ISCED) working at an inappropriate skill level (measured by the International Standard Classification of Occupations – ISCO) to all workers within that ISCED level. The same can be done for different education and ISCO levels, and if the required data is available, it is also possible to compare the mismatch by occupation for different age groups. An example of this approach can be found in OECD (2010), where educational and occupational mismatches were calculated for young individuals from 2003 to 2007.

Data needed

In order to calculate the mismatch by occupation, it is necessary to have data on employment by education level and occupation. To analyse a specific age range (youth population for example), the same data should be available also by age groups. This data should be available from LFS, but examinations of the available data reveal the same weakness that was found for the coefficient of variation: the data is not always provided for the same age ranges.

Strengths and weaknesses

This indicator gives information about employed people and how well their educational competences are utilised in the job they have. On the other hand, the assignment of education levels to occupational levels can be somewhat arbitrary. Furthermore, the method does not take into account the population which is not employed due to mismatch (how many people, who would otherwise be over-skilled, prefer not to work at all?).

All in all, given that data are available, this method can provide valuable insights in terms of occupational mismatch, but it should be used in conjunction with another method which draws upon data on unemployment.

2.8 EMPIRICAL METHOD

This method can be used in cases where data sets do not include specific questions on over-education or over-skilling; it is nevertheless quite a simplistic measurement and must be interpreted as a proxy. The empirical method is a purely statistical measure where the distribution of education is calculated for each occupation; over-education is defined as existing when the level of education is more than one standard deviation above the mean (Bauer, 2002) or above the mode (Mendes de Oliveira et al., 2000) for the education level for a given occupation. The educational mean and/or mode for each occupation is thus assumed to be a match for that occupation, but this may very well be a false assumption. In theory everybody employed in a given occupation could be mismatched. This may sound outlandish, but it is possible to imagine an occupation that in principle requires a PhD, even though none of the people employed in that particular occupation hold PhDs. These individuals should, in principle, all be considered as mismatched, but the empirical method will define a group of them as having an exact match, and in this example the mean may well be yet another education level, lower than is actually required (e.g. if we imagine that the example is from the United Kingdom where it is not uncommon to enter the labour market with a Bachelor’s degree, the mean here may well be Bachelor level). Furthermore, the conversion of education levels into numerical values (in order to calculate the mean, the mode and the standard deviation) is not a straightforward matter, and errors here will have a negative impact on the overall results.

Data needed

Data on education and occupation are needed for the implementation of this empirical method, and LFS or household surveys should provide adequate data. ETF partner countries with regular LFS should therefore be in possession of the relevant data.

Strengths and weaknesses

Basically this method is rather simple to calculate, which makes it attractive, but at the same time it cannot be considered as methodologically robust, and thus it should be reserved for extreme cases, where mismatch cannot be calculated according to any of the other methods. In contrast to mismatch by occupation, where each occupation is allocated on the basis of a judgement as to the relevant skill level, this methodology applies a strict mathematical match between education levels and occupations.

2.9 RETURNS TO EDUCATION

Returns to education are the increased earnings associated with an increase in education level. It can be interpreted as a return on the investment in education or as a reflection of the monetary value that the labour market assigns to various levels of education. Changes in returns to education can then, in turn, be interpreted as a signal of changes in the relative demand for education. A relative increase in the returns to education for university graduates compared to graduates from upper secondary education could thereby indicate that the labour market is experiencing a growing mismatch (where the demand for university graduates outstrips the supply).

In the United States this effect was analysed by Freeman (1976), who noticed that an increase in the number of college graduates was accompanied by a decrease in their returns. Years later, though, this phenomenon no longer occurred: a continuous growth in college graduate numbers was followed by a rise in wages for college graduates (Levy and Murnane, 1992). From a mismatch perspective, this can be explained by an oversupply of college graduates in the years prior to Freeman's research, and, despite rising numbers of college graduates, an undersupply in the years prior to the research conducted by Levy and Murnane.

Data needed

The most critical component needed is reliable data on wages, which can be had from LFS; however, it is not always possible to get reliable information on wages, even where the survey contains a specific question on wages. This is because individuals are reluctant to provide accurate information on their wages in surveys, possibly because the respondents do not trust that the information will not be passed to other authorities, such as the tax authorities, or that the information will be appropriately anonymised. In addition to information on wages, data must be available on educational attainment. This is generally not a problem in ETF partner countries.

Strengths and weaknesses

The main problem in using returns to education as a sign of mismatch is that the returns to education are based on a number of variables that are not linked to a mismatch between the supply and demand of skills. The monetary returns are based on negotiating power, which comes from a blend of scarcity of skills (so this part is linked to mismatch) and negotiating skills, and from an expectation of productivity. Higher levels of education are normally associated with higher levels of productivity, so, following that logic, returns to higher education should be larger than returns to upper secondary education. But changes in productivity, for example as a result of a better use of software which would be likely to prove more effective for knowledge intensive work, should be accompanied by a change in the returns to education, as the knowledge-rich individuals become more productive. The theoretical link between returns to education and mismatch is therefore tenuous at best.

2.10 RELATIVE WAGES BY EDUCATION LEVELS

This methodology simply compares the wages for each education level over time, either relative to a benchmark wage or indexed vis-à-vis a base year (typically the first available year). It can usefully be plotted in a diagram, as it is then very easy to see how certain education levels are more or less well remunerated than others over time. An education level that is seen to attract a higher income than that achieved by people with other levels of education can thus be a sign that this particular level of education is in higher demand on the labour market.

Data needed

Average wages for each education level are needed for several years to portray changes in the relative wages. Wage data typically come from labour force or household surveys, and due to the sensitive nature of the data, it is at times unreliable. Respondents may fear that information about their income is passed on to national or local tax authorities, which may result in underestimations of income. Simple distrust of the interviewer may also lead to incorrect information or outright refusals to respond.

Strengths and weaknesses

The strength of this methodology lies in its simplicity and intuitive interpretation. However, concerns over the reliability of the wage data mean that they may need to be interpreted with some caution. Another possible problem is that wages, as discussed above for returns to education, do not only reflect the demand of the labour market, but also relative political clout and negotiating skills.

TABLE 2.1 summarises the key strengths and weaknesses of the methodologies discussed in this methodological note, and includes information on the data availability in ETF partner countries. It is therefore easy to see that although the coefficient of variation, proportions of unemployed to employed and the variance of relative rates are somewhat simplistic measures, it is feasible to calculate them in ETF partner countries; whereas theoretically stronger measures, such as worker self-assessment or systematic job evaluation, suffer from poor data availability. The same is the case for the Beveridge curve and other methods relying on vacancy or wage data. More direct measures, such as 'skill shortage vacancies', which measure the extent to which vacancies are not filled due to a lack of skills, qualifications or experience, can be found for specific economic sectors, but these require large expensive surveys and are only conducted in very few countries (the United Kingdom being a leader in this direction).

TABLE 2.1 METHODOLOGIES FOR MEASURING MISMATCH

Methodology	Relevance	Strengths	Weaknesses	Data availability (ETF partner countries)
Coefficient of variation	Measures the fit between employed population and potential labour force	Simple to calculate	Generalises at a macro level	Good
Proportions of unemployed versus employed	Indicates the 'direction' of the mismatch: which education levels are needed	Intuitive and simple to calculate	Generalises at a macro level	Good
Variance of relative rates	Measures heterogeneity of unemployed across education levels	Simple to calculate	Generalises at a macro level	Good
Beveridge curve	Measures relationship between unemployment and vacancy rates	Includes a time perspective	Ignores the informal economy	Vacancy data unreliable in most countries
Systematic job evaluation	Establishes the level of qualification required to perform a specific job and verifies the fit in the population	Occupations and education levels can be paired	Requires the establishment of a link between each job and the required qualifications	Good, but requires access to micro-data
Worker (or employer) self-assessment	Evaluates how skills/competences are exploited in current job	Gives precise information	Survey dependent, subjective	Poor
Mismatch by occupation	Measures the ratio of workers at a given occupational and education level out of the total population at that education level	Occupations and education levels are compared	Does not consider unemployment	Not always comparable, but information can be had from LFS data, so good availability
Empirical method	Calculates the distance from the mean of each education level in a given job	Relatively easy to calculate	The mean does not necessarily reflect a match Difficult to interpret	Poor
Returns to education	Returns to education reflects the return on the investment in (more) education	Intuitive and easy to grasp	Dependent on good wage data May not actually reflect mismatch	Reasonable in theory Necessary micro-data may not be accessible
Relative wages by education levels	Changes in relative wages reflect change in demand for different skills levels	Intuitive and easy to grasp	Dependent on good wage data May not actually reflect mismatch	Reasonable Wage data comes from LFS as does the education data

3. MEASURING MISMATCH IN TURKEY

This chapter will examine the most recent data available for just one country: Turkey. Turkey has been chosen as a case study because of the rich availability of data, which makes it possible to calculate mismatch according to most of the objective methods discussed earlier. Despite the richness of data, it is not possible to discuss systematic job evaluation and the empirical method. The former has not been assessed here because it requires access to the micro-data and because it is necessary to make a theoretical fit between all of the occupations and all of the qualifications. It would be interesting to see if the results from a systematic job evaluation confirm the results found using the other methodologies. The latter methodology will not be examined, as it is theoretically flawed. The subjective worker self-assessment methodology requires detailed survey data which do not currently exist, to our knowledge. It would be very interesting to compare the results of a subjective self-assessment with the results of a systematic job evaluation. This would be a good topic for future research on mismatch in Turkey.

Turkey is characterised as having a young and fast-growing population[6], many of which leave education and training at an early age. The share of the population aged 18–24, with, at most, lower secondary education and not currently enrolled in education or training was 44.3% in 2009. This compares poorly to the EU average of 14.4% for the same age group. The overall employment rate for the population aged 15 and above in 2010 was relatively low at 43%, largely due to a very low employment rate for women of only 24% (ETF calculation on LFS data). Also, older workers are not as active as in other countries in Europe and the Western Balkans[7]. Only around one-third of the population in the 50–64 age group is employed in Turkey, according to Eurostat data. Unemployment rates are lower than in most of Western Balkans (11.4% for men and 13.0% for women in 2010), and, particularly, youth unemployment is impressively low compared to many other countries (21.7% in 2010 according to LFS data). Unemployment rates decline rapidly with age. In 2010 the unemployment rates were 14.9%, 10.3% and 9.6% respectively for the age brackets 25–29, 30–34 and 35–39. More than one-fifth of the labour force is still engaged in the agricultural sector.

It should be noted that there has been a general, rapid increase in education levels in Turkey over time. That means that the differences between education levels are also to some extent caused by differences between generations. The education levels junior high and primary were replaced in the 1990s with the new level called elementary. Labour force respondents who claim to have an educational attainment of either primary or junior high are thus clearly graduates from before this educational reform.

All of the remaining data in this chapter, except for data on vacancies, are taken from labour force surveys conducted since 2005 by the Turkish statistical institute, TurkStat. Vacancy data are collected by the Turkish Employer Organisation (ISKUR) and issued monthly. All the graphs in this chapter depict Turkish data from either one or both of these sources. Each methodology will be discussed separately before overall conclusions are drawn.

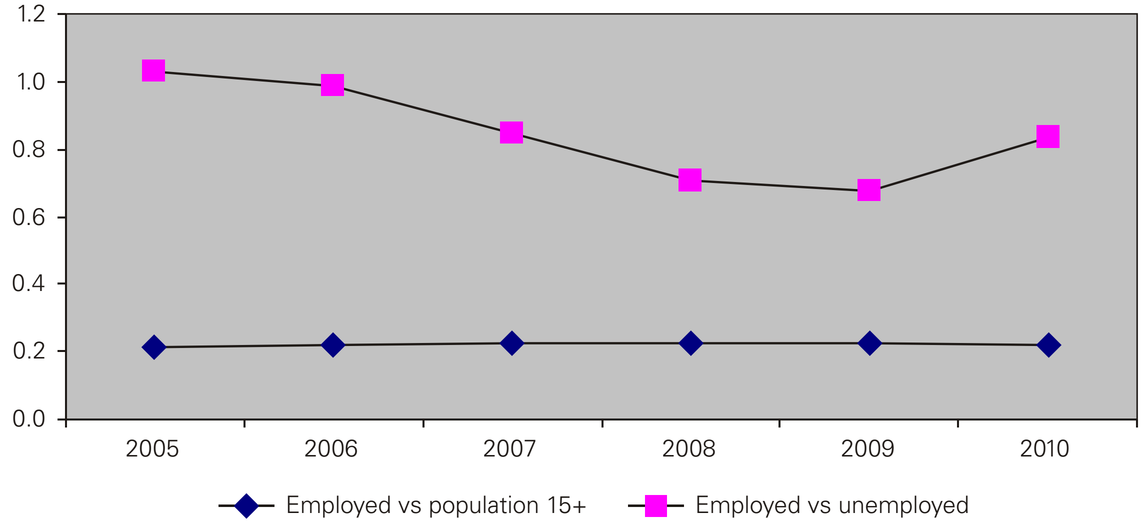
3.1 COEFFICIENT OF VARIATION

It is not surprising that the coefficient of variation is higher when the employed population is compared to the unemployed population than when comparing the employed population to the whole working-age population. The working-age population includes the employed, so a certain correlation is to be expected. This is not the case when comparing the educational profiles of the employed with the profiles of the unemployed. Those two groups are mutually exclusive. Over the last six years the mismatch had been generally declining, until 2010 when the situation deteriorated again, possibly because the economic crisis made conditions in the labour market harder. In financially difficult times companies are more likely to be cautious and recruit carefully.

6 More than a quarter of the population is under 15 years of age and the population growth rate has remained steady at 1.3% annually from 2006 to 2010 (World Bank data).

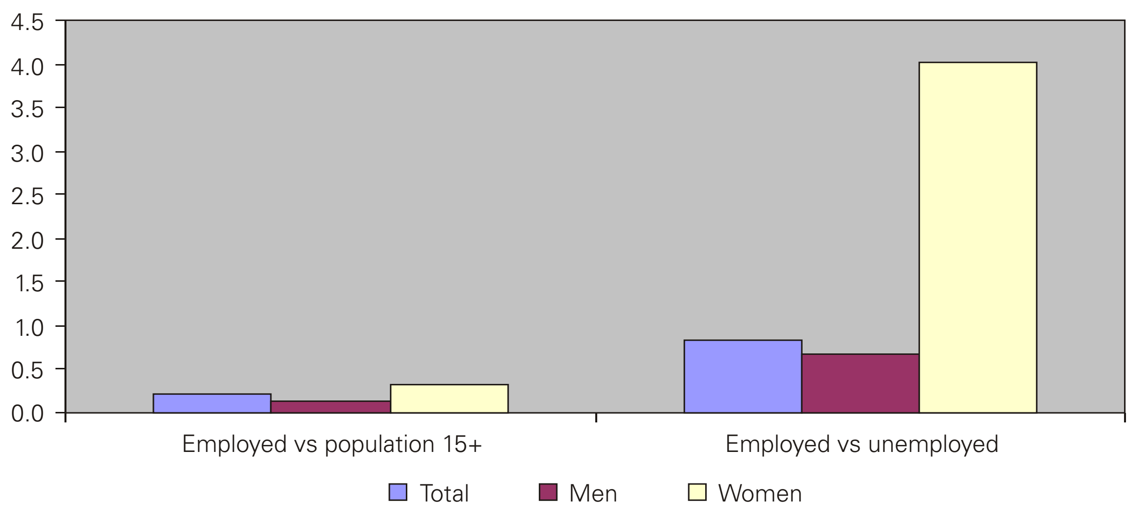
7 The data in this paragraph has been collected by the ETF from national LFS data and the World Bank. See also Majcher-Teleon and Bardak (2011) for more details on the Turkish labour market.

FIGURE 3.1 **COEFFICIENT OF VARIATION IN TURKEY, 2005–10 (LFS DATA)**



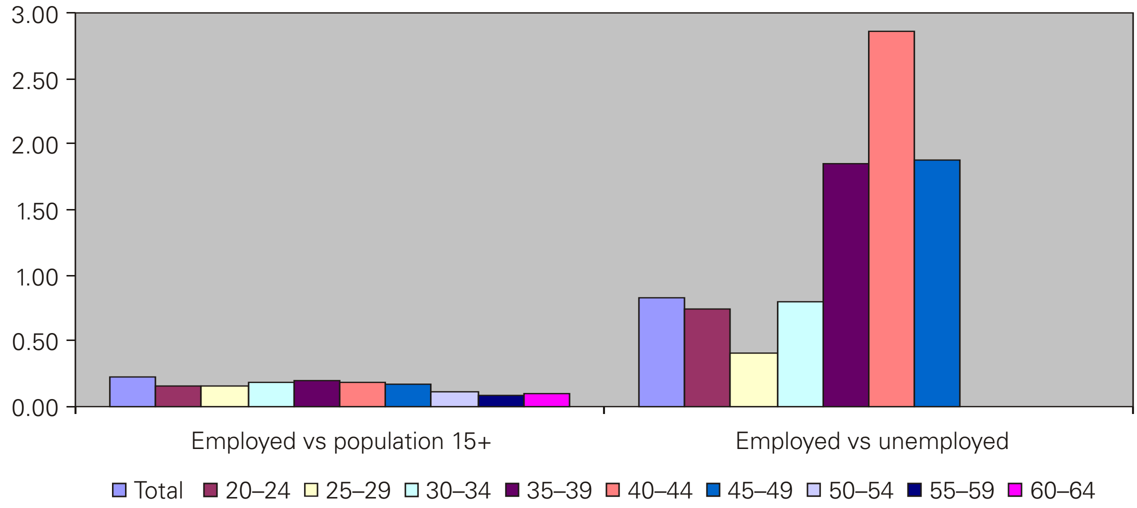
The difference is largely driven by women, however, as can be seen from **FIGURE 3.2**. Unemployed Turkish women have an educational profile which is very different from that of the employed population in general.

FIGURE 3.2 **COEFFICIENT OF VARIATION BY GENDER IN TURKEY, 2010 (LFS DATA)**



And from **FIGURE 3.3**, it is possible to pinpoint the greatest variation to the age group 35–49, in particular the 40–44 bracket. This is somewhat surprising. Young people often struggle to get into the labour market, and the data does show that there is a bit of mismatch for the youngest age groups, but these differences pale in comparison with those for older age groups. Young people in Turkey are disadvantaged in the labour market because of their lack of experience, not because of their educational qualifications.

FIGURE 3.3 COEFFICIENT OF VARIATION BY AGE IN TURKEY, 2010 (LFS DATA)

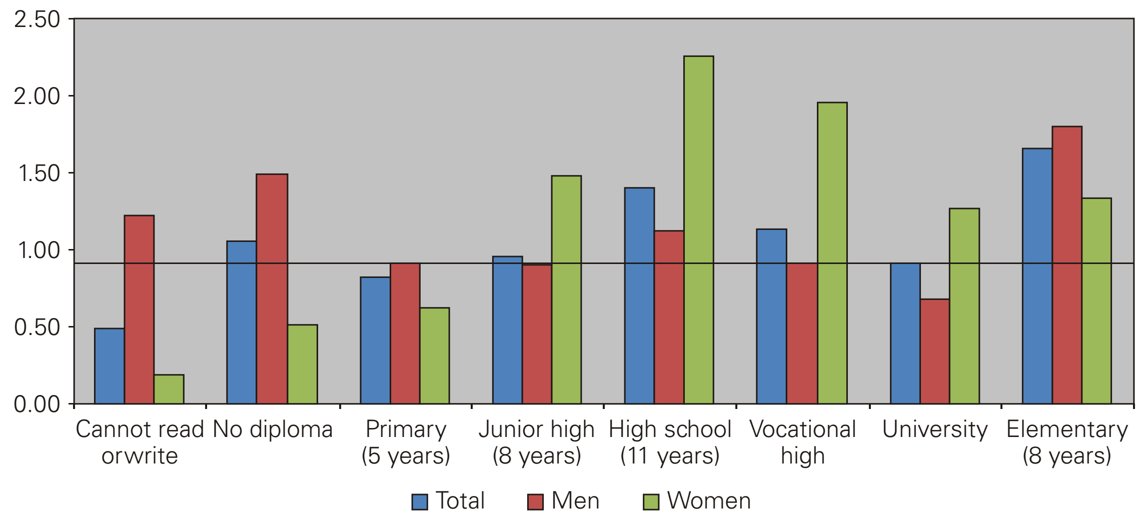


3.2 PROPORTIONS OF EMPLOYED VERSUS UNEMPLOYED

This particular methodology can be used in conjunction with other mismatch measurements, as discussed in the theoretical discussion of the coefficient on variation, or even on its own to identify the areas where there may be an excess supply or shortage of skills.

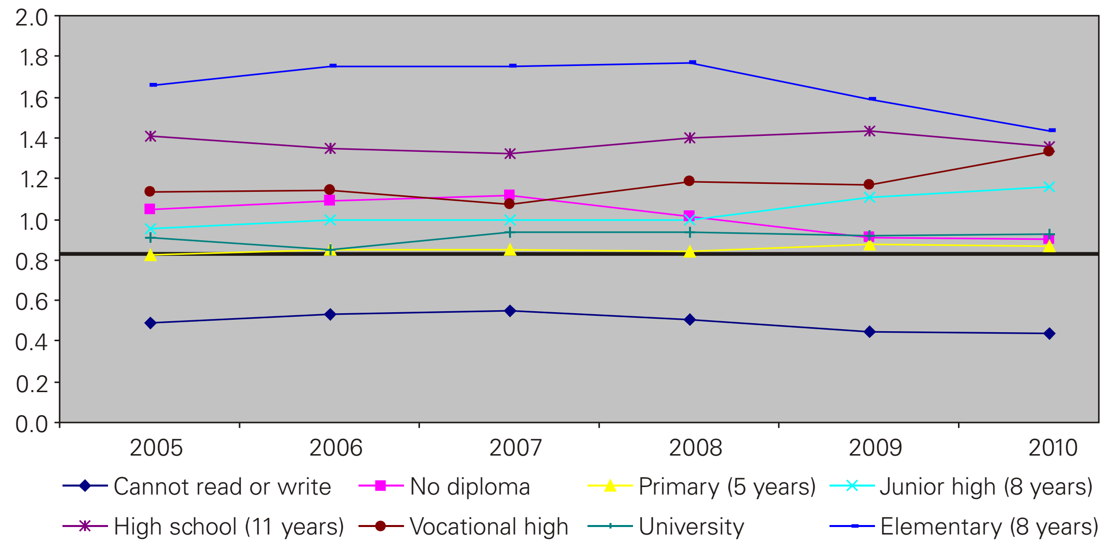
From **FIGURE 3.4**, for example, it is possible to see that unemployed men are in excess supply for the lowest categories of education (cannot read or write, no diploma, elementary and high school), since the proportion of unemployed over the proportion of employed exceeds 1, whereas unemployed women are in excess at the other end of the educational range (elementary, junior high, high school, vocational high and university). This indicates that many women are highly skilled, but not in high demand relatively speaking, while men have left the school system too early to acquire the skills necessary to be successful in the labour market.

FIGURE 3.4 PROPORTION OF UNEMPLOYED OVER THE PROPORTION OF EMPLOYED BY EDUCATION AND GENDER IN TURKEY, 2010 (LFS DATA)



The analysis above is based on data for 2010, and from **FIGURE 3.5** it is clear that the picture over the last six years has remained relatively stable. People with high school, vocational high and elementary education are consistently in excess supply. Only junior high graduates moved from a position of a small excess demand in 2005, via near equilibrium, to excess supply in 2009 and 2010. The very low proportion of unemployed who cannot read or write compared to the proportion of employed with the same characteristics may best be explained by the lack of a social safety net for such individuals. They are not in a position to be unemployed.

FIGURE 3.5 TREND IN THE PROPORTIONS OF UNEMPLOYED RELATIVE TO THE PROPORTIONS OF EMPLOYED IN TURKEY, 2005–10 (LFS DATA)



3.3 VARIANCE OF RELATIVE UNEMPLOYMENT RATES

This methodology is quite similar to the coefficient of variation, but the results provide a different type of information, which may be considered as complementary. **FIGURE 3.6** shows that the variance of relative employment rates is higher than the variance of relative unemployment rates. This means that employment rates by education level are more likely to differ from the total employment rate, while unemployment rates by education level are closer to total unemployment rate, i.e. the chances of getting employment is dependent upon the education attained.

FIGURE 3.6 VARIANCE OF RELATIVE UNEMPLOYMENT AND EMPLOYMENT RATES IN TURKEY, 2005–10 (LFS DATA)

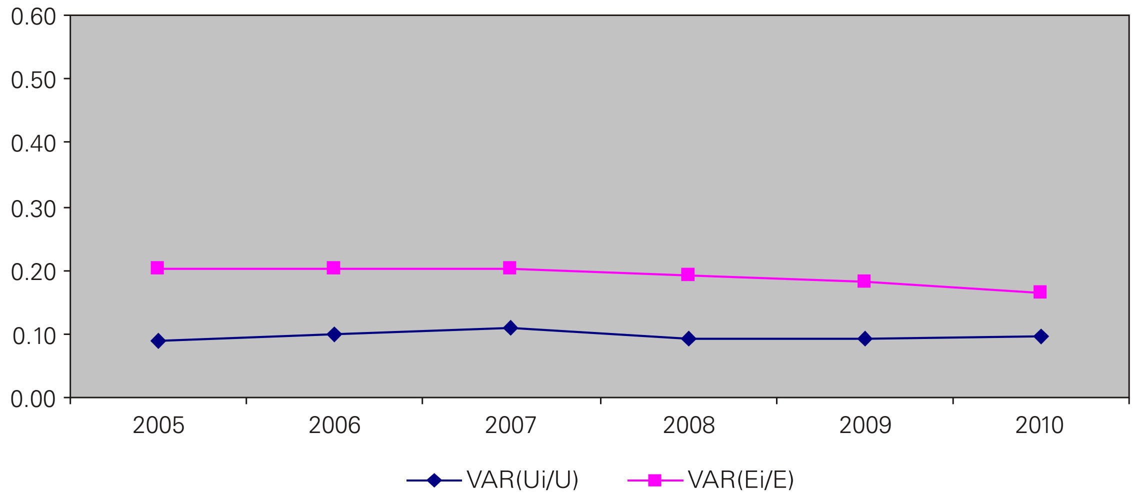
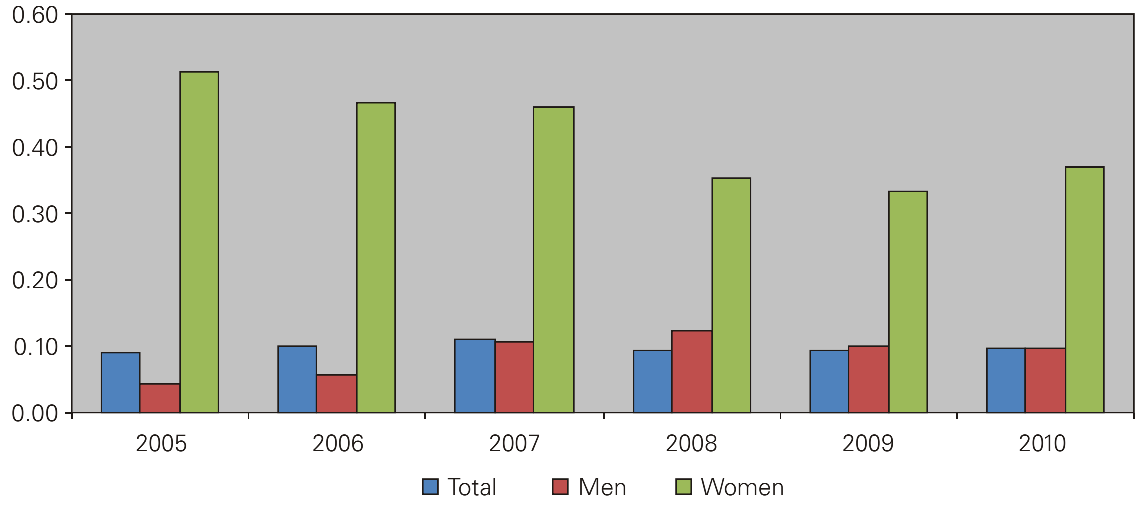
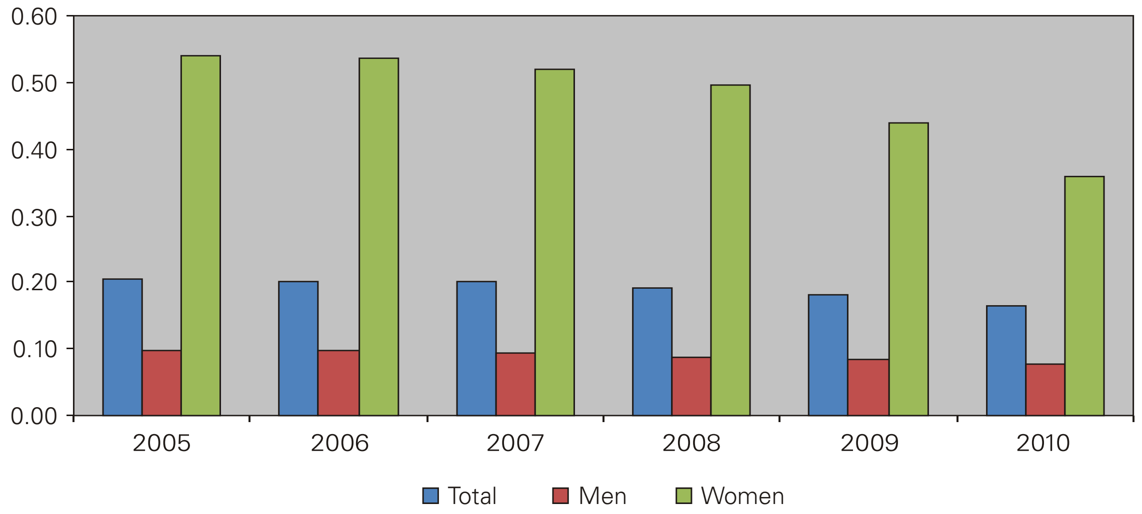


FIGURE 3.7 **VARIANCE OF RELATIVE UNEMPLOYMENT RATE BY GENDER IN TURKEY, 2005–10 (LFS DATA)**



For unemployed women the mismatch was steadily declining between 2005 and 2009, according to **FIGURE 3.7**. This contrasts with the impression given by the coefficient of variation, which is more volatile over time[8]. The picture is the same for employed women (see **FIGURE 3.8** below). They have a greater variance than the employed men, which means that in Turkey there is a greater dispersion of the employment rates by education level for women than there is for men. The education level attained can thus be said to have a greater impact on labour market attachment for women than it does for men in Turkey.

FIGURE 3.8 **VARIANCE OF RELATIVE EMPLOYMENT RATE BY GENDER IN TURKEY, 2005–10 (LFS DATA)**



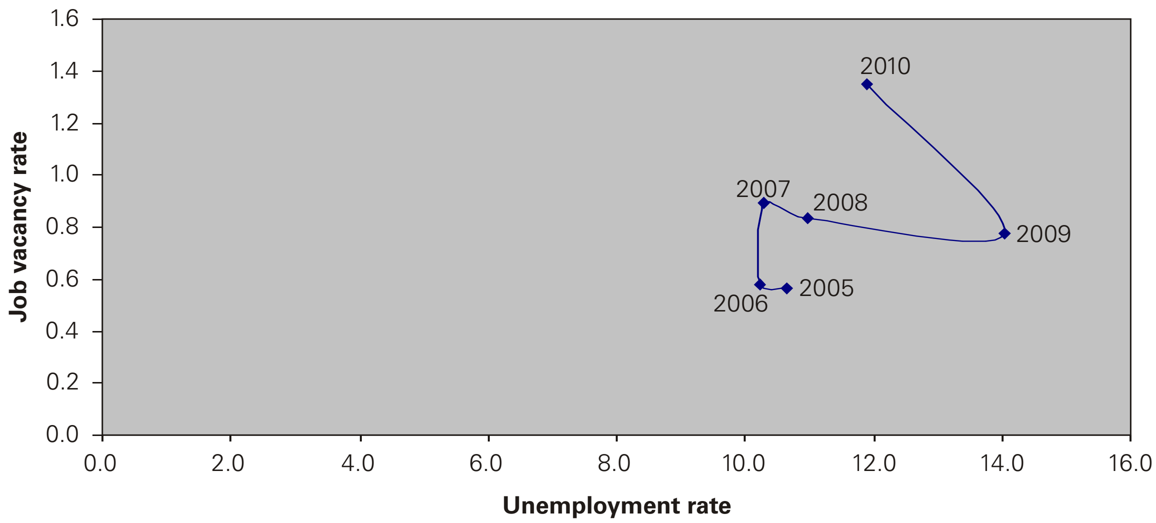
8 This is not shown in the graphs. Not all data is reproduced in this paper for reasons of simplicity. A more thorough examination of all the data is planned for a future publication. The reader is here kindly asked to have faith in the authors or contact them for more extensive data.

3.4 BEVERIDGE CURVE

Using annual data on vacancies and the annual unemployment rate for the period 2005–10, a picture emerges with generally high unemployment rates and low vacancy rates. Over the period examined, the movements were effected by the ongoing global financial crisis. From 2007 to 2009, but especially from 2008 to 2009, the unemployment rate increased greatly, without much noticeable change in the number of vacancies. After 2009, the number of vacancies increases, and the unemployment rate declines rapidly in line with the general improvements of the Turkish economy. There is a small shift in the Beveridge curve from 2006 to 2007, however, when both the unemployment rate and the number of vacancies increased, which is symptomatic of deteriorating matching mechanisms.

A clearer picture would have been possible had quarterly or even monthly data been available. Annual data may mask short-term shifts in the Beveridge curve which would be visible with more detailed data, although it would still not be possible to separate the movements along the curve from shifts of the curve. The curve shows the same movements if we only use the unemployment rates for low-skilled people, so the possible criticism that the vacancy data often only relate to jobs for low-skilled people has no effect. As the movements are identical, we only depict the Beveridge curve with total unemployment rates.

FIGURE 3.9 BEVERIDGE CURVE FOR TURKEY, 2005–10 (LFS AND ISKUR DATA)

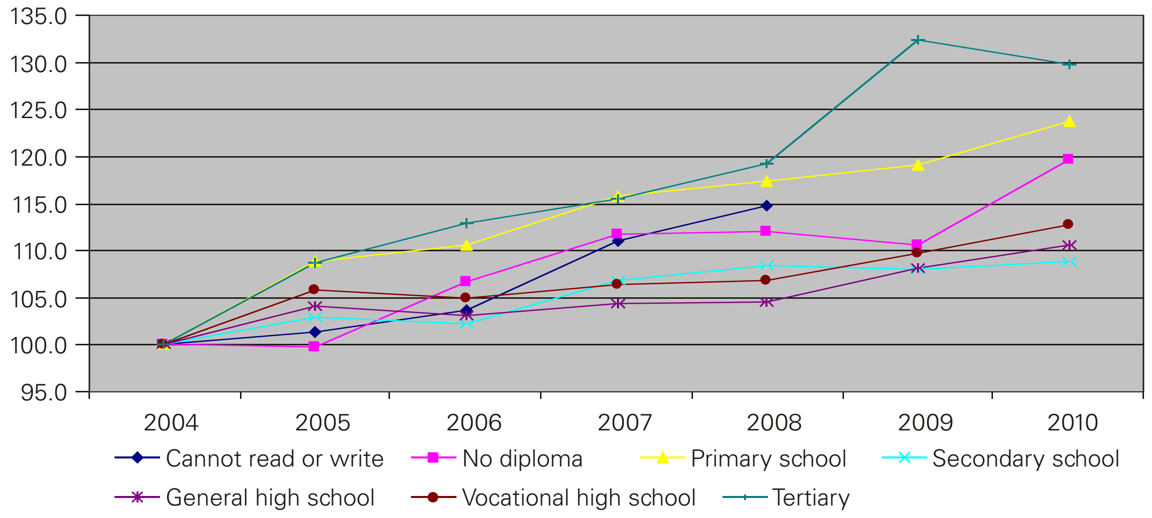


A different line of interpretation would question whether all of the points marked since 2006 are not in fact lying on Beveridge curves that have been shifted out from the curve which dominated earlier. The data points 2005 and 2006, 2007 and 2008, 2009, and 2010 would in such an interpretation lie on four (or more) different concave Beveridge curves akin to the curve depicted in Figure 2.1. Following this logic, one can argue that the outward shifts of the Beveridge curve signal a worsening labour market, where unemployment goes up despite more and more vacancies being available, and that the underlying mismatch is worsening.

3.5 RELATIVE WAGES BY EDUCATION LEVEL

Wages by education level attained can be indexed by setting the wage to 100 for each level in 2004 and then comparing subsequent wages with the baseline year. **FIGURE 3.10** shows that tertiary graduates throughout the period 2004–10 experienced faster growth in wages than graduates from any other level. The wages for tertiary graduates in 2010 were 30% higher than in 2004, whereas the education level that experienced the second highest growth only gained 20% over the same period. Inflation in Turkey has been high. In fact, with inflation running at 8–10% annually during most of this period, according to Eurostat (only in 2009 was inflation lower than 8%, with a rate for that year of 6.3%), these increases do not reflect real wage increases, but rather the opposite. From this cursory analysis, wages have not kept up with the inflation, although the tertiary graduates have been better at maintaining their salary levels.

FIGURE 3.10 **RELATIVE WAGES BY EDUCATION LEVEL IN TURKEY, 2004–10 (LFS DATA) – INDEXING WAGES (2004 = 100)**



The second and third highest growth rates were experienced by people with primary education or no diploma, whereas the mid-level education levels (secondary, and general and vocational high school) all experienced relatively low levels of growth. This is a reflection of a very strong demand for tertiary graduates, as well as a strong demand for low levels of skills, in the labour market from 2004 to 2010. This is not in itself a mismatch, but when tertiary graduates are able to command such a wage premium relative to other levels of education, it indicates that the supply, at least initially, could not match the increased demand: with the result that wages had to be increased to attract the best graduates.

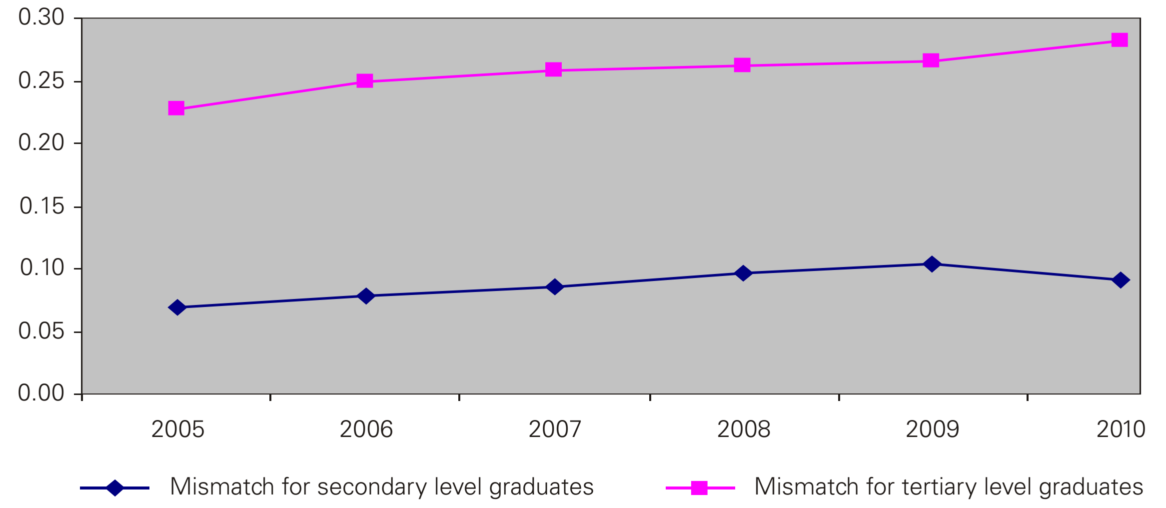
3.6 RETURNS TO EDUCATION

Research on returns to education in Turkey is limited (Tunaer and Gülcan, 2006), and without detailed micro-data we cannot replicate the research which has taken place. However, according to Tunaer and Gülcan (2006, p. 70), there are significantly increasing trends for higher education levels for the period 1994 to 2004, in particular within the industry sector and also for women with higher levels of education within the services sector. The levels that saw the increased returns to education were higher education, which included vocational high school and shorter university programmes, and postgraduate programmes.

3.7 MISMATCH BY OCCUPATION

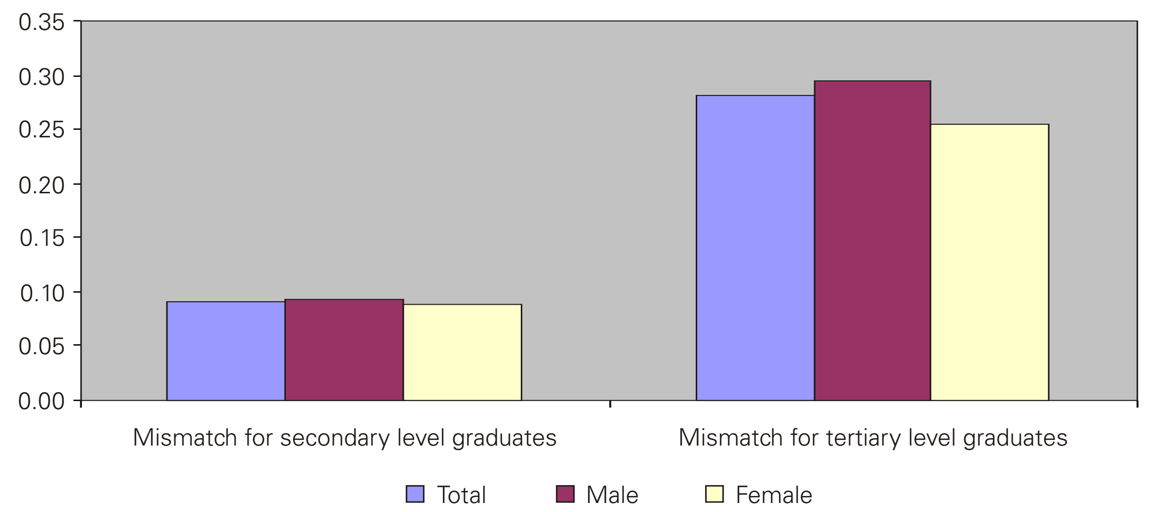
Throughout the period from 2004 to 2010 the mismatch by occupation increased slowly, but surely (**FIGURE 3.11**). This occurred irrespective of whether the mismatch was measured for secondary level graduates or for tertiary graduates. The level of mismatch is seen to be higher for tertiary graduates, which confirms the results from the analysis of the returns to education.

FIGURE 3.11 **MISMATCH BY OCCUPATION IN TURKEY, 2005–10 (LFS DATA)**



There is, however, very little evidence from this kind of analysis that there is any kind of gender imbalance. For secondary-level graduates the difference is negligible, and for tertiary graduates there appears to be a slightly higher level of mismatch by occupation for men than for women (see **FIGURE 3.12**). This contradicts earlier findings from the other methodologies that there are substantial gender imbalances.

FIGURE 3.12 **MISMATCH BY OCCUPATION AND GENDER IN TURKEY, 2010 (LFS DATA)**



3.8 CONCLUDING COMMENTS

It is clear from the examples above, that it is possible to follow trends in mismatch in Turkey, even if it may be difficult to assess the exact extent of the mismatch. The results do not all point in the same direction though. The data for both the trend in the level of mismatch and the possible existence of gender imbalances are inconclusive.

Judging from the data over the period examined, the level of mismatch could be said to be:

- initially declining, later increasing (coefficient of variation of employed versus unemployed);

- stable (proportion of unemployed relative to the proportion of employed, the variance of relative employment rates and the coefficient of variation of employed versus the working age population); or even
- increasing (primarily for tertiary according to relative wages by education levels and mismatch by occupation, but this is also reflected in the Beveridge curve).

Since only one methodology indicates an absence of gender imbalances (mismatch by occupation) and several other methodologies show a clear gender imbalance (coefficient of variation, variance of relative employment rates and proportions of unemployed relative to proportions of employed), the evidence seems to favour the interpretation that there are, in fact, gender imbalances disfavouring women.

Despite these apparent contradictions there are also some specific results, which stand out. The middle aged (35–49-year-olds) experience greater mismatch in the labour market than either younger people or older people. These individuals are at risk of becoming long-term unemployed or underemployed, as their skills do not match labour market requirements and they do not have the advantage of youth in the eyes of prospective employers. It is also remarkable that well educated women are in excess supply, along with less well educated men.

This analysis has been conducted purely on the basis of the available data, and by testing what the respective methodologies for measuring mismatch could say about the mismatch in Turkey. By using all of the methodologies, it is possible to contrast the different results and highlight the main trends. None of the methodologies examined here appear to hold a unique answer to the question of mismatch in Turkey.

Coupled with deeper knowledge of developments in the Turkish labour market since 2005, it would be feasible to make a more detailed analysis and to assess which of the mismatch measuring methodologies comes closest to providing a comprehensive picture of the mismatch issues in Turkey. A qualitative assessment of mismatch in Turkey involving trade unions, employers, and education and training providers, as well as local and national authorities, would also be beneficial at this stage.

4. CONCLUSIONS AND RECOMMENDATIONS

The main conclusion is that no single methodology should be used. Each methodology provides insights into different aspects of the complex matter of skills mismatch. Thus, using a range of methodologies would result in highlighting as many of these aspects as possible. ETF partner countries, and any other country for that matter, should therefore pursue several avenues simultaneously to explore the available data as fully as possible. The methodologies explored in the case of Turkey are very cost-effective, as the data already exist. More data can be made available in many cases, which would allow for further calculations, e.g. returns to education. Once the readily available data has been explored, it will become apparent to what extent it is worthwhile looking into the possibility of undertaking the more subjective methodologies, which unfortunately rely on more expensive surveys. Another option which should not be overlooked, is to combine these quantitative methods with qualitative methods, such as structured interviews, panel discussions and focus groups.

The most promising tool, given the typical level of data availability in most ETF partner countries, may be the proportion of the unemployed relative to the proportion of the employed, as it allows us to pinpoint the extent of excess supply or shortages for each education level, and thus gives direction to the problem of mismatch, where the coefficient and variance only give magnitude. This does not mean that other measures, such as the Beveridge curve for countries where data on vacancies are reliable, should be ignored. Even worker self-assessment can be examined for a few countries. The best results are likely to come from calculating mismatch through as many different methodologies as possible, and then comparing the results. Ideally, it would be possible to have several results for each of a number of ETF partner countries, so the results of the different methodologies could be compared for several countries. A follow-up paper is planned by the ETF to provide exactly such an analysis for a group of countries.

ACRONYMS

ETF	European Training Foundation
Eurostat	Statistical Office of the European Union
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
LFS	Labour force survey

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