ANALYSIS OF THE DETERMINANTS OF QUALIFICATION MISMATCH IN UKRAINE IN 2011-2015

by

Mariia Chebanova

A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Economic Analysis

.

Kyiv School of Economics

2018

Thesis Supervisor: Professor Olga Kupets

Approved by ___________________________________
Head of the KSE Defense Committee, Professor Tymofiy Mylovanov

____

____

____

Date ___________________________

Kyiv School of Economics

Abstract

ANALYSIS OF THE
DETERMINANTS OF
QUALIFICATION MISMATCH IN
UKRAINE IN 2011-2015

by Mariia Chebanova

Thesis Supervisor: Professor Olga Kupets

Efficient labor allocation constantly attracts attention of economists due to its important link to such concepts as long-term unemployment, productivity, technological advance and others. High incidence of qualification mismatch is one of the crucial representations of labor misallocation. Because of large structural changes and high economic turbulence, economies in transition, including Ukraine, are especially vulnerable to mismatch. This thesis focuses on the issue of identifying main determinants of qualification mismatch at the individual level. Despite the expectations, we do not find a great increase in undereducation and horizontal mismatch in 2014-2015 as compared to 2011-2013. We find that statuses of employment are associated with higher probabilities of qualification mismatch when compared to employees, which is especially profound for those working in self-employed in agriculture. Employees in small firms, those who enter into verbal agreements, females and younger workers are at the highest risk of qualification mismatch. These groups of workers are generally considered among the most vulnerable labor market participants. Therefore targeted government policies should be developed to prevent the further aggravation of labor misallocation in Ukraine.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

List of Tables continued

ACKNOWLEDGMENTS

The author wishes to thank her family (parents Valeriia and Volodymyr, brother Kyrylo and Berry), for their constant support and all the kicks they have been given me throughout the process of writing the thesis. we also thank my thesis advisor Olga Kupets for never failing to give competent counsel and her true and genuine feeling for each of her advisees.

Special gratitude goes to Kateryna Chernoknyzhna for her useful although caustic comments on my formatting and presentation, and for providing me with some great PowerPoint templates. we also want to mention my classmate Oleksii Romanko who has proven that for certain individuals it is possible to study well, work hard and still produce a decent thesis.

GLOSSARY

Qualification mismatch. Situation of imbalance in which the level or type of knowledge, abilities and competences available does not correspond to labour market needs.

Vertical mismatch. situation in which the level of education or skills is less or more than the required level of education or skills.

Overeducation. A situation in which an individual has more education than the current job requires (in terms of level).

Undereducation. A situation in which an individual has less education than the current job requires (in terms of level).

Horizontal mismatch. A situation in which the level of education or skills matches job requirements, but the type of education or skills is inappropriate for the current job.

EU. European Union.

ISCO. International Standard Classification of Occupations.

GRP. Gross Regional Product.

LFS. Labor Force Survey

OECD. The Organisation for Economic Co-operation and Development.

UK. United Kingdom.

SSSU. State Statistics Service of Ukraine.

Chapter 1

INTRODUCTION

Qualification mismatch stands for the situation on the labor market when workers' qualifications, individually or in the aggregate, differ from those required for the jobs they hold (Sattinger 2011). The term indicates an inefficiency, which becomes apparent on all levels of the economy.

First, mismatched workers face a great number of penalties that result from the inappropriate job-worker combination. These include:

1. Job dissatisfaction (disutulization of skills or pressure to overperform own abilities);
2. Wage penalty (potentially higher income in appropriate field/skills required);
3. Higher risk in time of economic turbulence etc.

Second, job-worker mismatches cause losses to companies through reduction in productivity. Under-qualified workers are likely to perform worse than their well-matched peers, while the firm does not receive its potential level of output, given the number of workplaces. Overqualified workers tend to show counterproductive behavior (shirking and high quit rates), and their dissatisfaction with the current tasks may be to blame.

Third, literature reveals that mismatches in the labor market have potential to explain a statistically significant share of cross-country workers' productivity gap (McGowan and Andrews 2015a). Therefore, it is tempting to conclude that the abovementioned underperformance of firms due to mismatch leads to constrained growth potential of the whole economy (Cedefop 2010). Turning to more global aspects of the problem, we should also mention the recent research that links qualitative mismatch to business cycles, job polarization[1] and increase in long-run unemployment due to rapid technological changes and related structural changes (Kjell, Salvanes, and Sørensen 2012; Zago 2017).

But research does not only provide evidence of productivity losses due to qualification mismatch. A non-trivial association between the differences in skill mismatch across countries and differences in the regulations has been discovered (Klosters, 2014). On average skill mismatch is lower in countries which adopted policies promoting competitive and open business and efficient reallocation (including residential mobility). Other important regulations with effect on labor allocation are flexible employment protection legislation and mild bankruptcy legislation (McGowan and Andrews 2015b).

In the developed countries, the problem of efficient labor allocation is constantly on the agenda of both national and local governments. OECD, for example, provides estimates on incidence of mismatch (both skill and education) in the member-countries. This aggregate indicator reflects the discrepancy between the supply and demand of skills and competences. In the long-tern perspective it shows to what extent current education system corresponds to real labor market needs in terms of qualifications. The concept of labor market qualification mismatch is widely used in projections of labor supply and demand by sectors of economy, expected structural changes and their implication for existing qualifications. In the UK a relatively recent study was issued by the UK Commission for Employment and Skills on the state level (Wilson and Homenidou 2012) and similar research was published on demand for labor and skills in London (Marsden and Hitchins

[1] Job polarization stands for concentration of labor force in the jobs requiring abstract and manual tasks instead of routine activities

2016). High time to consider this issue more closely, since incidence of both vertical and horizontal mismatch in the UK are among the highest in OECD members.

Literature reveals high incidence of qualification mismatch in the Ukrainian labor market (Kupets 2016a). Yet, Ukraine is far from introducing fine-tuned labor market policies aimed to reduce the obstacles to greater labor demand and supply match. Ukrainian Ministry of Education does not take into account projections of labor supply and demand when developing policies on secondary, tertiary and professional education programs and determining the number of state-financed places. This exacerbates the problem of qualification mismatch for fresh graduates. State Employment Service of Ukraine does not consider existing qualification mismatch and its structure for its training programs. Because of it the newly unemployed have a high probability of being misallocated in terms of their skills and knowledge. A continuous monitoring of job-worker match within firms can improve the on-job training systems and narrow the gap in skills acquired by workers and required by job specifics at the disaggregate level.

In our research we investigate the nature and dynamics of mismatch in the Ukrainian labor market on aggregate and separately for employees. More specifically we study:

1. The structure of job-worker mismatch by gender, age group, region and other dimensions;
2. The structure of qualification mismatch by type of mismatch: horizontal and vertical;
3. Dynamics of mismatch incidence over the period of 2011-2015.

Our key research question is what the main determinants of a qualification mismatch, defined in terms of both vertical and horizontal mismatch, on the Ukrainian labor market using LFS. The dataset contains microdata for a large sample of the participants of Ukrainian labor market (average number of observations per year is approximately two hundred thousand). To the extent of our knowledge, no research with similar focus on both education level and field-of-study mismatch in Ukraine has been conducted before. We find that horizontal mismatch prevails, accounting for almost half of total incidence of mismatch. Results also indicate that employees are less likely to be mismatched as compared to other statuses of employment. As for the dynamic changes in mismatch structure, LFS data does not point to a drastic increase in any of the studied types of mismatch over the period of 2011-2015.

The remainder of the thesis is structured as follows. In Chapter 2 we discuss how recent labor market theories view the origin and persistence of mismatch, principal classifications of qualification mismatch, and the place of this concept in the broad picture of modern labor market tendencies. We then focus on literature on modeling mismatch using microdata and studies that investigate the incidence of mismatch in Ukraine. In Chapter 3 we describe the data and methodology that the estimations were based upon with detailed discussion of model specification and estimation process. Chapter 4 presents the estimation results and robustness checks, as well as detailed discussion on the model implications. Finally, Chapter 5 contains conclusions and applicable policy implications with focus on Ukrainian labor market conditions.

Chapter 2

LITERATURE REVIEW

Qualification mismatch is a complicated phenomenon with neither a straightforward mechanism of origin, nor a simple solution. The formation and changes in the aggregate level of mismatch is both directly and indirectly connected to the ongoing processes in the labor market (both national and global), such as income distribution between areas and types of economic activities, technological advance, globalization, switch from narrow to broad specialists and others. At the same time, the examination of origins and tendencies in individual and aggregate qualification mismatches is related to a few modern theories of labor market, including, but not limited to, human capital theory, job screening model and matching theory. In the following subsections we discuss, without digging deep into the details and assumptions of the models, to which extent various labor economics theories differ in explaining the nature of mismatch, and how the latter is linked to world labor market trends. we further turn to individual characteristics of workers, that are associated with different types of mismatch.

2.1. Economic theory behind qualification mismatch and its relation to global tendencies

Theoretical framework related to sources and impact of skills mismatch in the labour market is represented by several economic theories. The fundamental ones include:

1. Human capital theory. It sees employees as receiving wage in form of marginal product of labour which is defined by their level of human capital. Thereby, the firms utilize all of workers' skills and no mismatch is possible. (Kucel 2011).
2. Matching Theory. In this framework, both workers and firms are engaged in search of job offers and employees respectively. The search is costly for both sides. Therefore, temporary mismatches are possible, but they are eventually corrected due to incentive for both sides to improve the match.
3. Job mobility theory explains skill mismatch, particularly overeducation, with the shortage of appropriate signals of workers` productivity. However, entering the labor market, workers obtain new experience and move to more appropriate jobs, either inside or outside the company. Hence, workers in the long-run gain the best job in terms of application of their skills (Kucel 2011).
4. Job competition model. It studies skill mismatch from the side of job characteristics as the only determinant of firms' productivity. According to the model the job market is described not as wage competition, but as human capital competition. That is, job opportunities are determined only by the level of education and trainings. Suchwise when a potential worker knows that his competitors invest in their education, he is also more likely to do so. This, in turn, creates overeductaion, because while some workers will be hired at the best jobs, others will receive positions which require less skills or education (McGuinness, Pouliakas and Redmond 2017).

5. Job-screening model. This model accepts the possibility of a prolonged overeducation. It considers the existence of asymmetric information, and in this case employer does not have a prior knowledge on the level of skills that the individual possesses, and so individuals have an incentive to invest in their education to signal that they are more skillful (in this characteristic it is similar to Spence's signaling model) (Allen and van der Velden 2001).

Many authors today argue that these models are obsolete due to drastic technological advance and other major changes that the world economy has witnessed. Along with them, the pace of changes in the requirements for most positions has increased. In addition, to fully understand the origin and lengths to which the problem reaches, researchers and policymakers should be able to distinguish between different types of mismatch. One dimension for classification of qualification mismatch is its duration. Sattinger (2011) distinguishes between short-term and long-term qualitative mismatches (author's terminology) and tries to argue, that as the reasons for the appearance of these two types of mismatch, the ways of their solution also follow a different path. By his definition, short-term qualitative mismatch is a consequence of various job and worker characteristics combined with imperfect information on wages and skills. Long-term aggregate qualitative mismatch, on the other hand, is a consequence of a change in the economy that alters the mix of job characteristics (through the technological change, capital investments, globalization), or the change in incentives for people to obtain education and professional training that alters the mix of worker characteristics (through subsidies to different levels of education, quality of preparation at earlier educational levels etc.). This distinction is important for policy implications as for short-term mismatch it is sufficient to establish "labor institutions to encourage more efficient matches, reduction in search and recruitment costs", while in case of a long-term aggregate mismatch the change in educational and training policies are needed to address the structural shifts in the market.

Another way in which the literature distinguishes mismatch is that related to having inadequate level of education versus having too much knowledge and skills to perform at a certain job. Some authors, such as Green and Zhu (2008) refer to it as formal (too many years of schooling) and real (underutilization of skills) overeducation. Note, that a number of researchers focus specifically on the issue of overeducation, rather than education mismatch in general, since previous evidence concludes that undereducation provides benefits for the workers in terms of their returns compared to their peers. When speaking in the context of real and formal overeducation, research highlights that the former plays a more remarkable part in workers' job dissatisfaction and wage penalty.

In our paper we consider in more detail on another broad aspect of mismatch classification, namely vertical (education level) and horizontal (field of study) mismatch. The former is widely reviewed and analyzed in the literature, especially in the context of relation of over/under-schooling to wages and job satisfaction. But horizontal mismatch has not been studied thoroughly, probably due to complications associated with measuring mismatch. Workers with college and university education may obtain several degrees in various spheres, and there are multiple cases when the major is related to several fields. Whatever the reason, researchers find education level much more attractive, based on the number of related studies.

All of the above types of mismatch are important when placing the issue in a more global setting. Studies like Zago (2017) and Restrepo (2015), underline the relation between the incidence of mismatch and such labor market phenomena as recession, job polarization and long-term unemployment. One subset of studies specifically points to probability of job-worker mismatch being higher in times of economic downturn, especially for young graduates (Kjell, Salvanes, and Sørensen 2012). Other literature, such as Birk (2001), focuses on the link between the structural changes in the economy, the following matching frictions. The latter in turn lead to firms creating fewer novel jobs and discouragement from skill acquisition for workers, and in the end increased overall unemployment. In fact, the structural change interacts with the business cycle, and this a significant and long-term increase in unemployment, concentrating in recessions. Related tendencies, such as job polarization, have been shown to accelerate during recessions, when routine jobs are destroyed faster than others. Current pace of technological advance, which affects the routine employment greatly and results in its skill-depreciation, may lead to ever larger decrease in cognitive-routine jobs and, thus, employment, with high probability of skill and knowledge mismatch for the newly unemployed. Once occurred, job-worker mismatch along with associated disadvantages tend to hold. Clark, Joubert, and Arnaud (2013) find overeducation to be a persistent phenomenon, and almost 80% of workers remain mismatched by education level after one year. Additionally, the probability of quitting this state tends to decrease strongly, going down 60% during the first 5 years in overeducation.

As the negative effects of qualification mismatch are not the primary focus of this research, we will only briefly mention them. First, various studies find that at the individual level education (vertical) and/or skill mismatch are associated with wage penalties, job dissatisfaction and even decline in cognitive abilities (Verdugo and Verdugo 1989; Duncan and Hoffman 1981; Groot and van den Brink 2000; de Grip et al. 2008, Eijs and van Heijke 1996). Interestingly, results of Clark, Joubert, and Arnaud (2013) point to existence of so-called scarring effects, which become apparent when overeducation at the early career stage has an impact on wages later. Second, at the firm level, companies with high incidence of mismatch may face declines in productivity. In case the mismatch is introduced in terms of education/skill level, two options should be considered. On the one hand, if undereducation prevails, the workers do not perform as efficiently as the well-matched workers could at the same positions and they may also face psychological pressure of doing a job that is too demanding. On the other hand, if the incidence of overeducated workers is high, they may underperform due to recognition of their wage penalty and dissatisfaction related to their job not being high-profile enough. Finally, a recent paper by McGowan and Andrews (2015b) considers the relation of labor market mismatch and related productivity gap due to labor misallocation to differences in income per capita for OECD countries. Authors argue that mismatches in the labor market have potential to explain a statistically significant share of cross-country workers' productivity gap. Unfortunately, while some studies look into economic losses in terms of potential productivity growth on the country level due to certain related concepts, such as skill shortages, no similar estimations were found for losses due to qualification mismatch.

Due to mismatch's significant impact on productivity at different levels, this issue remains at the agenda of modern labor economics. In this study, we decided to take on a "bottom-up" approach to qualification mismatch. In the next subsection we will concentrate on the works that try to identify determinants of mismatch on the individual level and those which have focused on Ukraine before this time. we will also explicitly state my contribution to the body of existing literature on job-worker mismatch.

2.2. Studies of determinants of qualification mismatch. Incidence of mismatch in Ukraine

Several meta-analyses that examined the prevalence of mismatch have found not only that it is a widely spread phenomenon, but also that its incidence varies strongly among countries and by type of measurement used to identify mismatch. we provide a more detailed discussion of the methods used to measure mismatch in Chapter 3. Here it is worth mentioning that one particular method, namely the one based on the mean value of years of education within occupation groups, tends to provide a much lower value for incidence of (education) mismatch (Verhaest and Omey 2010; Leuven and Oosterbeek 2011). While the reported incidence differs between studies, the average value shown in meta-analyses lingers to the interval 25-30% for the share of overeducated individuals.

When it comes to defining the most relevant determinants of mismatch, two broad approaches within research should be underlined. Meta-studies primarily try to identify the reasons behind a great range in mismatch values on the aggregate level, focusing mostly on overeducation. Interestingly, the evidence provided in this type of research appears quite confusing. For instance, when analyzing association between gender and mismatch probability, Groot and Brink (2000) in their fundamental meta-analysis find gender to be significant, with females being more frequently overeducated and the opposite being true for undereducation. Ten years later Leuven and Oosterbeek (2011) claim that there is no systematic difference between the shares of over/under-educated males and females in studies they use. As some authors note, the comparison between studies is complicated due to different model specifications (some of which may suffer from endogeneity) and different measurement of mismatch. In this light, study by McGuinness**,** Bergin, and Whelan (2017) is more consistent, as it only uses data from LFS of EU 28 countries. The author finds no evidence of a sharp rise in overeducation rates, and little convergence between countries over the years studied (for the most part in Peripheral and Central Europe, which had lowest incidence in 2002 and faced highest growth rates over the years). He also notes that different labor policies, including equality legislation, childcare provision and those promoting labor market flexibility have a potential to decrease incidence of mismatch on the aggregate level.

In the studies working with data at the individual level, the focus again mainly lies on mismatch in terms of education level. In related studies features used to model the mismatch probability can be divided into demographic characteristics and job characteristics. Among the former, gender, age, marital status, ethnicity, tenure and a proxy for unobserved abilities are widely used. Job characteristics may include formal/non-formal employment, economic sector, firm size etc. In their paper Clark, Joubert, and Arnaud (2013) used a probit regression with overeducation status as dependent variable and various personal features (gender, age, tenure, cognitive test score etc.). They show that when conditioning regression on level of education as opposed to using pooled dataset, most variables change their sign and/or their effect becomes insignificant. Remarkably, very little research addresses the issue of horizontal mismatch and relation of university major to the job. One of the few representatives of this direction of research is Robst (2007). Using logistic regression, the author finds that graduates from majors that provide more general skills such as Humanities and Arts have a significantly higher probability of being mismatched (as opposed to students from STEM fields).

Since this paper is focusing on Ukraine we should take into account the particularities of the economy in question. The issue of qualification mismatch in the Ukrainian labor market and its dynamics is best represented in Kupets (2015) and Kupets (2016b). She emphasizes that economies in transition are more inclined to qualification mismatches in the form of structural mismatches as a result of ongoing "structural transformations and concurrent labor reallocation". This should hold on until the labor demand adjusts to the highly educated labor force. At the same time, Ukrainian labor market seems to act in accordance with job-competition and job-screening models, with high education not necessarily meaning advanced skills. Thus, education level acquired may be a poor proxy for the true productive skills of an individual.

Kupets reports that overeducation indeed is present in the studied countries (Georgia, Armenia, Ukraine, Macedonia), but not to a greater extent than in other economies in transition (a little more than 33 percent are overeducated and from 5 to 7 percent are undereducated). The author applied multinomial regression with three categories as a function of individual and job characteristics, as well as indicators of job-related human capital and ability-related indicators. Author's main findings demonstrate that for Ukraine overeducation is associated with lower human capital (measured by abilities and skills), and that younger generation are significantly more at risk of overeducation.

This study contributes to the research on qualification mismatch by determining factors, associated with higher probabilities of both vertical and horizontal mismatch. Moreover, we study determinants of mismatch for employees for aggregate population of workers and employees separately, overviewing changes over the period from 2011 to 2015.

Chapter 3

METHODOLOGY AND DATA

Qualification is a broad term which covers both 'level of attainment in formal education and training, recognized in a qualification system or in a qualification framework' and 'level of proficiency acquired through education and training, work experience or in non-formal/informal/ settings' (Cedefop 2010). As it is often the case, such a wide concept is hard to grasp and is even harder to measure. In our study we try to look at the both dimensions of qualification, which we proxy by fields of study and level of formal education specific for an individual.

3.1. Data description and definition of mismatch

In my research we used monthly data from national LFS from 2011 to 2015. LFS is a stratified multistage sample survey, where sample is formed accounting for rotation scheme which provides for each household to be surveyed six times (3 months consecutively, 9 months without survey and 3 months consecutively again). The final dataset included data from 88 rotations. As any survey, LFS suffers from attrition over the period that a rotation lasts. Thus, to avoid loss of individuals which may be non-random, we choose to keep only observations from the date that the new rotation group set off. For example, if a rotation group started in June 2013, we save only these first observations that the rotation group contains. This implies assuming these data to be representative over the whole period that this particular set of people were surveyed. Although being a strong assumption, it is more viable than other approximations, as attrition may occur at different stages of the survey and adjusting for it might as well result in other very strong assumptions.

As was implied before, choosing between ways to measure mismatch at the individual level is an important and non-trivial task. Three main methods to estimate skill mismatch are generally identified:

1. Self-assessment. This method is based on interviewing individuals who are asked to specify skills which are needed to perform their duties. Then the answers are compared to the actual educational level of an individual. This approach, however, has some weaknesses. First, data collected with such approach is hard to apply in retrospect. Second, the answers are exposed to the same risks that most self-reported results, namely to respondents' personal bias, as noted in Kucel and Vilalta-Bufi (2012).

2. Empirical (realised matches). This method lies in measuring mean or mode of educational level within certain professional group and then determining whether workers have educational level lower or higher than the estimated mode/mean (mean usually with 1-3 standard deviations). This approach can be applied to almost any microdata that contains information on education and occupations. However, this method does not take into account skills required for a specific occupation. In addition, it depends greatly on the distribution of education levels/fields within the occupation.

3. Job assessment. This approach involves examining educational requirements and creating corresponding dictionaries for occupations. This approach may provide the most accurate measure, but at a large time cost. Moreover, occupational requirements vary with time and thus this approach requires

regular reviews of the dictionary (McGuinness, Pouliakas and Redmond 2017).

The general consensus is to choose an appropriate mismatch indicator based on data availability. As in Ukraine there is no official guide on the required skills and education (formal and/or informal) for different jobs, and LFS does not provide a direct question as to what extent a respondent's education and skills are appropriate for his/her occupation, we applied a so-called "empirical method". Our technique is similar to the one employed by Verdugo and Verdugo (1989) and more recently Clark, Joubert, and Arnaud (2013). We define a vertical or horizontal mismatch based on the deviation from the modal value for the distributions of workers in the same 3-digit occupation group per year from which the observation comes from.

To make our approach clearer, consider an example. Take an individual from the group "241" which stands for "Professionals in economics" who was surveyed in 2014. Then we find the mode educational level and modal field of study for this 3-digits occupation. We aggregated original groups by education level used in SSSU to obtain 4 major categories by education institutions: 1=Secondary school, 2=High school, 3=College or equivalent, 4=University. As for the diploma specializations, LFS data do not report fields of studies as college/university majors, but rather these specializations adjusted for national Classification of occupations (which in turn is adjusted to ISCO). Thus, we used a transformation of initial reported 4-digit diploma specializations into approximate fields of studies (Table 8 in Appendix C).

Thus, returning to the example, we define the worker as vertically (horizontally) mismatched if they have a different from the mode value level of education attainment (different diploma specialization). In case both individual level of education and specialization by diploma do not match the respective mode values for "241" group, we indicate this worker as mismatched by both criteria. In research the field of study in college is sometimes considered an approximation for the type of skill supplied (Kjell, Salvanes, and Sørensen 2012). Therefore, we believe that by our definition we may capture the notion of mismatch from various perspectives.[2]

Literature mentions a few drawbacks of using modes to define the required qualification. As mentioned earlier, the obtained values do not reflect the true skill requirements for a particular profession but rather the level of education and the area of expertise that the employer would expect of a candidate for a related position, as most of those working within this profession have them. At the same time, this may become an advantage if we consider the modal value as the one the potential employer "expects to see" from the candidate. Thus, by getting our individual benchmark straight from the data, we do not have to face a problem when our measurement approach does not represent the actual data. At the same time, as mismatch is defined based on modes for each year separately, we capture possible structural shifts in the market.

The relative frequencies for the variables used in the further parts of the study as determinants of various types of mismatch are presented in Appendix B. Overall, the sample is balanced in terms of gender, age, status of employment and other characteristics. At the same time, we notice that such dummies as "Having the second job", "Employer", "Family contributors", "Employed at household" and binary indicators for working 20 hours and less have small number of observations. For our purposes, we choose to keep them, as they may prove to be significant predictors of a mismatch.

[2] Horizontal mismatch was determined only for those whose highest level of education is college or university education

It is important to note that for our purposes we do not define the modes for field of study and level of education attainment on pooled data for all years. As we "instrument" the required education and skills by the most frequent realized combination, we consider it natural that these realizations may shift in time of a structural change. For this reason, we recalculate the modes for each year.

Despite its large sample size, the LFS still contains a small number of observations for some of the 3-digit occupation groups (less than 100 observations). For such cases we apply an approach, similar to the one in Clark, Joubert, and Arnaud (2013). When defining the mode for these occupations, we collapse the 3-digit occupation code into its corresponding 2-digit category, and then recalculate the mode for all occupations by this new 2-digit classification. Afterwards, for those occupations which have fewer than 100 observations, we replace the calculated mode with that of its corresponding 2-digit category (62 out of 136 3-digit occupations were evaluated using this technique).

Figure 1 represents the incidence of mutually exclusive types of mismatch by year. First, we should not that we find a significantly different structure of education level mismatch than in Kupets (2016a), with lower values for overeducation and significantly higher value for undereducation throughout the period. Second, analyzing the chart we cannot confirm that incidence of either category of mismatch rose after the economic crisis of 2014, which would be an intuitive result. But since the structure of sample did not change after the events of 2014, it is possible that the 2014-2015 LFS sample did not capture the major structural changes in the labor market. Figure 4 in Appendix D demonstrates the same graph for employees. As can be concluded, the structure of mismatch is the same as for the total population, but the incidence of overeducation is lower by 2 p.p. on average, possibly because it excludes family contributors and self-employed in own agriculture units. Overall, horizontal mismatch is dominating over vertical mismatch for the whole period for both aggregate population of workers and employees separately.

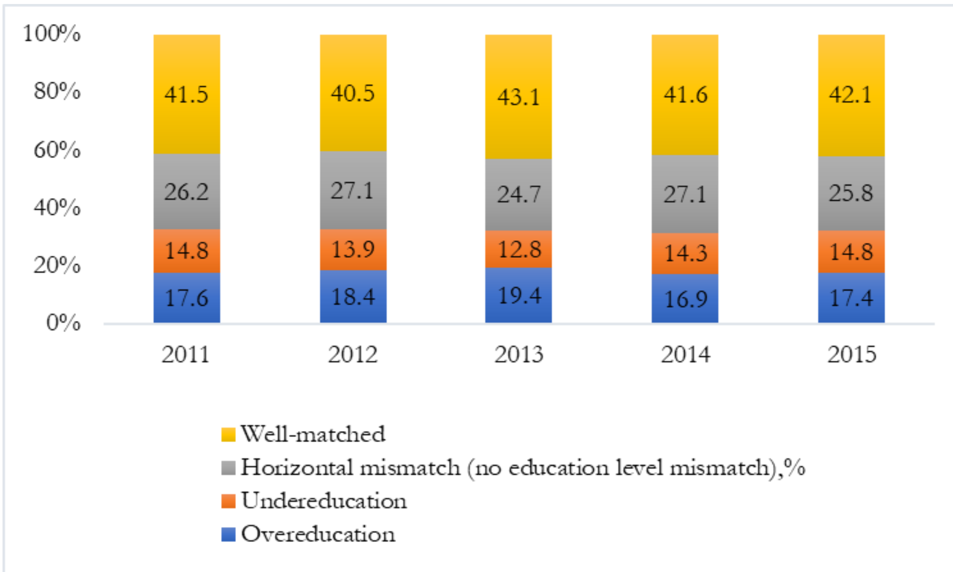

Figure 1. The incidence of mismatch by years and types, %

Figure 2 below shows the aggregate breakdown of mismatch over 2011-2015, and Figure 3 shows the same content but separately for employees. As we observe from both graphs, the largest share in the latter is taken by the category "Horizontal mismatch". At the same time for the total labor force the share of those who are mismatched by both types of mismatch simultaneously is much higher. This suggests that the allocation of labor force across Ukrainian economy is not optimized, which could add to the gap between the potential and real output produced within the country.

Appendix C contains proportion of mismatched individuals by gender, age, region and groups of types of economic activity defined (see Appendix A). This descriptive analysis leads us to preliminary belief that on aggregate women have a higher probability to be horizontally mismatched and be undereducated (Table 11). But when separating the sample for employees our results are in line with most studies that find higher incidence of overeducation among women and of undereducation among men (Table 12). Male employees re also more likely to be horizontally mismatched.

Dividing respondents by age groups allows us to conclude that education mismatch by level is most intensive for younger (up to 25) and older (older than 55) groups (Table 9). Large overeducation for older individuals in Table 9 can be explained by inclusion of family contributors and those working in own agriculture units, as this large overeducation ceases when we focus on employees (Table 10). The shift of undereducation incidence among the youngest group (aged 15-20) may be explained in the similar fashion. For employees, the highest incidence of overeducation is concentrated in the group aged 20-25, and this group also has the highest share of workers who are mismatched by both dimensions.

From Tables 13 and 14 serious regional variation can be observed, although no apparent pattern of mismatch incidence emerges. Donetsk and Lugansk oblasts had the highest incidence of horizontal mismatch while Zakarpattia and Chernivtsi oblasts had agreeably the largest share of vertically mismatched workers. Again, a visible change in incidence is observed when only employees are considered, but it is not as profound as in case of disaggregation by gender.

As for variation by economic sectors (Tables 15 and 16), the general pattern of mismatch incidence by types holds for all but one group, which contains workers in agriculture. This is most probably the source of most differences between the general workforce and employees, as we see a significant shift in terms of over/underschooling and incidence of horizontal mismatch between the two populations (all workers versus employees).

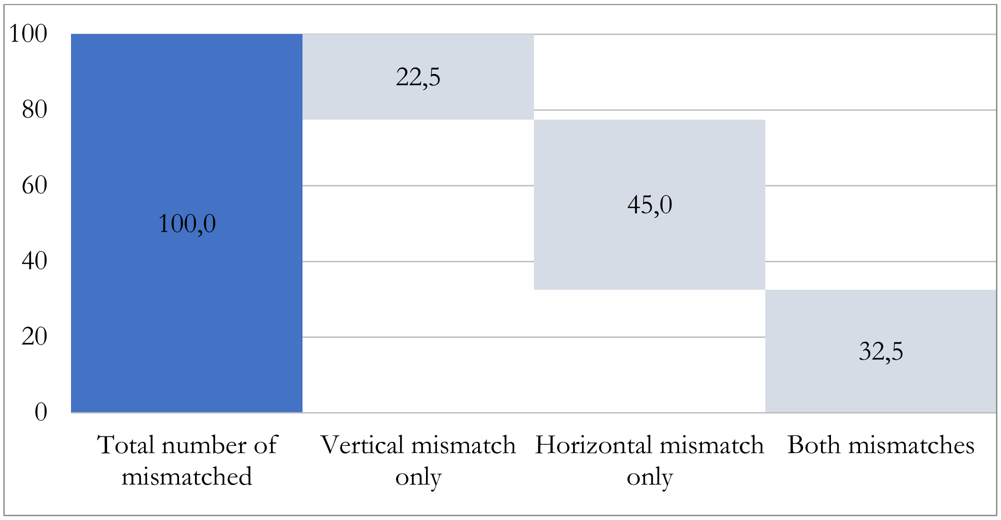

Figure 2. The breakdown of the of mismatch by types, %

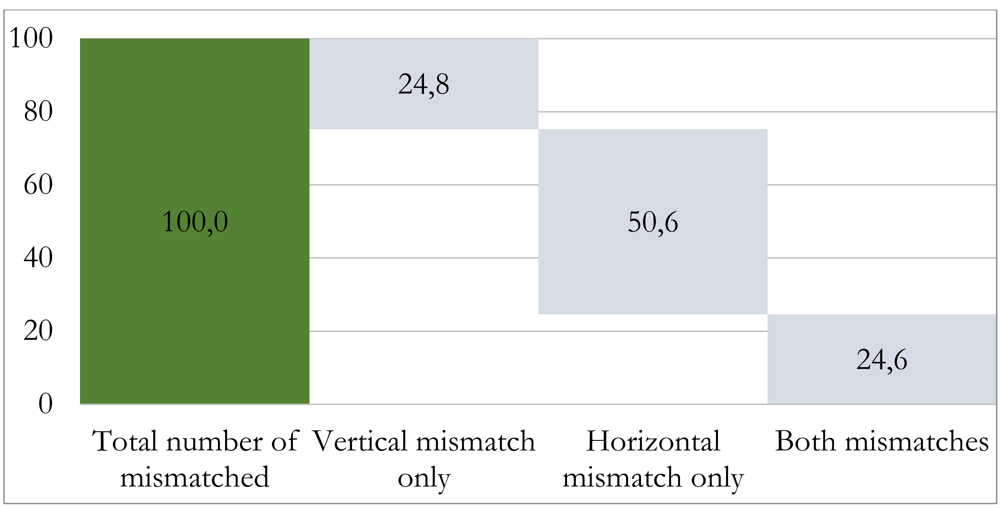

Figure 3. The breakdown of mismatch by types (employees only), %

3.2. Methodology for modeling mismatch at individual level

As noted before, for various reasons we identified mismatch applying a method that seems more straightforward in its reporting: through comparison of modes. Fundamentally, the approach lies in comparing the level of education (vertical match) and diploma specialization (field of study – horizontal match) to their modal values for each individual across 3-digit professional groups. Another advantage of the chosen method is that it makes the decomposition of mismatch into vertical/horizontal/both simultaneously quite trivial.

As was implied from the literature review, despite there being a large amount of research devoted to job-education and job-skill mismatch and related issues, we have come across only a small number of studies that looked at determinants of over/undereducation or skill mismatch at the individual level. In general, it can be deduced that while working with probabilities either separate logit/probit models may be used, or, in case categories of mismatch are mutually exclusive, multinomial logistic regression may be used. As we decided to construct a model not only for mutually exclusive mismatch types (such as over/under-education and horizontal mismatch for those who are not mismatched by level), the final specifications were derived using logistic regression. First, we determine factors that are associated with different dimensions of qualification mismatch for the whole labor force (1).

$$P(Mismatch) = \beta_0 + \beta_1 educlevel + \beta_2 age + \beta_3 gender + \beta_4 status + \\ + \sum_i^m \beta_i industry_i + \sum_j^k \beta_j regiondev_j + other + \varepsilon \quad (1)$$

where mismatch refers to vertical (including total and over/under-education separately) mismatch, age and gender are self-explanatory, educlevel - the highest level of education attained, status – dummies for status of employment, $industry_i$ – dummies for industries by KVED, $region_j$ – dummies for regions of residence.

While it is important to know approximately what part of the labor force is allocated inefficiently according to their education and skills, the model for the total employed sample is not expected to be too informative. The abovementioned specification interests us primary in terms of greater/smaller probability of mismatch associated with different employment statuses, age groups, gender and years. To fully exploit the unique LFS data a separate model for employees was constructed, where we also focus on job characteristics in estimating the mismatch probability (2). For employees we look at both vertical and horizontal mismatch. Table 1 in subsection 3.2 presents description of variables used in the modelling.

$$P(Mismatch) = (as\ in\ previous) + \beta_1 oral + \beta_2 non-formal + \\ + \beta_3 workhours + \beta_4 firmsize + \beta_5 ownership + \varepsilon \quad (2)$$

All variables that were used in construction of both models including the expected effects are presented in Table 1. Literature focuses on models for employees and, even more often, fresh graduates because these samples are more homogeneous than aggregate population. Considering this tendency, we choose the specification for employees with features of job characteristics as our main working model.

Table 1. Variables used for building the model

Variable	Description	Expected effect
Male	Dummy: 1- male.	-
Urban	Dummy: 1- urban.	Ambiguous
Age	Age in years and age squared	+ in younger and older groups
Kyiv residence	Dummy: 1- residing in Kyiv.	-
Residence in Eastern areas	Dummy: 1- residing in Donetsk, Lugansk, Dnipropetrovsk, Zaporizhia. Kharkiv oblast	+
Year	2011 to 2015 as categories to allow for changes in time.	+ for later years
Month	January to December to allow for seasonal changes.	Ambiguous (used for control)
Group by regional development	Three groups of 8 regions per each based on GDP per capita in 2015.	- for more developed regions
Group of types of economic activity	10 groups, derived from Appendix A.	
Marital status	5 groups: married, unmarried, divorced, widowed, unmarried aged under 18.	Ambiguous (used for control)
Status of employment	Five groups: employees, employers, family contributors, self-employed in agriculture, self-employed not in agriculture.	+ for all compared to employees
Region	25 administrative units (without Crimea and Sevastopol)	Ambiguous (used as control)
Education level	Four groups: 1 – secondary and lower, 2 – high school, 3 – college and 4 – university.[3]	Ambiguous (used as control)
Additional variables for a model for employees only		
Oral agreement	Dummy: 1- having oral work agreement.	+
Firm size (number of employees)	Four groups: less than 5 people, 5 to 10 people, 11 to 50 people, more than 50.	- with increase in size
Type of ownership	Eight groups: public sector, private enterprise, sole proprietorship, corporation, household, international organization, employed at sole proprietorship, NGO.	Ambiguous
Average number of hours worked	Six groups: less than 20 hours, 20 hours, 20 to 40 hours, 40 hours, 40 to 80 hours, more than 80 hours.	Ambiguous
Non-formal employment	Dummy: 1- non-formally employed.	+

Source: LFS data

Note: Among all, only marital status and type of firm ownership contained missing values in the final dataset (20 and 1178 observations respectively). In order not to lose information (in case weights are used in further analysis for instance) and since possible error on such a small subsample is unlikely to cause great harm, we decided to use a standard imputation technique, namely regress the variables with missing observations on other features (package “mice” in Rstudio).

[3] Following Kupets (2016b) we do not distinguish between those with bachelor’s, specialist’s and master’s degrees due to their virtual equivalence in the Soviet system

One of the major drawbacks of the LFS data on individual education is the unavailability of data on the characteristics of study programs and/universities that respondents were enrolled at. As Vilalta-Bufi (2012) suggest, program characteristics are important controls for tackling the relative quality differences of skills signal across education establishments. Thus, we suspect that not including the possible characteristics of the quality of education obtained by the individuals may introduce a bias into our model. Despite having unique microdata with multiple socio-demographic features, LFS does not contain any proxy for the quality of education gained. We hope to partly control for this problem using the region of residence as a control factor.

The specification in this chapter allows us to build models to evaluate the probability of vertical mismatch and horizontal mismatch at individual level. Modelling the situation when both vertical and horizontal mismatches occur is not straightforward as different education groups must be used to define these two types of mismatch, and therefore they pull the whole marginal effect when used as factors.

C h a p t e r   4

ESTIMATION RESULTS

Using the specifications from Chapter 3, we construct models for multiple dimensions of mismatch, including aggregate vertical mismatch, overeducation, undereducation, aggregate horizontal mismatch and horizontal mismatch with no mismatch by education level. These models were built for aggregate labor force and employees separately. The results, namely the marginal effects of the variables are presented in the Table 2. Marginal effects are calculated from the odds ratios (logistic regression coefficients) and should be treated as coefficients in simple least-squared model.

Using empirical method of mismatch determination, we found all of workers in the lowest education category to be undereducated. Moreover, workers in this category cannot be overeducated (due to specificities of the approach), while for workers in the highest education level category the opposite is true. At the same time, in models on horizontal mismatch only workers with education level that exceeds high school were used. Thus, number of observations changes between models. The corresponding number for each model specification and sample are included in the header of Tables 2 and 3.

Overall, we may derive interesting conclusions. First, let us look at vertical mismatch and its components. On the aggregate, males have a significantly higher probability of being overeducated and lower probability of being undereducated. They also have a lower probability of horizontal mismatch, especially for those not who are vertically matched (decrease in probability by 0.09). With additional year the probability of overeducation declines by almost 0.02, but tends to rise for undereducation, although the effect is lower in absolute terms. Age proves not to be associated with likelihood of horizontal mismatch. Interestingly, age squared is statistically significant, but the effect is close to zero (we decided not to report it).

There is no indication of a structural break in terms of a qualification mismatch probability over the period of 2011-2015, although results imply that in later years (2013-2015) there was a statistically significant positive shift in terms of horizontal mismatch (for those who are vertically matched). We suspect that these results would be different if the change in sample of 2014-2015 accounted for internally displaced people.

Residence proves to be an important determinant of all categories of mismatch. First, urban workers have a higher probability of being horizontally mismatched. This may be because urban areas have a greater number of job options. Nevertheless, living in Kyiv decreases this probability, as well as the likelihood of overeducation by surprising 0.136. The pattern of significance across model specifications for Kyiv is similar to that of developed regions (in terms of GRP) compared to regions with the lowest levels of GRP. Surprisingly, residence in Eastern regions decreases the probability of all mismatched, especially of horizontal mismatch without over/under-education.

Analyzing effects from employment statuses we can see that compared to employees, employers have a much lower probability of being overeducated and remarkably higher probability of being undereducated (by almost 0.25), as well as horizontally mismatched. These results are intuitively consistent, as employers often start businesses in non-related to their education spheres. Family contributors and self-employed in own agriculture show an enormous increase in probability of being mismatched (it implies that in the data almost all working in own agricultural units are mismatched). In general, self-employed are more likely to be mismatched in terms of all types of qualification mismatch.

Table 2. Estimation results for models with total labor force (marginal effects and significance)

Variable	Model specification (number of observations)				
	Vertical mismatch (257443)	Over-education (179950)	Under-education (196149)	Horizontal, (179950)	Horizontal vertically matched (120348)
Male	-0.021 ***	0.074 ***	-0.007 ***	-0.047 ***	-0.093 ***
Age	0.003 *	-0.017 ***	0.001 ***	-0.003 .	0.001
Urban	-0.017 **	-0.014 .	0.001	0.018 **	0.022 ***
Kyiv	-0.081 ***	-0.136 ***	0.006 ***	-0.08 ***	-0.063 ***
East	-0.090 ***	-0.033 ***	-0.015 ***	-0.103 ***	-0.124 ***
High GRP	0.019 ***	-0.001	0.003 ***	-0.045 ***	-0.047 ***
Middle GRP	-0.008 ***	0.045 ***	-0.005 ***	-0.079 ***	-0.074 ***
High school	-0.030	-	0.13 ***	-	
College	-0.027	-0.307 ***	-	-0.038 ***	-0.016 .
d2012	0.002	-0.009	0.001	-0.001	0.01
d2013	0.003	0.006	-0.001	-0.037 ***	-0.039 ***
d2014	-0.004	0.013	-0.001	-0.004	-0.018 *
d2015	0.010 .	0.007	0.002 *	-0.013	-0.018 *
Employer	0.143 ***	-0.178 ***	0.242 ***	0.228 ***	0.321 ***
Family contributor	0.148 *	0.495 ***	-0.014 ***	0.279 ***	0.256 ***
Self-employed in agro	0.119 ***	0.811 ***	-0.113 ***	0.382 ***	-0.464 ***
Self-employed not in agro	0.124 ***	0.31 ***	-0.004 .	0.242 ***	0.156 ***

Source: author's calculations, LFS

Note: Dummies for economic sectors, types of ownership and months of observations for structural differences and seasonality were used. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '.' 1

In Table 3 we present results for the same specifications but for employees. We see that some of the patterns for this specification hold, such as significant decrease in probability for those residing in the East, and lower likelihood for overeducation and horizontal mismatch in Kyiv and regions with higher GRP. For employees additional year of age decreases both probabilities of being over- and undereducated, but its effect is not significant for horizontal mismatch. Again, age squared proved to be statistically but not economically significant. Indicators of having a second job, an oral work agreement and non-formal employment tend to increase the probability of overeducation, with oral agreement having the largest absolute effect of 0.077. Employees working by oral agreement compared to contract are also by 0.114 more likely to have a different from the modal field of studies.

With increase in the size, the firms tend to allocate the workforce more efficiently. Workers in small entities with less than 5 people on average have by 0.077 higher probability to be undereducated and by 0.092 higher probability of a horizontal mismatch. At the same time working in big firms with more than 50 employees is associated with a lower (by 0.021) likelihood of undereducation. The base level for this estimation was working in firms with 11 to 50 employees.

Additional hours of work (baseline 20) increase the likelihood of horizontal mismatch, while working less than 20 hours per week greatly decreases the probability of all types of mismatch. This may result from most of the observations with work week of 20 hours or less comes from trainees, who usually tend to get experience in the same field as their current education. Employees working 40 hours and more face a higher risk of field-of-study mismatch for those who are matched by education level.

Company's type of ownership proves to be an important determinant of mismatch with all categories being significantly different from the base level "Employed at household". From the marginal effects by dummies of other ownership types, we assume that those employed at household are usually overqualified for this work.

Table 3. Estimation results for models with employees only (marginal effects and significance)

Variable	Model specification (number of observations)				
	Vertical mismatch (185055)	Over-education (144505)	Under-education (131192)	Horizontal, (144505)	Horizontal vertically matched (113588)
Male	-0.003	0.036 ***	-0.046 ***	-0.061 ***	-0.091 ***
Urban	0.000	-0.018 ***	0.019 ***	0.012 *	0.021 **
Second job	0.038 **	0.030 ***	0.01	0.049 *	0.031
Non-formal	0.018	0.056 ***	-0.035 ***	0.029 .	0.007
Kyiv	-0.065 ***	-0.066 ***	0.055 ***	-0.071 ***	-0.054 ***
East	-0.104 ***	-0.025 ***	-0.111 ***	-0.117 ***	-0.120 ***
High GRP	0.029 ***	-0.001	0.040 ***	-0.046 ***	-0.051 ***
Middle GRP	-0.005 ***	-0.002 *	-0.003 **	-0.088 ***	-0.081 ***
Age	-0.007 ***	-0.005 ***	-0.003 ***	-0.001	-0.002
High school	0.302 ***	-	0.611 ***	-	-
College	-0.123 ***	-0.198 ***	-	-0.064 ***	-0.038 ***
d2012	0.003	-0.009 *	0.015 **	0.002	0.008
d2013	-0.001	-0.003	0.001	-0.037 ***	-0.037 ***
d2014	0.005	-0.022 ***	0.03 ***	-0.018 *	-0.015 .
d2015	0.007	-0.024 ***	0.042 ***	-0.026 **	-0.015
Oral	0.005	0.073 ***	-0.039 ***	0.114 ***	0.087 ***
Workers 5 to 10	0.027 ***	0.007 .	0.033 ***	0.024 ***	0.023 ***
Workers more 50	-0.021 ***	-0.002	-0.021 ***	-0.001	0.006
Workers less than 5	0.054 ***	-0.003	0.077 ***	0.082 ***	0.092 ***
40 hours	0.002	-0.03 **	-0.03 **	0.021	0.062 **
Less than 20 hours	-0.156 ***	-0.122 ***	-0.122 ***	-0.321 ***	-0.244 ***
From 20 to 40 hours	-0.048 ***	-0.063 ***	-0.063 ***	-0.131 ***	-0.074 ***
From 40 to 80 hours	0.025 **	0.001	0.001	0.093 ***	0.14 ***
Employed at sole	0.057 **	-0.108 ***	0.276 ***	-0.27 ***	-0.156 ***
Corporate entity, ltd.	0.07 ***	-0.148 ***	0.3 ***	-0.254 ***	-0.138 ***
Private entity, family business	0.068 ***	-0.131 ***	0.287 ***	-0.258 ***	-0.147 ***
Sole entrepreneurship	0.038 *	-0.096 ***	0.244 ***	-0.208 ***	-0.098 *
State or communal entity	0.084 ***	-0.166 ***	0.285 ***	-0.231 ***	-0.127 **

Source: author's calculations, LFS. Note: same dummies and significance levels as in previous table

We should briefly comment on controls used in the models, namely regions of residence and economic sectors. Within most specifications the controls were significant, which indicates that there are indeed important differences within types of economic activities and Ukrainian administrative units.

To perform a simple robustness check on our data we excluded all observations from Kyiv, as this region is significantly different from others by the majority of socio-economic characteristics (such as gross regional product, unemployment, average wage, quality of education etc.). From the results we got, none of the initial variables changed their significance and the absolute values of marginal effects stayed in the vicinity of the original estimates. This proves that our results are not driven by outliers and are robust to small changes in sample.

The adequacy of the econometric model is usually estimated through various goodness-of-fit indicators. Since the coefficients in logistic regression are optimized through the maximum likelihood estimation comparing to the minimizing sum of squares functional in simple OLS, another measure of goodness of fit for logistic regression is used, so called pseudo R-squared. Essentially, this measure represents the ratio of improvement of the fitted model, comparing to the model that includes only the intercept. There are a few variations on the exact formula, we used the one developed in McFadden (1974). While the interpretation of pseudo R-squared is similar to traditional R-squared in the least squares, McFadden states that values of the former tend to be considerably lower, and values of 0.2 to 0.4 for rho-squared (McFadden's term) should be considered as a good fit. The corresponding values for our working model with several specifications are given in Table 5.

Following the argument of Caroleo and Pastore (2013), who report that higher unemployment shares are frequently associated with larger shares of the overeducated workers, we add the average annual share of unemployment at the regional level to the regressors. As we understand that the regional unemployment rate may be highly correlated with other characteristics of regional development (such as the level of GRP), we estimated biserial correlations between the newly added unemployment rate and some of the variables in the initial model. This type of correlation measurement is used when dealing with dichotomous variable on one side (which are most of the regressors in the starting specification) and continuous variable on the other side (which we assume unemployment rate to be). The value of the point biserial coefficient is calculated through the following formula:

$$r_{pb} = \frac{M_1 - M_0}{s_n} \sqrt{\frac{np_0(1 - p_0)}{n - 1}} \tag{3}$$

where M_1 – mean value of the continuous variable that corresponds to the '1' value group of the binary variable; M_0 – mean value of the continuous variable that corresponds to the '0' value group of the binary variable; s_n – standard deviation if the continuous variable; p – proportion of the '0' values in binary variable (Sheskin, 2011).

As illustrated in the Table 4 below, the highest value for biserial correlation is for Kyiv indicator, but it does not exceed 70%, so we decided to move on with adding unemployment to our analysis.

Table 4. Biserial correlations between the newly introduced regional unemployment and regional indicators

Dichotomous variable	Correlation coefficient
Indicator for Kyiv	-0.682
Indicator for East	-0.228
Indicator for High GRP	-0.505
Indicator for Middle GRP	0.310
Indicator for Low GRP	0.491

Source: authors' calculations

In the models we built (but not reported here) using regional unemployment as additional variable and excluding Kyiv, the estimates of marginal effect of the regressors and the respective confidence intervals did not change, as significance pattern stayed. Interestingly, the regional annual unemployment level is marginally significant only when determining the probability of being horizontally mismatched, which gives the same intuition as the dummy for those residing in regions within the group of the highest GRP.

Table 5 contains estimates on goodness-of-fit and accuracy of the models. The estimates show large range in terms of accuracy for different types of mismatch. Accuracy was calculated based on predicted values, where "1" was assigned if the predicted probability was greater than 0.5, which were then compared to actual "1"s in the dataset:

Table 5. Indicators of models' predictive power and goodness of fit

Dependent variable	All employment statuses		Employees only		Employees only (no Kyiv)		Including unemployment	
	Accuracy	Pseudo R^2	Accuracy	Pseudo R^2	Accuracy	Pseudo R^2	Accuracy	Pseudo R^2
Vertical mismatch (total)	0.663	0.030	0.750	0.122	-	-	-	-
Overeducation	0.845	0.356	0.832	0.096	0.827	0.097	0.837	0.094
Undereducation	0.897	0.433	0.864	0.376	0.866	0.382	0.871	0.376
Horizontal mismatch (total)	0.678	0.135	0.616	0.066	0.618	0.068	0.615	0.065
Horizontal mismatch (vertically matched)	0.634	0.077	0.624	0.078	0.628	0.079	0.623	0.077

Source: authors' calculations, LFS

As can be concluded from the table above, the highest accuracy is achieved when using the chosen specification to define the probability of being undereducated. The worst is model's performance when predicting horizontal mismatch on the individual level (both total and for those individuals who are not mismatched by education level). The model's bad performance for predicting horizontal mismatch may be explained by error that may arise from introducing self-developed system of fields of studies derived from diploma specializations that are included in LFS (as mentioned before, original data is adjusted by ISCO). Again, as with robustness check, it is a good sign that accuracy indicator does not shift much when changing specification or sample.

With adequate results on individual significance of variables employed in the specification, proven robustness but reasonably low post-estimation results, trying different algorithms such as random forest may be a good option in terms of predicting power, especially since it performs well with categorical features and is easy to interpret. But high predictive power should be the concern only if the main purpose is to classify a large sample of individuals into those who are mismatched and those who are not. Therefore, this approach is useful when assessing the incidence of mismatch for a sample. Yet, this paper is primarily focusing on significant determinants of different dimensions of qualification mismatch. The latter serves to identify which categories of workers are more at risk of being misallocated on the labor market and construct appropriate policy instruments.

Chapter 4

CONCLUSIONS AND POLICY RECOMMENDATIONS

Prevalence of vertical and horizontal mismatches can be linked to many phenomena, starting from structural changes in the economy, market failures such as incomplete and asymmetric information or transaction costs and ending with rigid and obsolete education and training systems (ILO 2014). Whatever the cause, a large share of labor force being mismatched is a sign of inefficient allocation of resources and possible productivity gap.

In Ukraine the increase of job-worker mismatch is high, at approximately 17% of overeducated, 14% of undereducated and 27% of horizontally mismatched individuals (the latter referring to matched individuals). in incidence of overeducation over 2014 and 2015 was observed as compared to earlier years, which was proven within the estimation procedure. Moreover, employment status other than “employee” sharply increases the probability to be vertically (except for employers) and horizontally mismatched. This is especially profound for individuals employed at their own agriculture units, for whom this marginal effect equals to 0.811. For employees the smaller the size of the firm, the higher is the likelihood of undereducation and horizontal mismatch. Those non-formally employed, especially with an oral agreement, are at higher risks of overeducation. Traditionally, gender and age effects were considered. Males are consistently found more likely to be overeducated than females, and less likely to be undereducated and horizontally mismatched. Additional year lowers the probability of being oveducated but its effect is overall minor. This is consistent with youth aged 20-25 having the highest incidence of qualification mismatch.

The results of this research delivers useful information to the labor economists and competent government bodies, first, by drawing attention to the high incidence of both vertical and horizontal mismatch in Ukrainian labor market, defining individuals who are more at risk of being mismatched and thus potentially facing wage and job satisfaction penalties (as evidence shows), and sectors/regions where contribution of inefficient labor allocation may be greater.

Our results also suggest that a more in-depth and targeted study is needed, in particular as to the reasons of large regional and sectoral differences of qualification mismatch. The other suggestion is to expand LFS by relevant self-assessment questions on skill utilization, questions on the university attended and actual broad field of study rather than profession by diploma. Additionally, a targeted study of internally displaced people after 2014 should be conducted. The pattern of incidence and mismatch determinants for regions where they moved may differ substantially from what we obtained. All of the above may add to our estimations on main determinants of qualification mismatch and help in projecting future prevalence of various types of mismatch.

The starting point for Ukrainian policymakers in terms of a more efficient labor allocation should be development of effective job placement services, subsidization of firms to develop a system of incentives to change workforce skill sets and additional training and re-training opportunities. This is even more crucial and more so when job openings are scarce as is the case with Ukraine after the global financial crisis of 2008 and national economic and political crisis of 2014-2015.

WORKS CITED

Allen, J., and van der Velden, R. 2001. "Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction, and On-the-Job Search." *Oxford Economic Papers* 53, no. 3, 434–452.

Badillo Amador, L., López Nicolás, Á., and Vila, L. E.2011. "The consequences on job satisfaction of job-worker educational and skill mismatches in the Spanish labour market: a panel analysis." *Applied Economics Letters* 19, is. 4. https://doi.org/10.1080/13504851.2011.576999.

Birk, A. 2001. "Qualification-Mismatch and Long-Term Unemployment in a Growth-Matching Model." HWWA Discussion Paper 128. https://www.econstor.eu/bitstream/10419/19423/1/128.pdf.

Caroleo, F. E., and Pastore, F. November 2013. "Overeducation at a Glance: Determinants and Wage Effects of the Educational Mismatch, Looking at the AlmaLaurea Data." IZA Discussion Paper, no. 7788. http://ftp.iza.org/dp7788.pdf.

Chevalier, A. 2003. "Measuring Over-education." *Economica* 70 (279), August: 509–531. https://doi.org/10.1111/1468-0335.t01-1-00296.

Clark, B., Joubert, C., and Arnaud, M. 2013. "Overeducation and skill mismatch: a dynamic analysis." Preliminary draft. http://www.unc.edu/~joubertc/ClarkJoubertMaurel_SOLE.pdf.

Duncan, J., and Hoffman, S. 1981. The incidence and wage effects of overeducation. *Economics of Education Review* 1, no 1: 5–86.

Eijs, P., and van Heijke, H. 1996. "The Relation between the Wage, Job-related Training and the Quality of the Match between Occupations and the Types of Education." ROA Research Memorandum 003, Maastricht University, Research Centre for Education and the Labour Market (ROA). https://ideas.repec.org/p/unm/umaror/1996003.html.

European Centre for the Development of Vocational Training (Cedefop). 2014. *Terminology of European education and training policy*. 2nd ed. Luxembourg: Publications office of the European Union.

Green, F., and Zhu, Yu. January 2008. "Overqualification, Job Dissatisfaction, and Increasing Dispersion in the Returns to Graduate Education". University of Kent Department of Economics Discussion Paper. http://dx.doi.org/10.2139/ssrn.1143459.

de Grip, A., Bosma, H., Willems, D., and van Boxtel, M. 2008. "Job-Worker Mismatch and Cognitive Decline." *Oxford Economic Papers, New Series* 60, no. 2: 237–253. http://www.jstor.org/stable/25167687.

Groot, W., and van den Brink, H. M. 2000. "Overeducation in the labor market: a meta analysis." *Economics of Education Review* 19, is. 2: 149–158.

International Labour Office, Department of Statistics. 2014. *Skills mismatch in Europe: statistics brief.* Geneva: ILO. http://www.ilo.org/wcmsp5/groups/public/---dgreports/---stat/documents/publication/wcms_315623.pdf.

Joel Marsden and Hadyn Hitchins, Trends in the demand for labour and skills in London and the East Sub - region, GLA, 2016 https://www.london.gov.uk/sites/default/files/working_paper_79.pdf

Kjell, K. L., Salvanes, G., Sørensen, E. Ø. 2012. "Good Skills in Bad Times: Cyclical Skill Mismatch and the Long-Term Effects of Graduating in a Recession." IZA Discussion Paper, no. 6820. http://ftp.iza.org/dp6820.pdf.

Klasyfikatsiia vydiv ekonomichnoi diialnosti. ДК 009:2010. Zatverdzheno Nakazom Derzhspozhyvstandartu Ukrainy vid 11.10.2010 r. № 457 [Classification of types of economic activity. SK009:2010. Approved by Order of the State Consumer Standard of Ukraine of October 11, 2010, No 457]. http://kved.ukrstat.gov.ua/KVED2010/kv10_i.html [in Ukrainian].

Klosters, D. 2014. "Matching Skills and Labour Market Needs Building Social Partnerships for Better Skills and Better Jobs." In *World Economic Forum, Global Agenda Council on Employment, Davos-Klosters, 2014*, 22–25. http://www3.weforum.org/docs/GAC/2014/WEF_GAC_Employment_MatchingSkillsLabourMarket_Report_2014.pdf

Kucel, A. 2011. "Literature Survey of the Incidence of Over-education: A Sociological Approach." *Reis (Revista Española de Investigaciones Sociológicas)* 134, Abril / Junio: 125–142

Kucel, A., and Vilalta-Bufí, M. 2012. "Graduate labor mismatch in Poland." *Polish Sociological Review,* no. 179 (3): 413–429.

Kupets, O. 2015. "Skill mismatch and overeducation in transition economies." *IZA World of Labor,* no. 224. https://www.econstor.eu/handle/10419/148449 .

Kupets, O. 2016a. "Education in Transition and Job Mismatch: Evidence from the Skills Survey in Non-EU Transition Economies." *The Journal of Comparative Economic Studies* 11: 117–150.

Kupets, O. 2016b. "Education-job mismatch in Ukraine: Too many people with tertiary education or too many jobs for low-skilled?" *Journal of Comparative Economics* 44: 125–147.

Leuven, E., and Oosterbeek, H. February 2011. "Overeducation and Mismatch in the Labor Market." IZA Discussion Paper*,* no. 5523. http://ftp.iza.org/dp5523.pdf.

Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., and Wei, Zh. July 2010. "Job Mismatches and Labour Market Outcomes: Panel Evidence on University Graduates." IZA Discussion Paper*,* no. 5083. http://ftp.iza.org/dp5083.pdf.

McFadden, D. 1974. "Conditional logit analysis of qualitative choice behavior." In *Frontiers in Econometrics*, edited by P. Zarembka, 105–142. Amsterdam: North Holland Publishing Co. http://eml.berkeley.edu/~mcfadden/travel.html.

McGowan, M. A., Andrews, D. 2015a. "Labour Market Mismatch and Labour Productivity: Evidence from PIAAC Data". *OECD Economics Department Working Papers*, no. 1209, OECD Publishing, Paris. http://dx.doi.org/10.1787/5js1pzx1r2kb-en.

McGowan, M. A., Andrews, D. 2015b. "Skill Mismatch and Public Policy in OECD Countries." *Economics Department Working Papers* no. 1210. https://www.oecd.org/eco/growth/Skill-mismatch-and-public-policy-in-OECD-countries.pdf.

McGuinness, S., Bergin, A., and Whelan, A. March 2017. "Overeducation in Europe: Trends, Convergence and Drivers." IZA Discussion Paper*,* no. 10678. http://ftp.iza.org/dp10786.pdf.

McGuinness, S., Pouliakas, K., and Redmond, P. May 2017. “How Useful Is the Concept of Skills Mismatch?” IZA Discussion Paper, no. 10786. http://ftp.iza.org/dp10786.pdf.

McGuinness, S., and Sloane, P. J. May 2009. “Labour Market Mismatch among UK Graduates: an Analysis Using REFLEX Data.” IZA Discussion Paper, no. 4168. http://ftp.iza.org/dp4168.pdf

Metodolohichni polozhennia shchodo klasyfikatsii ta analizu ekonomichnoi aktyvnosti naselennia. Zatverdzheno Nakazom Derzhavnoho komitetu statystyky Ukrainy vid 19.01.2011 r. № 12 [Methodological statements for the classification and analysis of the population economic activity. Approved by Order of the State Statistics Committee of Ukraine of January 19, 2011, No 12]. https://ukrstat.org/uk/metod_polog/metod_doc/2011/12/metod.htm [in Ukrainian].

NCSS Statistical Software. *Point-Biserial and Biserial Correlations.* Chapter 302. https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Point-Biserial_and_Biserial_Correlations.pdf

Restrepo, P. 2015. “Skill Mismatch and Structural Unemployment.” Unpublished manuscript. https://economics.mit.edu/files/11078.

Robst, .J. 2007. “Education and job match: The relatedness of college major and work.” *Economics of Education Review* 26, is. 4: 397–407.

Sattinger, M. 2011. “Qualitative Mismatches.” Foundations and Trends® in Microeconomics 8, no. 1–2: 1-168. http://dx.doi.org/10.1561/0700000052.

Sheskin, D. J. 2011. Handbook of Parametric and Non Parametric Statistical Procedure. 5th ed. Boca Raton, FL: Chapman and Hall / CRC Press.

European Centre for the Development of Vocational Training (Cedefop). 2014. *Terminology of European education and training policy*. 2nd ed. Luxembourg: Publications office of the European Union.

European Centre for the Development of Vocational Training (Cedefop). 2010. *The skill matching challenge. Analysing skill mismatch and policy implications.* Luxembourg: Publications office of the European Union.

United Kingdom. Office for National Statistics. March 2016. *Analysis of the UK labour market – estimates of skills mismatch using measures of over and under education: 2015*. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/analysisoftheuklabourmarketestimatesofskillsmismatchusingmeasuresofoverandundereducation/2015.

Verdugo, R., and Verdugo, N. 1989. "The impact of surplus schooling on earnings: Some additional findings". *Journal of Human Resources* 24, is. 4: 629–643.

Verhaest, D., and Omey, E. 2010. "The determinants of overeducation: different measures, different outcomes?" *International Journal of Manpower* 31 (6), 608–625. http://doi.org/10.1108/01437721011073337.

Wilson, R. A., and K. Homenidou (2012). Working Futures 2010-2020: Evidence Report. UK Commission for Employment and Skills: Wath on Dearne. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/303434/evidence-report-41-working-futures-2010-2020.pdf

Zago, R. December 2017. "Job Polarization, Skill Mismatch and the Great Recession." http://dx.doi.org/10.2139/ssrn.3004759.

APPENDIX A

GROUPS OF ECONOMIC ACTIVITIES

Table 6. Regrouping of sectors (economic activities) from Classifier of Economic Activities-2010 (NACE- 2010)

Number in LFS	Sector name	Sector code	New groups
1	Agriculture, forestry and fishing	A	I
2	Mining and quarrying	B	II
3	Manufacturing	C	II
4	Electricity, gas, steam and air conditioning supply	D	III
5	Water supply; sewerage, waste management and remediation activities	E	III
6	Construction	F	IV
7	Wholesale and retail trade; repair of motor vehicles and motorcycles	G	V
8	Transportation and storage	H	V
9	Accommodation and food service activities	I	VI
10	Information and communication	J	VI
11	Financial and insurance activities	K	VII
12	Real estate activities	L	VII
13	Professional, scientific and technical activities	M	VIII
14	Administrative and support service activities	N	VI
15	Public administration and defence; compulsory social security	O	IX
16	Education	P	IX
17	Human health and social work activities	Q	IX
18	Arts, entertainment and recreation + Other service activities	R+S	X

Source: http://kved.ukrstat.gov.ua/KVED2010/kv10_i.html

APPENDIX B

DESCRIPTIVE STATISTICS

Table 7. Descriptive statistics of the variables used in modeling mismatch

Variables (model for total sample)	% to total number of observations	Variables (model employees)	% to total number of observations
Male	0.50	Male	0.50
Urban	0.37	Urban	0.46
Kyiv residence	0.04	Kyiv residence	0.05
Residence in Eastern areas	0.24	Residence in Eastern areas	0.27
High GRP	0.36	High GRP	0.42
Mid GRP	0.33	Mid GRP	0.29
Low GRP	0.31	Low GRP	0.29
year2011	0.29	year2011	0.29
year2012	0.14	year2012	0.14
year2013	0.16	year2013	0.15
year2014	0.24	year2014	0.26
year2015	0.17	year2015	0.17
High School	0.30	High School	0.22
College	0.46	College	0.49
University	0.24	University	0.29
Residence in Eastern regions after 2013	0.09	Residence in Eastern regions after 2013	0.10
Employee	0.72	Second job	0.03
Employer	0.01	Non-formal employment	0.13
Family contributor	0.01	Oral agreement	0.11
Self-employed in own agriculture	0.18	Size: 11-50	0.33
Self-employed not in agriculture	0.09	Size: 5-10	0.13
		Size: more than 50	0.41
		Size: less than 5	0.13
		Employed at household	0.02
		Employed at sole	0.07
		Corporate entity, ltd.	0.27
		Private entity, family business	0.22
		Sole entrepreneurship	0.02

Table 7 continued

Variables (model for total sample)	% to total number of observations	Variables (model employees)	% to total number of observations
		State or communal entity	0.40
		Hours: 20	0.02
		Hours: 40	0.76
		Hours: less than 20	0.02
		Hours: 20-40	0.08
		Hours: 40-80	0.12

APPENDIX C

IDENTIFIED FIELDS OF STUDIES AND CORRESPONDING 3-DIGIT SPECIALIZATION CODE (ADJUSTED TO ISCO)

Table 8. Fields of studies and corresponding diploma codes

Field	Diploma 3-digit codes
Management and administration	341, 241, 522, 343, 122, 145, 421, 411, 147, 123, 146, 523, 342, 344, 121
Biology, Natural Sciences, Mathematics and Statistics	311, 211, 212
Electronics and Telecommunications	214
Mechanical	214, 821, 721, 723, 829, 731, 722
Education	331, 232, 233, 235, 332, 231, 234, 334, 333, 148
Architecture and construction	214, 712, 714, 713
Transport	832, 831, 833, 314, 828, 834, 413
Social and behavioral sciences, Social work	244
Health care	221, 322, 323, 222, 223, 324
Service sector	512, 514, 422, 511
Humanities, Culture and Art, Journalism	414, 347, 245, 243, 348, 531, 515, 246
Electrical engineering	214, 724, 816
Law	242
Production and technology	743, 826, 214, 357, 811, 742, 711, 355, 741, 833, 744, 734, 356, 812, 732, 733, 813, 825, 827, 353, 354, 143, 351, 352, 814, 359, 824
Chemical and bioengineering	214, 815, 822, 823
Information Technology	313, 412, 213, 312, 419
Agrarian Sciences and Food, Veterinary Medicine	321, 611, 614, 612, 921, 613, 141
Other	315, 516, 349, 914, 144, 513, 932, 346, 345, 941, 248, 915, 817, 145, 931, 247, 249

Source: LFS

APPENDIX D

MISMATCH INCIDENCE BY DIFFERENT DIMENSIONS

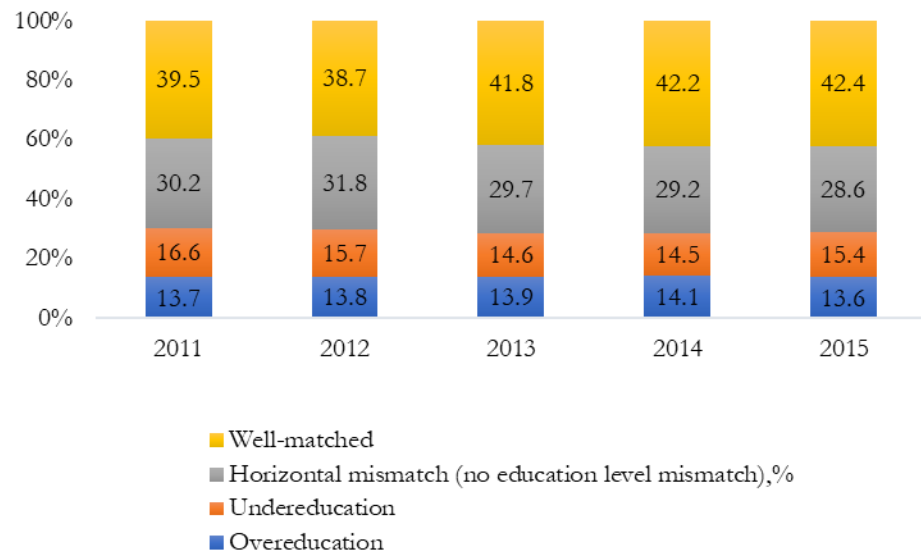

Figure 4. The incidence of mismatch by years and types (employees), %

Table 9. Proportion of mismatched individuals by type of mismatch and age, %

Age intervals	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
(15,20]	31.0	11.5	19.5	29.3	17.4	11.9
(20,25]	35.5	22.7	12.8	47.3	25.2	22.2
(25,30]	32.4	19.4	13.0	47.0	27.7	19.3
(30,35]	31.2	16.9	14.3	45.5	28.1	17.4
(35,40]	31.0	15.4	15.6	45.0	28.3	16.7
(40,45]	29.9	15.5	14.4	46.0	28.7	17.3
(45,50]	31.4	16.4	15.0	45.4	27.0	18.4
(50,55]	32.4	16.9	15.5	44.9	26.1	18.8
(55,60]	34.6	21.0	13.6	45.4	22.8	22.6
(60,65]	35.4	27.9	7.5	43.6	14.9	28.8
(65,70]	29.7	24.3	5.5	32.1	7.9	24.3

Source: author's calculation, LFS

Table 10. Proportion of mismatched employees by type of mismatch and age, %

Age intervals	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
(15,20]	35.5	7.5	28.0	33.1	24.9	8.1
(20,25]	33.4	19.5	14.0	46.9	28.1	18.8
(25,30]	30.8	17.1	13.7	46.8	29.9	16.9
(30,35]	29.2	14.4	14.8	44.7	30.0	14.7
(35,40]	28.3	12.6	15.8	44.0	30.6	13.3
(40,45]	26.2	11.7	14.5	44.2	31.4	12.8
(45,50]	27.8	12.3	15.5	43.7	29.8	13.9
(50,55]	28.5	11.6	16.9	43.1	29.9	13.2
(55,60]	28.5	10.9	17.6	43.6	30.6	13.0
(60,65]	27.6	12.3	15.3	46.2	31.3	14.9
(65,70]	28.0	12.1	15.9	41.6	28.5	13.0

Source: author's calculation, LFS

Table 11. Proportion of mismatched individuals by type of mismatch and gender, %

Gender	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Male	30.8	18.5	12.3	40.6	21.6	19.0
Female	33.2	17.5	15.8	49.3	30.5	18.9

Source: author's calculation, LFS

Table 12. Proportion of mismatched employees by type of mismatch and gender, %

Gender	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Male	29.8	12.9	16.9	48.6	34.4	14.1
Female	28.5	14.7	13.8	40.2	25.2	15.0

Source: author's calculation, LFS

Table 13. Proportion of mismatched individuals by type of mismatch and region of residence

Region	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Vinnytsia Obl	35.3	24.8	10.6	43.6	19.8	23.8
Volyn Obl	30.7	17.4	13.3	34.3	15.4	19.0
Dnipropetrovsk Obl	32.9	14.9	18.0	45.5	29.6	15.9
Donetsk Obl	28.8	16.0	12.8	55.6	38.4	17.2
Zhytomyr Obl	33.5	17.3	16.2	44.5	25.1	19.5
Zakarpattia Obl	36.2	10.9	25.2	25.0	13.1	12.0
Zaporizhia Obl	36.0	19.3	16.7	48.9	27.5	21.4
Ivano-Frankivsk Obl	35.3	18.5	16.8	38.6	20.2	18.4
Kyiv Obl	29.5	12.3	17.2	36.8	24.0	12.8
Kirovohrad Obl	29.0	17.7	11.3	47.5	28.3	19.2
Luhansk Obl	36.0	22.7	13.3	54.2	29.8	24.4
Lviv Obl	25.4	17.2	8.2	46.3	29.0	17.3
Mykolaiv Obl	36.2	19.7	16.4	46.7	24.9	21.8
Odessa Obl	36.2	16.2	20.0	36.7	20.0	16.6
Poltava Obl	34.7	20.8	14.0	49.2	27.0	22.1
Rivne Obl	34.7	24.2	10.5	42.8	18.3	24.5
Sumy Obl	36.0	24.8	11.1	50.4	23.4	27.0
Ternopil Obl	35.7	24.4	11.3	48.3	21.8	26.5
Kharkiv Obl	26.1	15.7	10.4	41.9	26.3	15.6
Kherson Obl	37.4	25.7	11.7	46.7	22.0	24.7
Khmelnytskyi Obl	31.7	21.0	10.7	40.8	20.0	20.8

Table 13 continued

Region	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Cherkasy Obl	31.4	20.0	11.5	44.8	23.4	21.4
Chernivtsi Obl	36.7	21.3	15.4	35.5	15.3	20.2
Chernihiv Obl	34.2	21.3	12.9	50.0	25.9	24.1
Kyiv	24.9	10.5	14.4	49.5	36.6	13.0

Source: author's calculation, LFS

Table 14. Proportion of mismatched employees by type of mismatch and region of residence

Region	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Vinnytsia Obl	30.8	16.5	14.3	43.4	27.4	16.0
Volyn Obl	29.9	14.9	15.1	34.2	18.5	15.7
Dnipropetrovsk Obl	31.5	12.9	18.7	45.0	31.2	13.8
Donetsk Obl	26.9	14.2	12.8	54.7	39.5	15.2
Zhytomyr Obl	30.9	12.4	18.5	43.5	29.1	14.4
Zakarpattia Obl	43.9	12.1	31.8	31.4	18.2	13.2
Zaporizhia Obl	31.8	14.0	17.9	46.4	31.0	15.4
Ivano-Frankivsk Obl	35.2	16.5	18.7	39.9	23.6	16.3
Kyiv Obl	28.5	10.6	17.9	35.7	25.0	10.7
Kirovohrad Obl	26.0	13.5	12.6	48.6	33.2	15.4

Table 14 continued

Region	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
Luhansk Obl	30.1	14.5	15.6	51.3	35.2	16.1
Lviv Obl	22.7	14.5	8.2	45.0	30.8	14.3
Mykolaiv Obl	32.2	14.9	17.4	45.0	28.5	16.5
Odessa Obl	34.9	12.4	22.5	35.3	22.6	12.6
Poltava Obl	31.5	15.6	16.0	47.6	30.9	16.7
Rivne Obl	27.9	11.7	16.2	41.5	28.6	12.9
Sumy Obl	29.0	16.3	12.7	47.5	30.3	17.2
Ternopil Obl	30.1	16.4	13.6	46.0	28.5	17.4
Kharkiv Obl	24.5	14.5	10.0	41.0	27.1	13.8
Kherson Obl	31.1	15.9	15.2	44.6	28.3	16.3
Khmelnytskyi Obl	28.5	15.5	12.9	39.2	24.0	15.2
Cherkasy Obl	25.5	14.0	11.5	42.1	27.9	14.2
Chernivtsi Obl	37.9	17.1	20.8	38.3	22.3	16.0
Chernihiv Obl	28.7	14.1	14.6	49.2	33.3	16.0
Kyiv	24.3	10.8	13.5	48.4	35.8	12.7

Source: author's calculation, LFS

Table 15. Proportion of mismatched individuals by type of economic activity

Type of economic activity	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
vd_gr_1	39.7	35.4	4.4	39.6	4.8	34.8
vd_gr_2	28.4	12.1	16.3	48.9	35.7	13.1
vd_gr_3	26.8	12.4	14.4	54.8	41.1	13.6
vd_gr_4	36.0	14.5	21.5	54.2	39.0	15.2
vd_gr_5	38.6	14.7	23.9	52.8	35.7	17.1
vd_gr_6	31.4	14.1	17.3	49.6	33.1	16.5
vd_gr_7	27.6	16.8	10.8	46.2	28.5	17.7
vd_gr_8	15.9	8.1	7.8	44.7	35.1	9.7
vd_gr_9	20.8	12.4	8.4	33.4	20.9	12.5
vd_gr_10	35.3	18.7	16.6	47.0	25.5	21.6

Source: author's calculation, LFS

Table 16. Proportion of mismatched employees by type of economic activity

Type of economic activity	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
vd_gr_1	31.8	18.3	13.5	34.3	15.6	18.7
vd_gr_2	28.1	12.2	15.9	48.8	35.8	13.0
vd_gr_3	26.7	12.3	14.3	54.8	41.2	13.6
vd_gr_4	34.9	14.7	20.2	53.8	38.7	15.1
vd_gr_5	36.5	14.4	22.1	50.2	34.9	15.3
vd_gr_6	31.2	14.3	16.9	48.7	32.6	16.1

Table 16 continued

Type of economic activity	Vertical (total)	Vertical, overeducated	Vertical, undereducated	Horizontal (total)	Horizontal (vertically matched)	Both
vd_gr_7	27.7	17.0	10.7	45.6	27.9	17.8
vd_gr_8	15.9	8.1	7.8	44.6	35.1	9.5
vd_gr_9	20.8	12.4	8.4	33.4	20.9	12.5
vd_gr_10	34.9	19.1	15.8	46.0	24.7	21.3

Source: author's calculation, LFS