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Field saturation and education-occupation mismatch in Vietnam

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ABSTRACT

This study measures field saturation and education-occupation mismatch in Vietnam's labor market, a country with a transitional economy. Using data from the 2018 Labour Force Survey, the study employs both the Job Analysis (JA) and Direct Self-Assessment (DSA) methods to measure education-occupation mismatch. A logistic regression model is applied to identify factors influencing mismatch, including provincial-level field saturation. The results reveal that the highest level of field saturation occurs among graduates in pedagogy and educational sciences. Saturation levels are generally lower for individuals with vocational training but significantly higher within the public sector. The econometric analysis indicates that living in provinces with greater field saturation increases the likelihood of job mismatch. Based on the JA method, the mismatch probability is higher for all other fields compared to pedagogy, except for social sciences, business, and law. The DSA method confirms similar patterns, with an exception for the health and welfare field. Field saturation contributes significantly to education-occupation mismatch in Vietnam's labor market, particularly in the public sector and highly saturated fields. Policies should prioritize improving labor market transparency, offering stronger incentives for proactive job search behaviors, and expanding on-the-job training to bridge skill gaps.

Contribution/ Originality: This study provides the first estimates of job mismatch and field saturation in Vietnam using both Job Analysis and Self-Assessment methods, and reveals that the field of study and field saturation significantly influence mismatch risks, offering new evidence to inform education and labor policy.

1. INTRODUCTION

Since the 1990s, Vietnam has undertaken a series of supply-side higher education reforms, primarily focused on remuneration policies and spending, with the aim of expanding the diversity of university programs offered (MOET, 2015). Specifically, the government has broadened access to tertiary education across all sectors, including public, semi-public, and private education providers, to expand existing institutions or establish new educational or training institutions (Doan, Le, & Tran, 2018). Consequently, the gross enrollment rate in postsecondary education increased significantly from approximately 9.40% to around 30.50% between 2000 and 2014 (World Bank, 2018). Over the past decades, drastic changes in tertiary education policies in the 2000s have resulted in a significant increase in the supply of highly educated workers (Tran & Van Vu, 2020). Notably, recent data reveal that unemployment rates are higher for better-educated individuals, raising concerns regarding the mismatch between acquired skills and labor market demands (Demombynes & Testaverde, 2018).

A mismatch between an individual's field of study and the job they hold (hereafter called "job mismatch") can have negative consequences, not only for individuals due to frustration at work, capacity deterioration, pay penalties, and job dissatisfaction (Allen & Van der Velden, 2001; Bender & Roche, 2013; Büchel & Mertens, 2004; Quintini, 2011; Tsang & Levin, 1985) but also for society (Somers, Cabus, Groot, & van den Brink, 2019). While recent studies have documented the negative impact of job mismatch on wage earnings in Vietnam (Tran, Pham, Vo, Luu, & Nguyen, 2019; Tran & Van Vu, 2020), to the best of our knowledge, no research thus far has investigated the causes of such mismatches. As emphasized by Boudarbat and Chernoff (2012), understanding the mismatch between postsecondary graduates and their subsequent employment enables a society to optimize returns on investments in postsecondary education. Given the importance of the topic and the gap in the literature, the current study was conducted to examine field saturation and the incidence of job mismatch in Vietnam's postsecondary system and labour market.

This study employs microdata from the Vietnam Labor Force Survey in 2018 (LFS 2018) to analyze job mismatch using both the Job Analysis (JA) and Direct Self-Assessment (DSA) methods. We limited our research sample to Vietnamese workers employed full-time, aged 15 to 60 years for men and 15 to 55 years for women, who had attained some level of postsecondary education. Our main research objectives were: (i) to measure field saturation and job mismatch using both the Job Analysis (JA) and Direct Self-Assessment (DSA) methods; and (ii) to quantify factors affecting the mismatch using a logit regression model. Our study makes a significant contribution to the existing literature by providing the first estimates of job mismatch and field saturation in Vietnam. More importantly, we offer econometric evidence on the impact of field of study and field saturation on the likelihood of job mismatch.

We find the highest level of field saturation for the pedagogy/educational science major. The level of saturation tends to be much lower for those with middle-level vocational and vocational college training, while it is much higher in the public sector.

Notably, our econometric analysis shows that living in provinces with higher saturation increases the likelihood of a worker encountering a job mismatch. Moreover, the probability of being mismatched according to the job analysis method is higher for those in all fields other than the pedagogy/educational science field (the reference group), except for those in the social sciences/business/law field. Apart from those graduating in the health and welfare field, a similar mismatch result was found using the direct self-assessment (DSA) method. Our research findings shed light on the main causes of job mismatch and offer valuable policy implications for decision-makers and education stakeholders in Vietnam.

The paper is organized into five main sections. Section 2 reviews the relevant literature on field saturation and education-occupation mismatch, followed by an outline of the data and econometric model in Section 3. Section 4 presents the empirical findings and discusses their implications, while Section 5 concludes the study and provides policy recommendations.

2. THEORETICAL AND EMPIRICAL EVIDENCE

Job mismatch can be categorized as either 'horizontal' or 'vertical.' Horizontal mismatch refers to situations where individuals are employed in occupations unrelated to their field of study, whereas vertical mismatch describes cases where a worker has either a higher or lower level of education than what is required for the job (OECD, 2016; Ortiz & Kucel, 2008).

Field saturation occurs when the number of graduates in a particular field of study exceeds the availability of corresponding job opportunities. When jobs are limited in number for a specific group, individuals are compelled to seek employment in unrelated occupations. Therefore, field saturation is closely associated with horizontal mismatch, while vertical mismatch is related to qualification mismatch (Quintini, 2011; Robst, 2008). Horizontal (education-occupation) mismatch may be a significant cause of field saturation when few jobs are available in the market, and an individual decides to work in a different field (OECD, 2016; Ortiz & Kucel, 2008).

According to the job competition model proposed by Thurow (1979) workers are assumed to apply for a particular job based on their field and level of education and must meet the application criteria Nevertheless, the nature of the work decides the job's productivity, not the employee's human capital stock (Hartog, 2000). In this case, a mismatch occurs when employers need more staff than are available in a specific occupational category and therefore have to look for workers further down the queue, recruiting people from different fields. Thus, assignment theory indicates that productivity will increase when job requirements match the worker's profile (Sattinger, 1993; Teulings, 1995).

However, a mismatch arises when a firm hires workers whose training does not align with the job requirements and gives them a brief period of training to accomplish the required task. The integration of assignment and job competition theories can be used to investigate education-occupation mismatch and field saturation (Hartog, 2000).

Since horizontal or job mismatch has adverse consequences, not only for individual workers and companies but also for society at large (Somers et al., 2019), a number of studies have identified factors affecting mismatch in several countries (Boudarbat & Chernoff, 2012; Robst, 2007a; Wolbers, 2003).

In general, these studies show that the prevalence of job mismatch varies considerably across different fields of study. For instance, a study in thirteen European countries by Wolbers (2003) found that relative to the reference group (educational science), those with degrees in humanities/arts, sciences, and agriculture were more likely to experience job mismatch. In contrast, graduates in social sciences/business/ law, engineering/ manufacturing/construction, and health/welfare and services faced a lower likelihood of mismatch. In the US, Robst's (2007a) study reveals that graduates in the computer/information sciences were more likely to secure jobs aligned with their fields of study than those in almost all other majors, except in library and health sciences. Majors at greatest risk of being mismatched include English and foreign languages, liberal arts, and social sciences. In Canada, Boudarbat and Chernoff (2012) reported that the likelihood of obtaining a job match was much greater for those in educational or health sciences. The findings suggest that the incidence of mismatch tends to be higher for majors providing more general skills than it is for those trained in more specific skills.

The literature indicates several other factors affecting education-job mismatch. In thirteen European countries, the probability of being mismatched is much higher for school-leavers working in small enterprises, the private sector, and those working under short-term contracts (Wolbers, 2003).

Notably, age, marital status, ethnicity, education level, good grades, and time devoted to study were found to be major factors affecting a job match (Wolbers, 2003). In Canada, Boudarbat and Chernoff (2012) reported that the probability of obtaining a job match was lower for those with grades in the top 25-50% and the lower 50% of the class than for those in the top 10%, while those in full-time study had a higher chance of finding a job match than those in part-time study.

Individuals completing master's or doctoral degrees are more likely to obtain a job match than bachelor's degree recipients in Canada and the US (Boudarbat & Chernoff, 2012; Robst, 2007b). In the United States, the risk of being mismatched tends to increase with age, the presence of a disability, and is higher among White and Asian individuals compared to Black, Native American, or Hispanic populations. Additionally, married individuals are more likely to be employed in jobs aligned with their field of study than those who have never married (Robst, 2007b).

As indicated in Figure 1, our theoretical framework and empirical model have been developed on the basis of assignment theory, the job competition model and previous research (Boudarbat & Chernoff, 2012; Robst, 2007a; Somers et al., 2019; Wolbers, 2003) to estimate factors affecting a mismatch, including the field of education, level of education, job sector, field saturation and other individual characteristics.

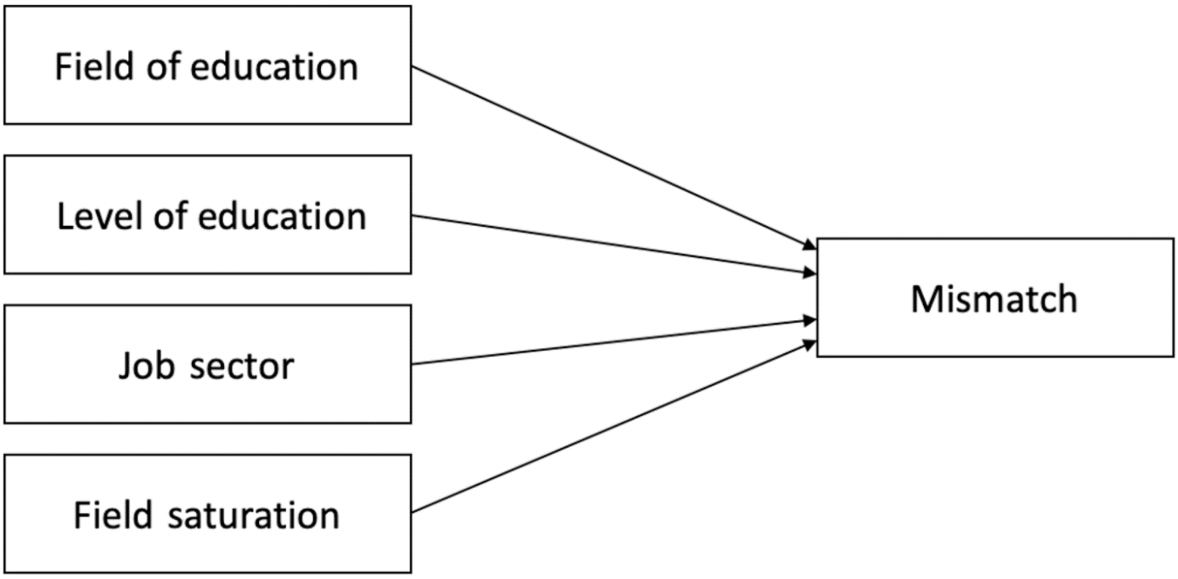


Figure 1. Framework for analyzing factors affecting mismatch in Vietnam.

3. BACKGROUND OF THE STUDY, DATA, AND ECONOMETRIC METHOD

3.1. Data and Study Indicators

3.1.1. Data

The current study utilized microdata from the 2018 Labor Force Survey (LFS), conducted by the General Statistical Office of Vietnam. The survey gathered labor market information from working-age individuals, as defined by the Labor Law of Vietnam, who were residing in the country at the time of data collection. The LFS offers comprehensive data on various socio-economic variables, including gender, age, educational attainment, occupation, income, working hours, and work conditions. The 2018 LFS covered all 63 provinces and cities in Vietnam, with a total sample size of 824,143 individuals. For the purposes of this study, a sub-sample of 76,102 individuals was selected, focusing on those within the working-age range (15–60 years for men and 15–55 years for women), who were employed full-time and had attained at least a middle-level professional qualification or higher.

3.1.2. Study Indicators

Both objective and subjective approaches can be used to measure education-occupation mismatch (job mismatch), each utilizing different measurement methods. This study employs both the Job Analysis (JA) and Direct Self-Assessment (DSA) approaches. Under the JA method, educational qualifications are grouped into nine major fields according to the International Standard Classification of Education (ISCED 2011), while occupations are categorized using the three-digit level of the International Standard Classification of Occupations (ISCO-08). A mismatch is identified when an individual's field of study does not correspond with the field commonly linked to their current occupation. To define mismatch within the JA approach, this study follows the education-occupation linkage framework proposed by Montt (2017). In contrast, the DSA method captures workers' subjective perceptions by asking them directly whether their current job is related to their field of education.

To measure field saturation, Montt (2017) proposed a ratio between the number of graduates in a specific field (as classified by ISCED 2011) and the number of jobs available in that field within a country, based on the ISCED–ISCO linkage. In the present study, this concept is applied at the provincial level using the full sample of the 2018 LFS. The saturation level for field f in province p is defined as:

$$S_{f,p} = \frac{G_{f,p}}{W_{f,p}}$$

Where $G_{f,p}$ represents a number of individuals (both employed and unemployed) graduating from the field f in province p, and $W_{f,p}$ represents a number of workers currently employed in occupations related to that field in the same province. In the education-occupation link, some occupations may be matched to more than one field of study, so $G_{f,p}$ is based on a single response per respondent, and $W_{f,p}$ is based on the attribution that allows for an occupation to be classified in more than one field. Since there is no interpretable scale for field saturation, this is standardized to have a mean of 0 and a standard deviation of 1, so that positive (negative) values indicate that for a given field, there is higher (lower) saturation than for the average field across provinces. A value of 1 (-1) indicates that field saturation is one standard deviation above (below) the average observed across all fields and provinces.

3.2. Econometric Model

Since the dependent variable is binary coded as 1 for job mismatch and 0 for job match a logistic regression model is employed to examine the influence of the field of study and field saturation on the probability of an individual experiencing a job mismatch, while controlling for a range of individual characteristics. The logistic transformation of the dependent variable allows for the estimation of probabilities through the maximum likelihood method. Essentially, the logit function represents the natural logarithm of the odds of the event occurring and indicates the likelihood that a mismatch will take place. The equation for the logit model, along with the expression for its marginal effects, is provided below.

$$\Pr(mismatch = 1|E,S,J) = \frac{e^{(\beta_0+\beta_1 E+\beta_2 S+\beta_3 J)}}{1+e^{(\beta_0+\beta_1 E+\beta_2 S+\beta_3 J)}}$$

Where a dummy variable of job mismatch (1 = yes; 0 = no) is used, E represents individual education, including the field and level of education, denotes field saturation, and includes a vector of other individual characteristics.

To interpret the outcomes of the logit model, we utilize the marginal effect, which is derived through a two-step procedure. First, following the estimation of the model, we calculate the fitted value ($\hat{p}_i$) of $Probability(mismatch = 1)$ for individual i.

$$\hat{p}_i = \frac{e^{(\hat{\beta}_0+\hat{\beta}_1 E_i+\hat{\beta}_2 S_i+\hat{\beta}_3 J_i)}}{1+e^{(\hat{\beta}_0+\hat{\beta}_1 E_i+\hat{\beta}_2 S_i+\hat{\beta}_3 J_i)}}$$

Secondly, the marginal effect of an explanatory variable (X_k) on the probability of being mismatched can be computed using the following expression.

$$\frac{\partial \hat{p}_i}{\partial X_k} = \frac{e^{(\hat{\beta}_0+\hat{\beta}_1 E_i+\hat{\beta}_2 M_i+\hat{\beta}_3 J_i)}}{\left(1+e^{(\hat{\beta}_0+\hat{\beta}_1 E_i+\hat{\beta}_2 M_i+\hat{\beta}_3 J_i)}\right)^2}.\hat{\beta}_k = \hat{p}_i(1-\hat{p}_i)\hat{\beta}_k$$

The marginal effect reflects the change in the probability (expressed as a percentage) of being mismatched when the explanatory variable increases by one unit. Following the framework presented in Figure 1 and previous research (Boudarbat & Chernoff, 2012; Robst, 2007a; Somers et al., 2019; Wolbers, 2003), a range of control variables are incorporated in our logit regression model. The name, definition and measurements of these variables are presented in Table 1.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics of the Research Sample

Table 1 presents important information about the research sample regarding education by field and level. For the field of education, it shows that three majors attracted the largest number of learners, namely social sciences/business/law, pedagogy/educational science, and the engineering/manufacturing/construction disciplines. Combined, they account for about 70% of the total sample. Looking at the field of study by gender reveals that men prefer the engineering/manufacturing/construction disciplines, whereas women are more likely to enter social sciences/business/law degree programs.

Table 1. Education by field and level.

Education qualification	**Total**	**Male**	**Female**
Field of study (Percentage)			
Pedagogy and educational science	22.1	10.3	33.8
Humanities, languages, and arts	2.4	1.6	3.1
Social sciences, business, and law	30.4	23.5	37.1
Science, mathematics and computing	4.9	6.9	3.0
Engineering, manufacturing, and construction	20.0	35.1	5.2
Agriculture and veterinary	3.5	4.7	2.3
Health and welfare	9.8	6.7	12.9
Services	6.8	11.1	2.6
Education level (Percentage)			
Middle-level professional	19.7	18.3	21.1
Middle-level vocational	7.3	12.9	1.8
College	16.7	12.9	20.4
Vocational college	2.8	4.9	0.7
Undergraduate	50.6	47.8	53.4
Postgraduate	3.0	3.3	2.6
Overall (Percentage)	100	49.5	50.5

Sources: Authors' calculation from the 2018 LFS.

The level of education can be divided into two main categories: professional and vocational. The professional category encompasses middle-level professions that require a college, undergraduate, or postgraduate degree, whereas vocational training prepares individuals for middle-level vocational roles or vocational college education. A significant majority of individuals (90%) opt for professional certificates, while only 10% pursue vocational training. Among professional qualifications, undergraduate degrees are the most common (50%), whereas fewer than 20% of workers attain a college degree. Gender differences are evident in both educational pathways. A higher proportion of women (21.1%) than men (18.3%) pursue middle-level professional education, and 20.4% of women aim for a college certificate, compared to 12.9% of men. In contrast, 12.9% of men complete a middle-level vocational certificate, while only 1.8% of women do so.

Table 2. Some main characteristics of individuals.

Length of employment (Percentage)	**Total**	**Male**	**Female**
Less than 6 months	3.3	3.2	3.3
6 to 12 months	2.9	2.8	3.1
1 to 5 years	33.1	32.7	33.4
5 to 10 years	24.9	25.2	24.5
More than 10 years	35.9	36.1	35.7
Employment by occupation (Percentage)			
Unskilled manual workers	4.9	5.9	3.9
Skilled manual workers	13.2	21.2	5.3
Mid-level technicians and associates	19.4	18.7	20.1
High-level technicians and professionals	62.5	54.2	70.7
Type of labor contract (Percentage)			
Less than 1 year /No contract	27.1	32.0	22.3
1 to 3 years	16.6	16.5	16.6
Long term	56.3	51.5	61.1
Job sector (Percentage)			
Households, freelance	22.3	26.9	17.9
Private sector	21.5	23.5	19.4
State-owned enterprises	7.5	9.6	5.4
FDI enterprises	5.0	4.9	5.1
Public sector	42.5	34.3	50.6
Other	1.3	0.8	1.7
Age (Percentage)			
15-24 years	9.3	7.5	11.0
25-34 years	43.8	41.4	46.2

Length of employment (Percentage)	**Total**	**Male**	**Female**
35-44 years	27.9	28.1	27.6
More than 45 years	19.1	23.0	15.3
Marital status (Percentage)			
Single	22.4	22.7	22.1
Married	77.7	77.4	77.9
Field saturation (Mean score)	0.5859	0.3924	0.7753
Number of observations (n)	76,102	37,639	38,463

Sources: Authors' calculation from the 2018 LFS.

Regarding the length of employment, Table 2 shows that 60% of individuals, both male and female, had more than five years of experience. For the overall sample, considering employment experience, 62.5% of individuals qualified as high-level technicians with professional experience. Men tend to have more experience in skilled manual work (21.2%) than women (5.3%). More women qualified as high-level technicians with professional experience (70.7%) than men (54.2%). Workers with business owner status, the self-employed, and individuals working for their own household are considered to have no labor contract. The survey indicates that most laborers held long-term job contracts (56.3%).

Moreover, more women than men held long-term labor contracts of one to three years. Regarding overall employment, the public sector is the largest employer, accounting for about 52.4% of total employment, followed by the household and freelance sector (22.3%) and domestic private enterprises (21.5%). A larger proportion of women worked in the public sector (50.6%), while a higher percentage of men were employed in the private sector (26.9%) and the household and freelance sector (23.5%). In terms of age, 40% of the sample consists of individuals aged 25-34 years and married. Finally, the mean score of field saturation is estimated at 0.7753 for the entire sample, 0.775 for women, and 0.392 for men.

Table 3 indicates the level of education-occupation mismatch measured by two methods, together with field saturation. The estimated mismatch proportion differs considerably between the two methods; the JA method gives much higher results (about 34%) than does the SDA method (about 24%). According to the JA method, the mismatch proportion is highest in the field of science, mathematics, and computing, followed by the humanities/languages/arts and agriculture/veterinary disciplines, while the lowest incidence was found for the social sciences/business/law disciplines. However, the results are considerably different when using the DSA method, with the highest and lowest mismatch levels occurring in the agriculture/veterinary and pedagogy/educational science fields, respectively. In general, Table 3 indicates that using the objective measurement method results in a higher mismatch for all fields (except the field of social science/business/law) than using the subjective method.

Regarding the mismatch incidence by job sector, the results in Table 3 using both methods indicate the highest mismatch in the household and freelance sector, followed by the FDI sector. Surprisingly, the results from the two approaches show a significant difference in the incidence of mismatch within the public sector. Specifically, the JA method shows the mismatch at approximately 26.70%, compared to only about 6.14% using the DSA method. A plausible explanation is that public employment is less likely to require specific qualifications and skills, which, in turn, makes public servants feel that their field of study is relevant to their current jobs.

Regarding mismatch by education level, the results using both methods show a very high mismatch incidence among individuals with middle-level professional training. Also, the estimates using the JA method reveal that approximately 45% of wage earners with a middle-level professional degree were identified as mismatched, whereas the corresponding figures are about 47% for those with a college degree. Using the JA approach, we find the highest mismatch proportion for workers with a middle-level professional education (about 45%) and college degrees (about 36%). Also, the JA method shows the highest mismatch rate among those who have completed college (about 47%), whereas the DSA results indicate the highest incidence among those with vocational college degrees (about 38%).

Notably, the results from both methods confirm the lowest mismatch incidence for those with undergraduate and postgraduate degrees.

Table 3. Field saturation and job mismatch.

Factors	Field saturation	Job analysis mismatch (%)	Direct self-assessment mismatch (%)
Overall	0.00	33.67	24.21
Field of education			
Pedagogy and educational science	1.69	36.20	14.09
Humanities, languages and arts	-0.40	63.54	25.53
Social sciences, business and law	-0.43	19.90	25.91
Science, mathematics and computing	-0.31	66.20	30.93
Engineering, manufacturing and construction	-0.64	33.38	31.11
Agriculture and veterinary	-0.91	55.16	37.45
Health and welfare	-0.16	35.25	20.58
Services	-0.63	40.51	22.38
Education level			
Middle-level professional	-0.16	44.69	35.87
Middle-level vocational	-0.61	30.88	34.78
College	0.35	46.81	30.82
Vocational college	-0.62	29.70	37.75
Undergraduate	0.08	26.24	16.38
Postgraduate	-0.12	23.80	4.59
Job sector			
Households, freelance	-0.22	56.91	61.91
Private sector	-0.41	25.94	22.81
State-owned enterprises	-0.46	23.55	13.67
FDI enterprises	-0.41	36.36	34.46
Public sector	0.44	26.73	6.14
Other	0.28	36.63	11.26

Sources: Authors' calculation from the 2018 LFS.

4.2. Econometric Analysis of Job Mismatch

Table 3 reports the determinants of education-occupation mismatch, estimated using the logit model and based on two measurement approaches. For each method, we present the estimated coefficients, their standard errors, and the marginal effects of explanatory variables on the probability of being mismatched.

Pedagogy and educational science are used as the reference group for the field of study in our econometric analysis. The estimated coefficients for most fields of study are statistically significant, indicating notable variation in mismatch probabilities across disciplines. A positive coefficient implies that the probability of being mismatched in a given field is higher relative to the reference group. Graduates from the *Science, Mathematics, and Computing* fields face a significantly higher probability of mismatch, with the Job Analysis (JA) method indicating an increase of 36.8 percentage points compared to the reference field. Conversely, using the same method, the *Social Sciences, Business, and Law* field shows a lower mismatch probability of 5.3 percentage points below the reference category. Under the DSA method, the mismatch probabilities vary significantly across fields of education, but the range is smaller. The highest probability is observed in the *Humanities, Languages, and Arts* field, which exceeds the reference field by 5.8 percentage points. In contrast, the fields of *Health and Welfare* and *Services* show lower mismatch probabilities than the reference group, at 3.2 and 2.1 percentage points, respectively. Our research finding is partly consistent with Boudarbat and Chernoff (2012) who found that in Canada, university graduates in education and the health sciences were most likely to find a match between occupation and their education.

With regard to the education level, all estimated coefficients are statistically significant at the 1% level, providing strong evidence that, according to the Job Analysis (JA) method, the probability of education-occupation mismatch varies significantly by educational attainment. Using *middle-level professional training* as the reference category, most other education levels exhibit a lower likelihood of mismatch. Specifically, the probability of mismatch for individuals with *middle-level vocational training* is 16.2 percentage points lower than that of the reference group. Similarly, graduates of *vocational colleges* have a mismatch probability 16.0 percentage points below the reference level. In contrast, individuals with a *college* education face a mismatch probability 4.6 percentage points higher than the reference level. The probability of DSA method mismatch for most educational levels is also lower than for the reference level. The differences range from 1.5 to 8.3 percentage points below the reference category, indicating a consistent but less pronounced pattern across educational levels.

Table 4. Factors affecting job mismatch.

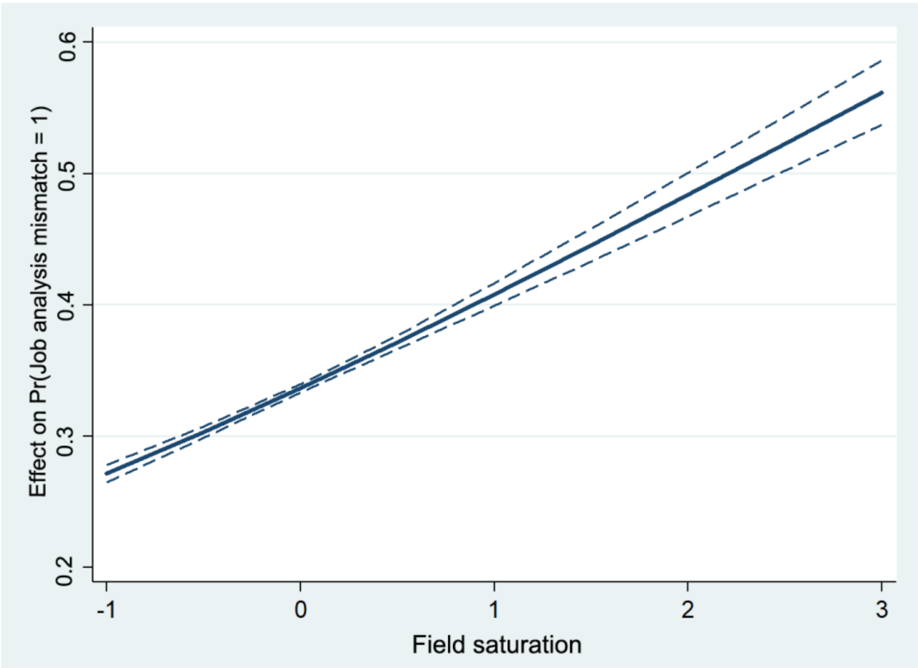
Factors	Job analysis mismatch	Direct self-assessment mismatch
Saturation	0.0670***	0.0160***
Field of study		
Teacher training and education science	Ref	Ref
Humanities, languages and arts	0.3930***	0.0693***
Social sciences, business and law	-0.0527***	0.0519***
Science, mathematics and computing	0.3860***	0.0577***
Engineering, manufacturing and construction	0.1050***	0.0405***
Agriculture and veterinary	0.2300***	0.0603***
Health and welfare	0.0330***	-0.0252***
Services	0.1520***	-0.0158*
Education level		
Middle-level professional	Ref	Ref
Middle-level vocational	-0.1620***	-0.0518***
College	0.0459***	-0.00018
Vocational college	-0.1600***	-0.0324***
Undergraduate	-0.0621***	-0.0145***
Postgraduate	-0.0501***	-0.0827***
Employment by occupation		
Unskilled manual workers	Ref	Ref
Skilled manual workers	-0.3910***	-0.445***
Mid-level technicians and associates	-0.2280***	-0.282***
High-level technicians and professionals	-0.4730***	-0.611***
Tenure		
Less than 6 months	Ref	Ref
6 to 12 months	-0.0307**	-0.0319***
1 to 5 years	-0.0435***	-0.0483***
5 to 10 years	-0.0876***	-0.1020***
More than 10 years	-0.1150***	-0.1500***
Type of labor contract		
Less than 1 year /No contract	Ref	Ref
1 to 3 years	-0.0373***	-0.0931***
Long term	-0.0107	-0.0482***
Job sector		
Households, freelance	Ref	Ref
Private sector	-0.1060***	-0.0760***
State-owned enterprises	-0.0769***	-0.0853***
FDI enterprises	-0.0048	0.0051
Public sector	-0.0547***	-0.1190***
Other	0.0048	-0.1160***
Gender (Female = 0)	0.0063*	-0.0072**
Marital status (Single = 0)	0.0114***	0.0045
Age	0.00235***	0.0022***
Area (Rural = 0)	0.0056	0.0003
Correctly classified	74.56%	84.86%
Prob > chi2	0.000	0.000
Pseudo R2	0.176	0.366
Observations	76100	76100

Note: *, **, *** mean statistically significant at the 10%, 5% and 1% levels, respectively. Estimates account for sampling weights and are clustered at the commune level.

In the employment sector, workers in the private sector have a lower probability of experiencing job mismatch compared to those employed by households or working as freelancers, with a difference of 10.6% according to the JA method and 7.6% according to the DSA method. Furthermore, the likelihood of a mismatch is significantly lower for individuals employed in state-owned enterprises and the public sector when compared to the reference job sector. In contrast, mismatch probabilities in other sectors do not show significant differences from the reference group.

Figure 2 illustrates the marginal effects of field saturation on the likelihood of being job-mismatched in Vietnam. The results indicate that the probability of job mismatch increases as field saturation increases. The marginal effects are estimated at the mean values of three factors in the model: field of education, level of education, and job sector. When field saturation is high, it has a direct effect on the mismatch. In the graph, when field saturation is at the mean value (zero), the marginal effect on job mismatch is approximately 34%; when field saturation increases by one point, this also directly affects the mismatch. Similarly, the marginal effect for DSA mismatch is 25%. An increase in field saturation from -1 to 3 indicates an increase in the marginal effect for mismatch from 27% to 56% (JA method) and from 22% to 35% (DSA method).

Figures 3, 4, and 5 illustrate the marginal effect of field saturation on mismatch probability across different categories: field of study, level of education, and job sector, respectively. For the field of study, workers with degrees in humanities, languages, arts, science, mathematics, and computing exhibited the highest mismatch rates, both at 67%, using the JA method at zero mean field saturation. Conversely, the agriculture and veterinary fields showed the highest mismatch rate of 32% at zero field saturation, according to the DSA method. Regarding education level, workers with college certificates experienced the highest mismatch rate of 44% at zero mean field saturation via the JA method. Using the DSA method, middle-level professionals demonstrated the highest mismatch rate of 31% at zero field saturation. In the employment sector, workers engaged in household and freelance work exhibited the highest mismatch rates, 55% and 59%, respectively, at zero mean field saturation, as measured by the JA and DSA methods.



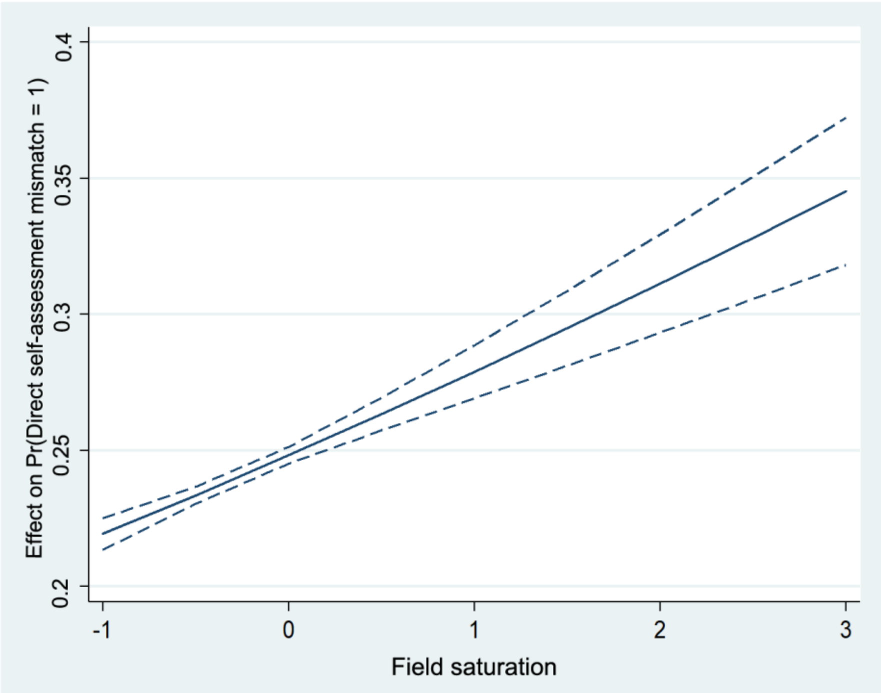


Figure 2. Marginal effects of field saturation on mismatch probability.

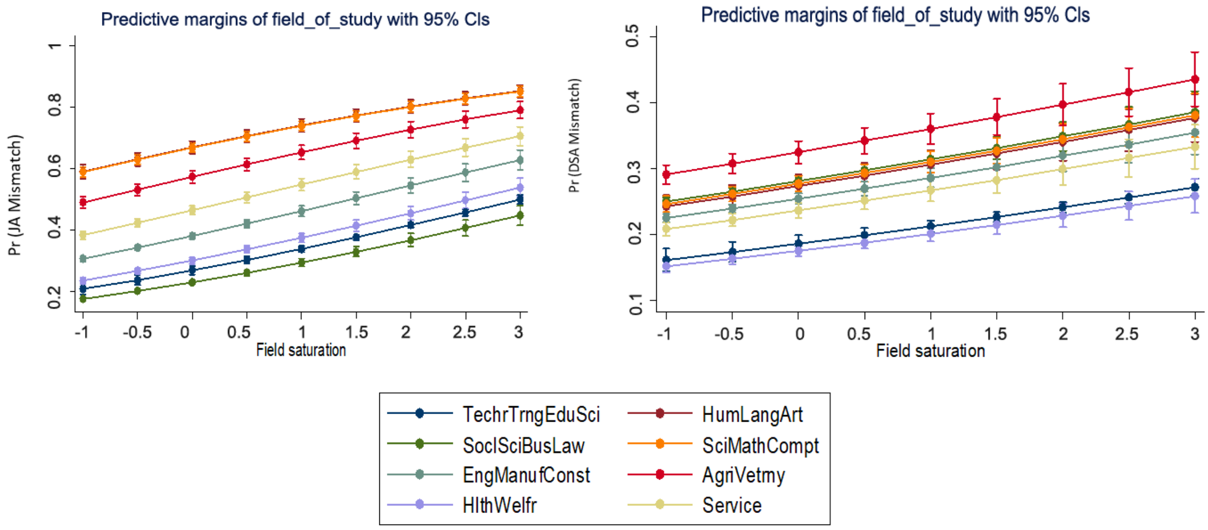


Figure 3. Marginal effects of field saturation on mismatch probability by field of study.

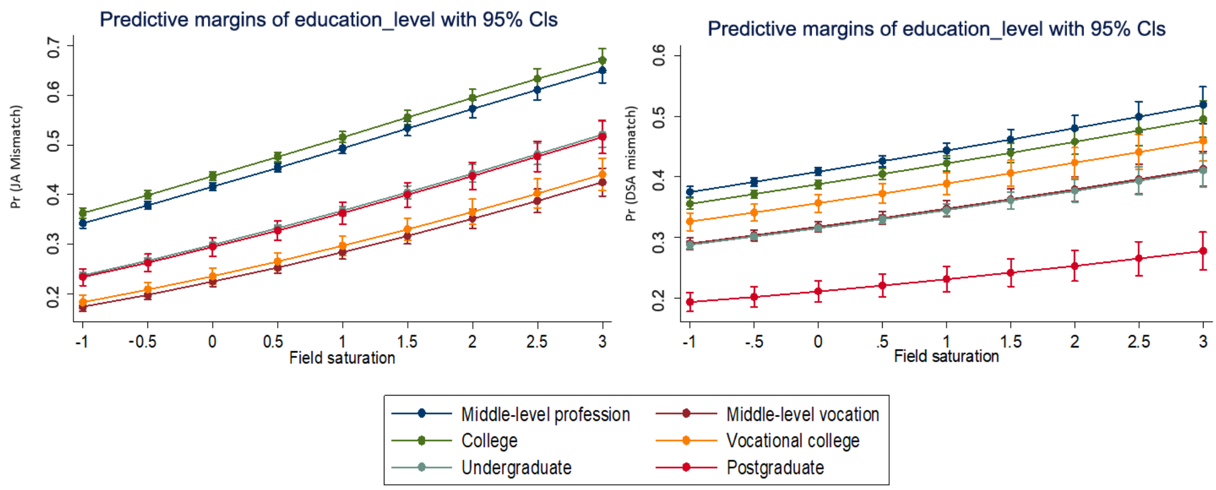


Figure 4. Marginal effects of field saturation on mismatch probability by educational level.

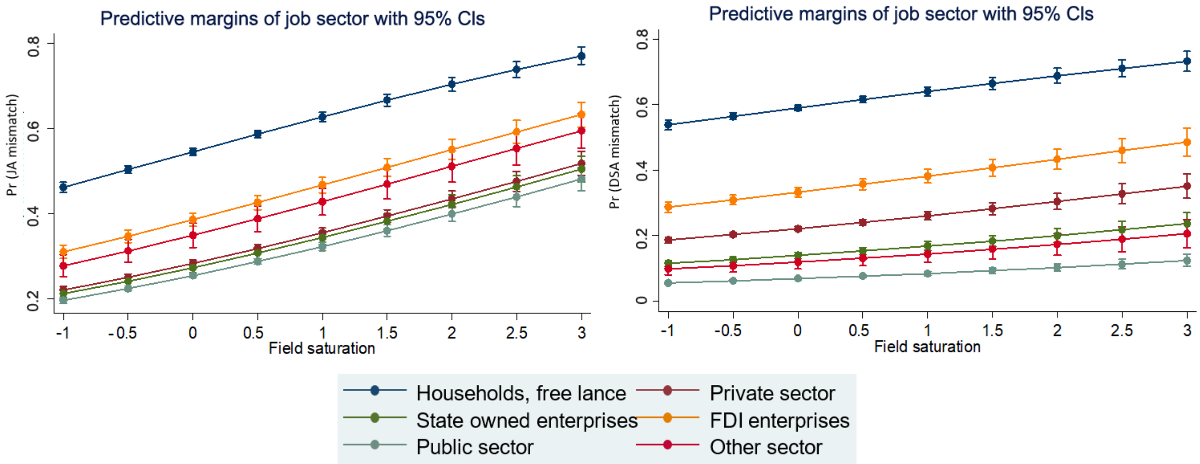


Figure 5. Marginal effects of field saturation on mismatch probability by job sector.

5. CONCLUSION AND POLICY IMPLICATIONS

This study applies both the Job Analysis (JA) and Direct Self-Assessment (DSA) methods to examine field saturation and education-occupation mismatch across employment sectors, fields of study, and education levels in the Vietnamese labor market. The findings indicate that while the two methods yield differing mismatch proportions, they exhibit consistent trends, reinforcing their comparative reliability. Logit model results align with the group results in comparable proportions. A group with a smaller mismatch proportion is also less likely to show a mismatch in the logit model. In the models, this pattern holds across nearly all variables, including field of education, level of education, and job sector. Additionally, the results confirm the stability and robustness of both measurement approaches.

From a policy perspective, the findings highlight the urgent need to improve labor market matching mechanisms. This can be achieved through enhanced information sharing, incentivizing active job search efforts via improved reward structures, and fostering on-the-job training programs to continuously upgrade employees' expertise and educational profiles. The issue of ability mismatch has recently garnered increased attention within labor market reforms due to its adverse effects on both individuals and society (Doan et al., 2018; Le Quang & Tran-Nam, 2019). The study's results indicate that workers who graduate in the fields of science, mathematics, and computing are at a high risk of being mismatched. Moreover, skilled workers generally experience lower mismatch rates compared to their unskilled counterparts. Notably, workers in the private sector seem to show a better fit between their jobs and their fields of education. In addressing these concerns, Vietnamese institutions of higher education are not yet accustomed to operating in a dynamic education sector as independent entities, where students can acquire education in skills and knowledge that are in high demand in the job market.

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