ผลกระทบของรายได้คาดหวังต่อการเลือกทำงานไม่ตรงสาขาที่เรียนในหมู่นักศึกษาจบใหม่

นายดล ตะวันพิทักษ์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาเศรษฐศาสตรมหาบัณฑิต
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Effect of Earnings Expectations on Major-Occupation Mismatch Decisions among New College Graduates

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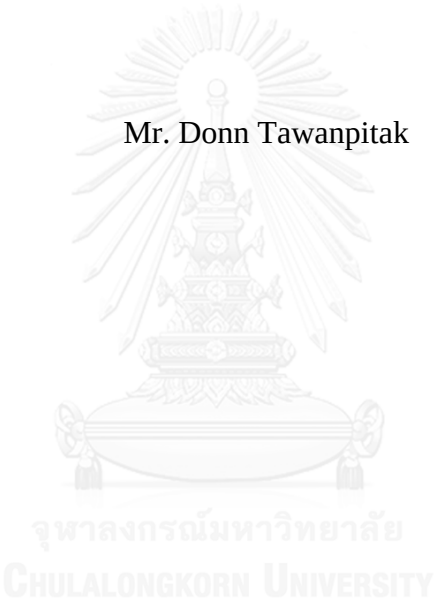

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ดล ตะวันพิทักษ์ : ผลกระทบของรายได้คาดหวังต่อการเลือกทำงานไม่ตรงสาขาที่เรียนในหมู่นักศึกษาจบใหม่ (Effect of Earnings Expectations on Major-Occupation Mismatch Decisions among New College Graduates) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: อ. ดร. เนื้อแพร เล็กเฟื่องฟู, 49 หน้า.

การทำงานไม่ตรงสาขาที่เรียนคือเหตุการณ์ที่นักเรียนหรือนักศึกษาเรียนจบออกมาในสาขาหนึ่งแต่กลับเลือกที่จะทำงานในอีกสาขาหนึ่งที่ไม่เกี่ยวข้องกัน การทำงานข้ามสาขานั้นแสดงว่านักเรียนหรือนักศึกษาจะขาดทักษะหรือความรู้บางอย่างที่จำเป็นไปซึ่งส่งผลให้การทำงานมีประสิทธิภาพลดลง ผลที่ตามมาคือผลตอบแทนที่จะได้รับจะลดลงไป สิ่งเหล่านี้แสดงให้เห็นว่าทั้งฝ่ายผู้ว่าจ้างและฝ่ายลูกจ้างต่างสูญเสียผลประโยชน์จากการทำงานไม่ตรงสาขาที่เรียน

วิทยานิพนธ์ชิ้นนี้มีจุดมุ่งหมายในการศึกษาปัจจัยที่มีผลต่อการตัดสินใจเลือกทำงานไม่ตรงสาขาที่เรียนโดยเน้นไปที่กลุ่มนักศึกษาจบใหม่ ปัจจัยที่เลือกศึกษาคือเงินเดือนคาดหวัง โดยศึกษาว่าเงินเดือนคาดหวังมีผลต่อการตัดสินใจดังกล่าวหรือไม่อย่างไร ข้อมูลที่ใช้นำมาจากประวัติผู้สมัครงานซึ่งอยู่ในเว็บไซต์หางานในประเทศไทย ผลลัพธ์จากการศึกษาแสดงให้เห็นว่าเงินเดือนคาดหวังมีผลต่อการตัดสินใจเลือกทำงานอย่างชัดเจน ถ้าหากอาชีพที่ไม่ตรงสาขามีเงินเดือนเพิ่มขึ้นโอกาสที่นักศึกษาจะหันไปเลือกอาชีพดังกล่าวก็จะเพิ่มขึ้นด้วย ขนาดของผลกระทบจากเงินเดือนคาดหวังนั้นขึ้นกับว่าสาขาที่นักศึกษาจบมานั้นฝึกฝนทักษะเฉพาะทางมากน้อยเพียงใด ผลกระทบจะสูงสำหรับนักศึกษาจากสาขาที่ฝึกทักษะเฉพาะทางในระดับที่เหมาะสม นักศึกษาที่มาจากสาขาที่มีความเฉพาะทางน้อยมากหรือสูงมากจะได้รับผลกระทบน้อยกว่า

ในเชิงนโยบาย ผลลัพธ์แสดงให้เห็นว่าการขึ้นเงินเดือนสามารถลดอัตราการทำงานไม่ตรงสาขาได้สำหรับบางอาชีพ โดยอาชีพเหล่านี้ต้องใช้ทักษะเฉพาะทางในระดับที่ไม่มากหรือน้อยเกินไป

สาขาวิชา เศรษฐศาสตร์ ลายมือชื่อนิสิต .....

ปีการศึกษา 2559 ลายมือชื่อ อ.ที่ปรึกษาหลัก .....

5885157029 : MAJOR ECONOMICS
KEYWORDS: MAJOR-OCCUPATION MISMATCH / HIGHER EDUCATION / OCCUPATIONAL CHOICE / SUBJECTIVE EXPECTATIONS

DONN TAWANPITAK: Effect of Earnings Expectations on Major-Occupation Mismatch Decisions among New College Graduates. ADVISOR: NUARPEAR LEKFUANGFU, Ph.D., 49 pp.

Major-occupation mismatch is a phenomenon where students graduated from one field of study but choose to work in another unrelated one. Due to lack of necessary skills and knowledge, the job is underperformed. As a result, the worker receives lower returns to education. These outcomes show that mismatch worse off both employer and employee.

This Thesis aims at studying a potential factor that contributes to decision to choose mismatch occupation among college graduates with focus on new graduates. The factor studied is earnings expectation, whether it has effect on decision for graduates to opt for mismatch occupation. Data used in this research comes from resumes obtained from online job market in Thailand. Results indicate that earnings expectation consistently has positive effect on probability of a choice to be chosen. If graduates expect higher earnings from a mismatch occupation, they will be more likely to choose it over the match one. Size of effect from earnings expectation depends on whether the major they graduated from trains general or specific skills. Mismatch probability changes significantly for graduates from majors that train an appropriate level of specific skills. Graduates from majors training either highly general or highly specific skills will be less responsive to earnings expectation changes.

For policy implication, the results indicate that raising earnings can reduce major-occupation mismatch for some occupations. They must require an appropriate level of specific skills, not too general or too specific.

Field of Study: Economics Student's Signature .....
Academic Year: 2016 Advisor's Signature .....

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Chapter 1: Introduction

1.1 Importance of horizontal mismatch problem

Postsecondary education, mostly known as college education, is one important phase of individual's life before he/she enters labor market. One aspect is that postsecondary education equips its students with skills necessary for working in some specific occupation. Upon matriculating in college, students will choose field of study, also known as college major, that suits their interested occupation. For example, students aim at working as electrical engineer should choose electrical engineering as their college major. Another aspect is that postsecondary education usually comes with high cost, both money and time. Decision to enroll in college is thus one big investment for every individual's life. From perspective of firms, all employers always want to have productive workers join them and perform jobs in their organization, so they could gain higher profit. The higher income of firms could somehow reflect higher earnings for individuals in the society, leading to higher welfare for the economy as a whole. When welfare becomes related, policy maker will also have to pay attention. So, it is always of interest for firms and policy maker to support production of these human resources.

One problem observed in labor market is that college graduates work in a job unrelated to their field of study. The phenomenon is called major-occupation mismatch, or horizontal mismatch. This creates losses for both employer and employee. For employer side, the mismatch worker will not be able to perform job at full capacity due to lack of some necessary skills and knowledge. Result is the job yields less productivity for firm. For employee side, on the other hand, as the job being underperformed, he/she will also receive less returns, in this case earnings. This is proven by findings from the growing body of literature of horizontal mismatch. All find negative impact of horizontal mismatch on earnings, with different degree in different major-job pairs. Compared to workers who graduated from the appropriate field of study, with the similar amount of money and time investment, they could reap more benefits from the job. These shows both employer and employee are worse off from being mismatched: lower productivity for firm and lower returns to education for worker. For the economy as a whole, welfare of the society would also drop.

As the problem becomes more and more prevalent nowadays, efficiency of economic activities would now decline sharper than ever. Thus, it is economist's job to explore, understand, and find a way to solve, or at least mitigate, this problem.

1.2 Objective

This research aims at being a starting point of exploration on factors that contributes to the major-occupation mismatch. In this research, I choose to study effect of earnings expectation on mismatch decision among college students, focusing on new graduates. This research would reveal whether earnings expectation has impact on mismatch decision and at how much degree. It will also analyze mismatch behavior of graduates from various college majors, whether they are similar or different. Finally, the research will suggest whether policy maker could reduce major-occupation mismatch through earnings intervention, such as setting minimum earnings for some occupations.

1.3 Expected benefits

This research will contribute knowledge to the sparse literature of horizontal mismatch by examining potential factor affecting major-occupation mismatch decision. In this case, economists will start to see how earnings expectation has impact on the mismatch decision. Empirical evidence found here will also give both economists and education-related policy makers a better understanding of the situation in the job market: how college graduates form earnings expectation, how responsive to earnings expectation they are, how many graduates want to switch to other occupation right after graduation, etc. Finally, results from this research will help suggest policy makers on what could be done to reduce major-occupation mismatch in the job market, at least for some occupations.

1.4 Scope of the study and limitations

There are two main scope of this study.

1. Only new college graduates are studied. The main reason for this is the potential learning occur during their past jobs. If college graduates already have some work experience, it is possible that they have entered the match job of their field of study and find it unpleasant, thus they switch afterward. Such behavior may not be considered as mismatch because they already tried the match job. Also, this case cannot be observed easily. To exclude such potential problem, I limit my analysis to only new college graduates.
2. Only those applied for full-time job are studied. This is because there are as much as four types of jobs in the market: full-time, part-time, intern, and freelance. Each has almost distinct structure of pay and working behavior. As majority of openings is full-time, and so as job seeker, I choose only college graduates who seek full-time job.

There are also some limitations for this study. Nevertheless, the research is still worth conducting.

1. Mismatch observed in this research is not actual mismatch, but rather "intention to be mismatched". Data used in this research reflects how college graduates think and expect about each occupation along with their chosen occupation choice. Results from this research are thus how mismatch decision of college graduate's changes when earnings expectation changes. I cannot observe whether the actual job they get is the match or mismatch one, so the actual mismatch in the job market may be different. For example, a college graduate indicates that he graduated from economics but he wants to work as a reporter with some level of earning expectation. However, if they actual offer is lower than his expectation, he might not accept the offer and instead return to his match occupation. Nevertheless, results remain fruitful as we will understand how these graduates think and react to changes in earnings expectation. No matter how the actual mismatch rate would be, these behaviors of college graduates will still be the same.
2. Results from the research may not represent the entire population. Observations used in this research are only those who used online job market to find job openings. Also, the market chosen consists of primarily middle and lower class of jobs. If these observations have some specific traits that are different from the rest of population, then results would be biased. However, from the fact that most households now have access to the Internet and that number of applicants is large, it is believable that they have no selection bias. Furthermore, since middle and lower class of jobs are the major portion of jobs in the market, results could represent majority of population, though not entirely.

Chapter 2: Literature Review

When people make decision about occupation, one aspect is to maximize their expected lifetime utility. An individual chooses an occupation that best match their skills and yield the most returns. But before individuals enter labor market, they must acquire skills necessary for their target occupation. These skills are mostly provided through education. So, individuals have to make schooling decision before entering labor market. At first, economists assume schooling to provide the same skill. Only number of years of schooling makes differences. Individuals thus make both schooling and occupation decision at the same time. Some remarkable researches in this approach are (Willis & Rosen, 1979), (Miller, 1984), and (Keane & Wolpin, 1997).

As the literature grows, heterogeneity in postsecondary education starts to play role. College education provides students with skills necessary for each specific occupation, not all the same as previously assumed. This lead to an emergence of research on college major choice. Students choose an optimal choice set to maximize their expected lifetime utility conditioned on their abilities and preferences. Earlier works have focused on monetary returns to major choice. For example, (Berger, 1988) found that major yielding higher earnings stream has higher probability to be chosen. Some research studied other factors affecting returns to college education, such as returns to mathematical ability (Paglin & Rufolo, 1990), college selectivity (Loury & Garman, 1995) and economic trend (Grogger & Eide, 1995). However, as research progress, economists started to find significant differences that cannot be explained by differences in earnings alone. Gender difference between majors (Turner & Bowen, 1999), probability to graduate from major (Montmarquette, Cannings, & Mahseredjian, 2002), and ability sorting (Arcidiacono, 2004) have been studied. All found that earnings can explain these phenomena but there remains large unexplainable portion.

To present, findings about domination between pecuniary and nonpecuniary returns in college major decision are quite mix. (Altonji, Blom, & Meghir, 2012) provides a very good review for this literature. Two examples are (Beffy, Fougère, & Maurel, 2012) and (Long, Goldhaber, & Huntington-Klein, 2015) who used expected earnings fluctuation caused by business cycle as a source of variation. (Beffy et al., 2012) studied in the context of France and Long et al. studied in the context of United States. (Beffy et al., 2012) argued that expected earnings have low impact, (Long et al., 2015) insisted that expected earnings have high impact on college major choice. This difference in conclusion may stem from difference in admission system between France and United States, or it could be other factors. Lately economists have started using subjective expectation in this field such as in studying college major choice (Arcidiacono, Hotz, & Kang, 2012; Wiswall & Zafar, 2015; Zafar, 2013). Nevertheless, some may criticize the results from these researches because they were conducted in extremely selective private college: Duke, Northwestern, and New York University respectively. These facts could be used to argue that students in these universities already have high level of ability and can expect high returns. In this research, I can shed further light on this argument. My samples are college graduates from institutions all over the country. One can expect a wide range of socio-economic background in this dataset. Results will then have no ability bias.

Though these literatures have progressed satisfactorily, there is a phenomenon that raise concerns among economists: education-occupation mismatch, which has become of interest recently. Education-occupation mismatch, hereafter horizontal mismatch, is a phenomenon where individuals graduated from one college major but work in another that is unrelated to their field. For example, student graduated from engineering major but instead work as a librarian. This kind of mismatch can be thought of specialization mismatch: some skills gained in college are unused. This leads to lower match quality and lower returns to investment because some invested human capital is not used. Two questions arise from this phenomenon are 1) why does it occur and 2) what effect does it has?

Literature of horizontal mismatch so far has focused on the second question: impacts of being mismatched. (Robst, 2007) used NSCG 1993 in his study and found that horizontal mismatch has negative effect on wages. Research following (Robst, 2007) also found the same result, for example (Nordin, Persson, & Rooth, 2010) in the context of Sweden and (Lemieux, 2014) in the context of Canada. (Altonji, Kahn, & Speer, 2016) also found drop in earnings from being mismatched. Those from a, seemingly, more specific college-major, such as STEM from (Science, Technology, Engineering, Mathematics), experience more severe penalty. This is probably due to its specificity of skills trained, so it is less portable. Those from more general major that skills are more portable experience less degree of penalty, consistent with (Gathman & Schönberg, 2010) who found high returns on task-specific skills because of less portability. (Kinsler & Pavan, 2015) and (Silos & Smith, 2015) focused on course bundles taken in college and found the same result. However, causes of horizontal mismatch remain unknown. Under conventional belief that students choose college major based on target occupation, horizontal mismatch might stem from learning processes. Learning occurs throughout college period both in term of students' fit to major and returns to major. Students receive information and update their expectations in rational ways. In the first two year, college students learn about of their abilities and tastes. (Stinebrickner & Stinebrickner, 2012) showed that students' dropout rate will reduce by 40% if no learning occurred. Also, students tend to be overoptimistic in their abilities. (Stinebrickner & Stinebrickner, 2014) indicated that students are mostly optimistic about taking science major at the time of matriculation. However only roughly one-third of those graduated with science major. In the last two years, students are having more accurate information about wages and the most accurate in their last year of study, found in (Dominitz & Manski, 1996) and (Bettes, 1996). Another possible cause may be a university admission system. (Bordon & Fu, 2015), who studied admission system in Chile, showed that under major-university specific admission system, uncertainty is even more severe as students have no time to learn about their fit to major before choosing one. Thailand's admission system also works this way. (Altonji, 1993), who studied in the context of university-specific system in USA, also pointed that students are still much uncertain about their choice of college major and occupation at the time of choosing college major, means that uncertainty is already high even in less restricted system. Furthermore, cost of switching is very high because, in general, they would have to dropout and re-admission again. As such, concluded in (Malamud, 2011), students may choose to stay in the university rather than dropout even if their fit to major is found low. Thus, students will graduate in one major but may choose to work in an occupation unrelated to their field of study.

Chapter 3: Conceptual Framework

The concept builds upon classical Roy's model of occupational choice. In decision making, life-cycle approach suggests that it is the present value of future earnings stream that matters, not initial earnings. Individuals then choose occupation to maximize their lifetime utility. I model individual's lifetime utility function U_{ijk} as:

$$U_{ijk} = \rho_{0jk} + \rho_{1j} Y_{ijk} + \mathbf{X_{ij}}\boldsymbol{\omega}_{\mathbf{jk}} \quad (1)$$

where Y_{ijk} is prediction of lifetime earnings by individual *i* who graduated from college major *j* for an occupation *k*. $\mathbf{X_{ij}}$ is a vector of individual's characteristics: gender, GPA, etc. Individual will choose occupation k_2 over k_1 if $U_{ijk_2} > U_{ijk_1}$. However, as this study examines effects on mismatch, that is choosing one occupation over another, we will not focus on utility itself but instead on comparative utility. When speaking about occupation mismatch, we always interested in difference between two occupations, mainly mismatch compared to the match. Utility gains from choosing occupation k_2 over k_1 is:

$$U_{ijk_2} - U_{ijk_1} = (\rho_{0jk_2} - \rho_{0jk_1}) + \rho_{1j}(Y_{ijk_2} - Y_{ijk_1}) + \mathbf{X_{ij}}(\boldsymbol{\omega}_{jk_2} - \boldsymbol{\omega}_{jk_1}) \quad (2)$$

The model implies higher likelihood for occupation k_2 to be chosen over k_1 if difference in lifetime earnings expectations rises: Y_{ijk_2} increases or Y_{ijk_1} decreases or both. I will call this difference a lifetime earnings expectation gap. The parameters $\rho_{0jk_2} - \rho_{0jk_1}$ and $\boldsymbol{\omega}_{jk_2} - \boldsymbol{\omega}_{jk_1}$ can be thought as compensated wage for accepting k_2 over k_1. $\rho_{0jk_2} - \rho_{0jk_1}$ is compensated wage based on occupation. It is independent of individual's characteristics. For example, consider an occupation of clerk compared to factory worker. Naturally, clerk offers better work environment in terms of safety and comfortability. Thus, for this pair, we can expect $\rho_{0j,clerk} - \rho_{0j,factory}$ to be positive. $\boldsymbol{\omega}_{jk_2} - \boldsymbol{\omega}_{jk_1}$ is compensated wage based on individual's characteristics. Consider gender in the context of previous example of clerk and factory worker. Given that women prefer safety more than men, as clerk offers more safety than factory worker, then $\boldsymbol{\omega}_{j,clerk} - \boldsymbol{\omega}_{j,factory}$ will be positive for women. The same method applies in case the occupation trait is indifference or discourages some gender.

Though the model first used lifetime earnings expectation gap in specification, empirical evidence from the literature helps simplify this matter. According to (Beaudry & DiNardo, 1991), (Baker, Gibbs, & Holmström, 1994), (Nordin et al., 2010), and (Altonji et al., 2016), earnings difference persists across firm-entry cohort and nominal raises are very stable throughout time regardless of occupation, roughly 10 percent. Real raises also seem stable at around 6 percent. This means real raise is also the same across occupations.

The above evidence that raises are equal both across occupations and time period allows me to assume the functional form of wage growth as:

ASSUMPTION 1: Real raises for all occupations are the same for all time period.

$$W_t = W_0 e^{rt}$$

where W_t is earnings at time *t*, W_0 is earnings at initial time t_0, and *r* is real yearly raise. Thus, real earnings gap between any two occupations becomes:

$$W_{k_2,t} - W_{k_1,t} = (W_{k_2,0} - W_{k_1,0})e^{rt}$$

From this point, we can calculate lifetime earnings gap using simple integration. Given that *T* is maximum years of working, lifetime earnings gap between two occupations is then:

$$Y_{k_2,t} - Y_{k_1,t} = \int_0^T (W_{k_2,t} - W_{k_1,t})\, dt = (W_{k_2,0} - W_{k_1,0})(\frac{e^{rT}-1}{r}) \qquad (3)$$

As *T* is constant for any single individual and *r* is always stable, the last term in equation (3) is then equivalent to a constant. Equation (3) therefore implies linear relationship between lifetime earnings gap and initial earnings gap. As this relation is regardless of individual and college major, we can substitute equation (3) into equation (2) to yield the new conceptual model as:

$$U_{ijk_2} - U_{ijk_1} = (\rho_{0jk_2} - \rho_{0jk_1}) + \rho_{1j}(W_{ijk_2} - W_{ijk_1}) + \mathbf{X_{ij}}(\boldsymbol{\omega}_{jk_2} - \boldsymbol{\omega}_{jk_1}) \quad (4)$$

where W_{ijk} is initial earnings expectation of individual *i* who graduated from college major *j* for an occupation *k*. This adaptation will not interfere with our later calculation of elasticity, or responsiveness, to earnings expectation as initial earnings gap exhibits linear relationship with lifetime earnings gap. However, interpretation of parameter ρ_{1j} will be effect of expectation of initial earnings instead.

There is another problem regarding decision making estimation: preference. Including preferences from individuals requires that dataset is specifically designed for such purpose. To mitigate this problem, I assume that:

ASSUMPTION 2: Unobserved preferences are homogeneous for graduates from the same college major.

The fact that students self-selected themselves into each major makes this assumption credible. When students choose any specific major, it means they find that major, or target occupation, pleasant. Students in the same major thus would share majority of preferences although there will still exist some idiosyncratic preferences. With this assumption, individual's personal preferences can be disregarded.

In Asian societies such as Thailand, even though there are evidence that parents have significant influence on children's educational decision, as mentioned in (Chao & Tseng, 2002), I believe this assumption remains valid for majority of students due to two reasons. First, parents are likely mandating whether to attain education rather than field of study, especially if it is the field unfamiliar by parents. Preference influenced by parents is considered self-preference, not mandated, and still qualify the assumption. Second, postsecondary education requires lots of effort. If students do not have aptitude for the chosen major, they are unlikely to survive through the degree. (Stinebrickner & Stinebrickner, 2012) shows that students are likely to drop out if they learn they cannot perform well in college. This should remain true regardless of societies.

Chapter 4: Data and Analysis

4.1 Data

Primary data source for this study comes from resumes obtained directly from a single online job market. They are available for viewing on the website for free and no registration is required. I retrieved resumes of all applicants since November 2006 until the end of October 2016, exactly 10 years or 120 months. For information related to job, each resume contains three occupation categories and positions applicant wishes to work. The categories are provided by the website but positions are typed by applicant himself. However, I will use only the first choice stated in order to preserve data consistency as applicants prior to 2014 can only state one position. It is also psychologically reasonable that the first choice is the most preferred position. Other information includes intended province, type of work (full-time, part-time, freelance, or internship), earnings expected, time to start working, availability to work abroad, and years of work experience. On personal information, it consists of age, gender, education profiles for all degree and level of study. Each profile has year of graduation, institution, degree, major, and GPA received.

In this study, I limit my analysis only to new college graduates, that is having no full-time work experience, and applied for full-time work only. There are two reasons for this. First, if applicants already have some work experience, I cannot rule out the possibility of learning during the previous position. Mismatch may occur because college graduates already worked in the match occupation and learned that they are unfit, and therefore they switch. Such reason is hard to observe and, in fact, cannot be observed from this dataset. Using only new graduates helps excluding such unobservable. Second, payment structure for part-time, freelance, and internship positions are much different from full-times. Majority of applicants are also applying for full-time positions. I therefore study only those applied to full-time position to represent norm in occupation behavior. The main dataset consists of 40,038 resumes with 39 majors and 38 occupations. See cleaning details in **Appendix A**.

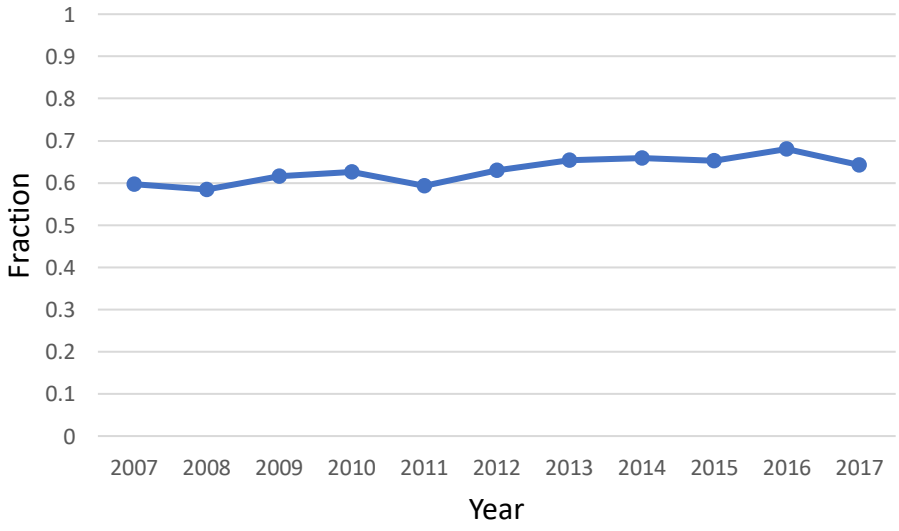
Table 1 presents summary statistics for this dataset. Mean age of graduation is 22.5 years old, close to actual age when creating resume, which makes the dataset credible that samples really are new graduates. In overall, roughly two-third are female. MISMATCH is defined as dichotomous variable equals to unity if individual's graduated major and his occupation choice does not match. Looking by gender, female clearly have higher mismatch rate than male by about one-third of male. Interestingly, however, women performed better in college as their average GPA is higher. Willingness to work abroad is indifferent. There are 5,186 resumes elicited earnings expectation as 0, account for 13 percent of total observations. I interpret as them "negotiable" and will compute them using a model presented later.

Table 1: Summary Statistics

VARIABLES	(1) All	(2) Male	(3) Female
Mismatch	0.40	0.32	0.44
	(0.49)	(0.47)	(0.50)
Female	0.64	-	-
	(0.48)	(0)	(0)
Abroad	0.12	0.12	0.12
	(0.33)	(0.33)	(0.33)
GPA	2.75	2.65	2.80
	(0.42)	(0.40)	(0.42)
Age	23.82	24.14	23.64
	(2.46)	(2.64)	(2.34)
Graduation Age	22.45	22.65	22.34
	(1.03)	(1.09)	(0.98)
Observations	40,038	14,299	25,739

Notes: Column displays summary statistics for each type of subsample by gender: all samples, male samples only, and female samples only respectively. Mismatch, Female, and Abroad are dichotomous variables. Mismatch equals 1 if individual's graduated major and his/her occupation choice does not match i.e. Finance major applies for Marketing job. Female equals 1 if individual is female. Abroad equals 1 if individual is willing to work abroad. Standard errors in parentheses.

Figure 1: Fraction of Female in Online Job Market by Year



4.2 Descriptive analysis

I will begin analysis by examining representativeness of the observations in this online job market. The first is to look at composition of gender in this market. **Figure 1** shows how fraction of female in this online job market changes over time. I exclude the year 2006 as there are only two months to observe: November and December. This will also apply to further analysis regarding structure of the online job market. The fraction modestly increases from 60 percent in 2007 to 65 percent in 2016 which means composition of gender in this the market is quite stable, so we can be sure that there is no exogenous factor affecting gender composition. Next is to investigate geographical background. Though this market does not show where each applicant comes from, it is still reliable that there should be no geographical bias. According to statistics from the Information and Communication Technology Survey in Household in 2016, conducted by National Statistical Office of Thailand, individuals age between 15 to 24 years having access to the Internet increases from 55 percent in 2012 to 86 percent in 2016 and is trending upward. This range of age is the group I focus on. So, we can be sure that access to the Internet shall not pose geographical bias. Applicant's location background is then credibly random. The last is to inspect types of occupation openings which is where problem starts to occur. The market comprises of only private sector jobs. This clearly raises problem of selection bias. Occupational choice behavior of applicants graduated from public-sector-oriented majors may then be biased which we will see soon. Another one, but with less concern, is class of jobs. According to the latest International Standard Classification of Occupations (ISCO-08), the group of Managers, Elementary Occupations, and Armed Forces Occupations are not represented. But as I focus on new college graduates, Managers will not be of concern due to experience restriction. College graduates will also be overeducated for Elementary Occupations such as laborer, cleaner, street workers, etc. At this point, the main problem would be selection bias of graduates from public-sector-oriented majors.

Before moving on to occupational choice behavior analysis, there is some event occurred worth mention. In late 2011, Thai Government has enacted the new minimum wage law to be in effect by early 2012. It mandates minimum daily wage of 300 Baht and minimum salary for college graduates of 15,000 Baht. Effect of the law is heterogeneous because each occupation is affected by the law differently. For example, occupations having standard earnings lower than 15,000 Baht are of course affected. Such occupations include general office works and most of business-related jobs. Occupations with standard earnings over 15,000 Baht, though unlikely to be affected, are also affected through spill-over effect. Such occupations are science and technology-related fields and other jobs requiring occupation specific skills. There are two complications in this law should be mentioned. First, not all provinces in the nation applied the law immediately. Seven provinces in Bangkok Metropolitan are designated as pilot area in April 2012. The rest 70 provinces applied the law in January 2013. To reduce complication for resumes in 2012, those applying for positions in Bangkok

Metropolitan are considered law-in-effect all year round and the rest remain unaffected.

Table 2 shows time-line of how effect the law is considered in-effect in this new definition. Second, though minimum daily wage of 300 Baht is applied across the nation, minimum salary of 15,000 Baht for college graduates is applied only to government sector but only encouraged for private one. Some firms apply this law accordingly while others do not. As a result, college graduates cannot entirely expect to have a minimum salary of 15,000 Baht in private sector, which is the kind of job in this research setting. This is actually an advantage because earnings expectations will not be truncated at 15,000 Baht. The law only set new average standard for each occupation so earnings expectations can still vary normally.

Table 2: Timeline of the New Minimum Wage Law

YEAR	New Minimum Wage Law	
	(1) Bangkok Metropolitan	(2) Other provinces
2011 or earlier	NO	NO
2012	YES	NO
2013 or after	YES	YES

Notes: YES means the law is in effect in the respective time period and NO otherwise. Column reports effect separately by geographic area of Thailand.

I will start choice behavior analysis by illustrating difference in characteristic variables between period before and after the law. **Table 3** provides summary statistics for resumes separately be gender and time period before and after the minimum wage law is in effect. Column 1 and 4 illustrates summary for overall samples. Two types of age and GPA remain the same for both periods. Overall mismatch rate rises from 36 to 42 percent. Mean earnings expectation increased about 3,000 Baht, over 25 percent, to the amount close to the mandated value of 15,000 Baht. Also rises sharply is willingness to work abroad, from a single person to a quintile. Column 2 and 5 shows data for male and column 3 and 6 shows for female. Women clearly have high probability to choose mismatch occupation than men, both before and after the law. Mismatch rate for men and women prior to the law is 30 and 41 percent respectively. Both rates increased equally by 5 percent after the law. This suggests women are more likely to be mismatched than men by default. Another interesting variable is earnings expectation. Female always expect less earnings than male, about 900 Baht, even though their academic performance is slightly higher. These apply both before and after the law.

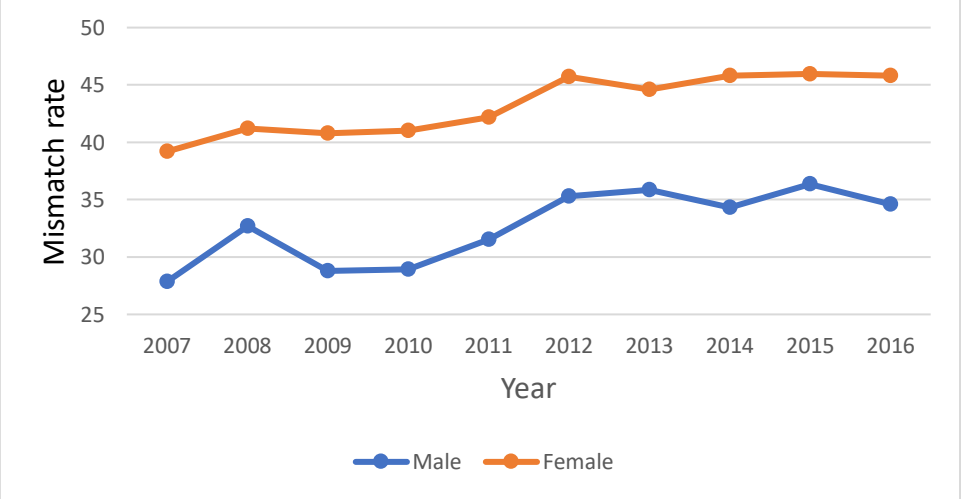
Table 3: Summary Statistics by Period of Minimum Wage Law

	Before Minimum Wage Law			After Minimum Wage Law		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	Male	Female	All	Male	Female
Earnings Expectation	11.5	12.1	11.2	14.6	15.1	14.4
	(2.9)	(3.0)	(2.7)	(2.8)	(2.9)	(2.7)
Log Earnings Expectation	9.32	9.37	9.29	9.57	9.60	9.56
	(0.24)	(0.24)	(0.23)	(0.19)	(0.20)	(0.19)
Mismatch	0.36	0.29	0.41	0.42	0.34	0.46
	(0.48)	(0.46)	(0.49)	(0.49)	(0.48)	(0.50)
Female	0.60	-	-	0.67	-	-
	(0.49)	(0)	(0)	(0.47)	(0)	(0)
Abroad	0.00	0	0.00	0.19	0.21	0.18
	(0.01)	(0)	(0.01)	(0.39)	(0.41)	(0.39)
GPA	2.71	2.62	2.77	2.77	2.68	2.81
	(0.41)	(0.39)	(0.41)	(0.42)	(0.41)	(0.42)
Age	23.83	24.20	23.59	23.81	24.10	23.67
	(3.04)	(3.25)	(2.87)	(2.07)	(2.14)	(2.02)
Graduation Age	22.49	22.73	22.34	22.43	22.60	22.34
	(1.04)	(1.10)	(0.97)	(1.02)	(1.07)	(0.98)
Observations	14,279	5,747	8,532	25,759	8,552	17,207

Note: Mismatch, Female, and Abroad are in the same way as Table 1. Earnings expectations are in thousand Baht. Standard errors in parentheses.

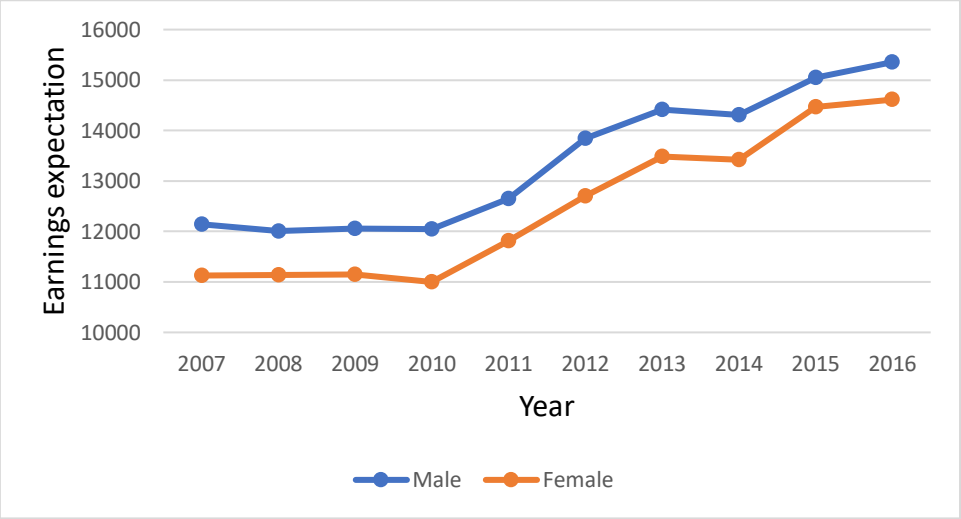
From the table, we will see that there are two potential factors that may contribute to rise in mismatch rate: earnings expectation and willingness to work abroad. We will therefore analyze them in more detail. **Figure 2**, **Figure 3**, and **Figure 4** shows, for male and female, how mismatch rate, earnings expectation, and willingness to work abroad changes overtime respectively. Mismatch rate increased significantly between 2011 and 2013 which is the period when earnings expectation clearly rose due to the new minimum wage law. Fraction of applicants willing to work abroad remained close to zero during this period but then rose sharply between 2014 and 2015. In this period, earnings expectation is raised somehow and also mismatch rate. From these figures, we start to see that rise in earnings expectation is the factor contributing to rise in mismatch rate. Willingness to work abroad is likely affect mismatch rate through raising earnings expectation. This is plausible as applicant who is willing to work abroad must be proficient in foreign language which could add value to him/herself. Interestingly, however, while mean earnings expectation is increased over 25 percent, mismatch rate rise is smaller at only 5 percentage point. I suspect that the rise in mismatch rate through earnings expectation is resulted from those who are already in college at the time of the law. When students realized that another occupation now have higher returns than previously expected, they may switch major if they find it beneficial. But under major-university specific system in Thailand where college students experience very high cost for switching, they may instead remain in their major but pursue occupation they realized having higher returns, as pointed out in (Malamud, 2011).

Figure 2: Overall Mismatch Rate by Year



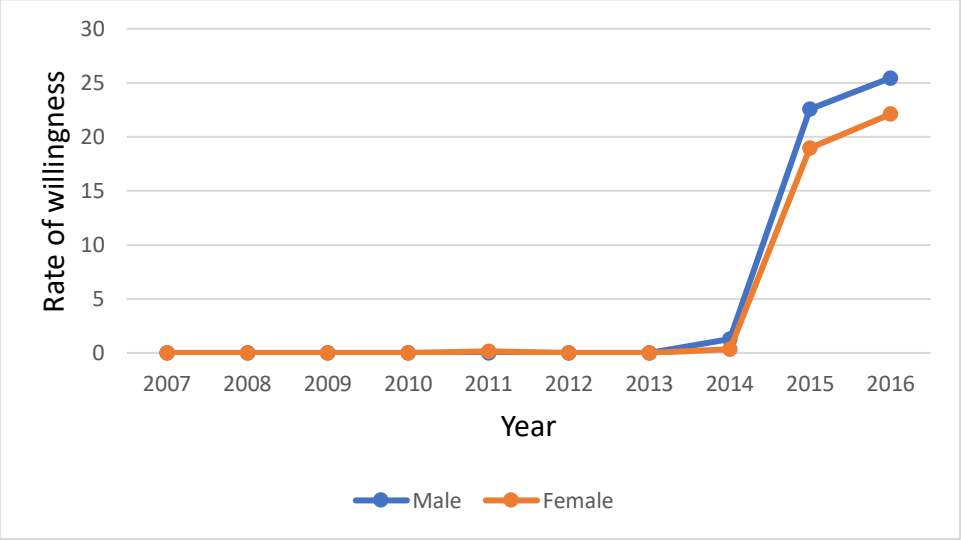
Note: Mismatch rates are presented in percentage.

Figure 3: Overall Earnings Expectation by Year



Notes: Earnings expectations are in Thai Baht (THB).

Figure 4: Overall Rate of Willingness to Work Abroad by Year



Notes: Rates of willingness to work abroad are presented in percentage.

Next, we will examine mismatch behavior of graduates from each college major and, again, separately by gender and time period of the minimum wage law. **Table 4** presents fraction of mismatch for each major broadly. For overall mismatch rate, Business, Science, ICT, and Engineering have quite low mismatch rate, generally 35 percent or less. In contrast, Education, Arts & Humanities, and Social Sciences have very high mismatch with all of them about 60 percent or more. The rest of majors including Agriculture, Health & Welfare, and Services have mismatch rate between 40 to 50 percent. At this point, we should start to recognize that specificity of skills might play role in determining mismatch rate as we know that science-related majors train primarily occupation specific skills while Arts & Humanities and Social Sciences focus more on general skills. For changes after the law, unlike overall mismatch rate in **Table 3**, it is not that all majors have its mismatch rate increased. Size and direction of changes are also heterogeneous. Nevertheless, except for ICT, changes in mismatch rate for male and female are still in the same direction.

To investigate further, **Table 5** illustrates each major in more detail level. For business-related majors, Accounting and Finance have far lower mismatch rate, probably because both are mathematics intensive. (Paglin & Rufolo, 1990) and (Kinsler & Pavan, 2015) found mathematical ability attributes largely to returns to education, which is a trait of specific skill. Thus, both majors and can be considered specific skill majors. The same inspection applies to Health Science which has as low mismatch rate as Science group. In contrary, Welfare are found being completely mismatched which is what contributes to high mismatch rate for Health & Welfare group. Likewise, for Services group, number of applicants from each major rise sharply while mismatch rate is either stable or decline. Community Sanitation, which is part to Public Health, and Occupational Health majors have their rate drastically decreased. Therefore, mismatch rate for Services group drops sharply. The previous inspection is further confirmed now that we see majors emphasizing occupation specific skills having lower mismatch rate while majors training general skills have higher rate, that is specificity of skills trained is negatively correlated with major-occupation mismatch rate. Mismatch rate between male and female are also close for male and female graduates from each major. Looking at composition of gender in each major, most majors have female more than male, except for Software Development and engineering-related majors that number of male is significantly higher than female. Compared between before and after the law, number of male and female in each major rise with the dominating gender remains dominate in number. This information tells us that most majors are dominated by women while Software Development and engineering-related majors are dominated by men. The domination also remains unchanged over time implying no significant change in structure of each major.

Table 4: Mismatch Rate for each Major (Broad-level)

		Before Minimum Wage Law			After Minimum Wage Law		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MAJORS (BROAD)	All	All	Male	Female	All	Male	Female
Education	65.4	64.4	69.4	59.8	65.8	73.0	63.4
	(1,013)	(326)	(157)	(169)	(687)	(174)	(513)
Arts & Humanities	58.8	56.4	48.3	59.7	60.0	57.4	61.1
	(3,797)	(1,248)	(358)	(890)	(2,549)	(742)	(1,807)
Social Sciences &	79.3	71.4	70.8	71.8	83.4	81.7	84.3
Journalism & Information	(3,951)	(1,331)	(523)	(808)	(2,620)	(929)	(1,691)
Business & Law	35.4	30.6	31.6	30.3	38.3	40.2	37.7
	(10,843)	(4,137)	(1,136)	(3,001)	(6,706)	(1,523)	(5,183)
Natural Sciences	23.5	25.0	29.1	23.2	22.8	25.1	22.3
	(2,595)	(769)	(230)	(539)	(1,826)	(358)	(1,468)
ICT	37.6	37.2	29.9	43.3	37.9	20.5	53.9
	(5,587)	(2,077)	(953)	(1,124)	(3,510)	(1,685)	(1,825)
Engineering &	14.8	11.4	8.8	17.3	17.3	12.7	23.0
Manufacturing	(6,524)	(2,736)	(1,903)	(833)	(3,788)	(2,101)	(1,687)
Agriculture	41.1	41.0	26.8	50.0	41.1	33.1	44.6
	(1,797)	(588)	(228)	(360)	(1,209)	(369)	(840)
Health & Welfare	47.7	29.9	38.2	27.0	62.2	67.7	60.7
	(891)	(398)	(102)	(296)	(493)	(99)	(394)
Services	45.2	62.3	49.0	66.4	40.3	33.6	42.5
	(3,040)	(669)	(157)	(512)	(2,371)	(572)	(1,799)

Notes: The table presents mismatch rate in percentage for graduates from the respective major. Total number of observation in parentheses.

Table 5: Mismatch Rate for each Major (Detail-level)

		Before Minimum Wage Law			After Minimum Wage Law		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MAJORS (DETAIL)	All	All	Male	Female	All	Male	Female
Education	65.4	64.4	69.4	59.8	65.8	73.0	63.4
	(1,013)	(326)	(157)	(169)	(687)	(174)	(513)
Arts	52.1	41.4	39.6	43.1	55.9	56.9	55.2
	(1,529)	(401)	(192)	(209)	(1,128)	(490)	(638)
Humanities	86.3	87.0	72.2	96.4	86.1	89.5	85.0
	(197)	(46)	(18)	(28)	(151)	(38)	(113)
Languages	61.2	62.2	56.8	63.4	60.6	52.8	62.1
	(2,071)	(801)	(148)	(653)	(1,270)	(214)	(1,056)
Economics	63.0	39.4	33.0	42.9	77.0	68.0	81.5
	(746)	(277)	(100)	(177)	(469)	(156)	(313)
Political Science	98.3	98.5	98.2	98.8	98.3	97.6	98.7
	(1,924)	(602)	(273)	(329)	(1,322)	(501)	(821)
Psychology	85.6	100.0	100.0	100.0	81.5	85.7	80.3
	(201)	(44)	(7)	(37)	(157)	(35)	(122)
Journalism	47.9	42.7	38.8	45.0	51.3	49.5	52.5
	(871)	(349)	(129)	(220)	(522)	(198)	(324)
Library & Information	87.6	93.2	85.7	95.6	85.3	92.3	82.9
	(209)	(59)	(14)	(45)	(150)	(39)	(111)
Accounting	17.8	7.7	8.8	7.6	24.5	19.7	24.9
	(2,713)	(1,074)	(125)	(949)	(1,639)	(147)	(1,492)
Finance	20.4	28.5	36.5	26.3	16.3	21.8	15.4
	(872)	(295)	(63)	(232)	(577)	(78)	(499)

Management	54.4	56.9	68.2	52.8	53.1	68.1	48.2
	(3,525)	(1,217)	(321)	(896)	(2,308)	(565)	(1,743)
Marketing	41.9	33.3	23.4	38.6	48.9	36.2	53.6
	(2,364)	(1,061)	(371)	(690)	(1,303)	(354)	(949)
Law	19.3	11.2	7.4	15.4	23.8	14.2	31.0
	(1,369)	(490)	(256)	(234)	(879)	(379)	(500)
Biological Sciences	15.6	19.5	17.2	20.2	14.3	17.3	13.8
	(892)	(221)	(58)	(163)	(671)	(104)	(567)
Environmental Sciences	32.0	29.2	31.8	28.4	32.9	28.4	34.2
	(388)	(96)	(22)	(74)	(292)	(67)	(225)
Physical Sciences	17.7	17.5	24.0	14.3	17.7	19.8	17.2
	(872)	(314)	(104)	(210)	(558)	(111)	(447)
Mathematics & Statistics	43.3	47.8	54.4	44.6	41.3	40.8	41.5
	(443)	(138)	(46)	(92)	(305)	(76)	(229)
Computer Use	47.2	44.4	28.8	54.4	48.7	27.4	64.4
	(3,965)	(1,355)	(531)	(824)	(2,610)	(1,106)	(1,504)
Software Development	14.1	23.7	31.3	13.0	6.4	7.4	4.7
	(1,622)	(722)	(422)	(300)	(900)	(579)	(321)
Industrial Engineering	21.6	14.3	14.2	14.4	30.0	12.6	50.3
	(723)	(386)	(261)	(125)	(337)	(182)	(155)
Chemical Engineering	9.6	5.4	6.2	4.8	13.8	12.4	14.7
	(438)	(221)	(97)	(124)	(217)	(81)	(136)
Environmental Engineering	17.5	13.1	8.3	16.2	18.9	13.2	22.6
	(252)	(61)	(24)	(37)	(191)	(76)	(115)
Electrical Engineering	10.6	6.4	4.6	23.5	13.8	11.2	28.6
	(833)	(361)	(327)	(34)	(472)	(402)	(70)
Electronics Engineering	11.4	6.4	4.2	16.4	17.3	16.5	22.0
	(701)	(378)	(311)	(67)	(323)	(273)	(50)
Mechanical Engineering	20.3	14.7	9.8	50.0	25.3	15.7	59.6
	(1,166)	(545)	(479)	(66)	(621)	(485)	(136)

Food Technology	12.1	12.0	12.9	11.7	12.1	18.0	11.3
	(1,002)	(301)	(70)	(231)	(701)	(89)	(612)
Manufacturing	34.4	33.2	28.6	40.9	35.4	27.9	44.2
	(404)	(178)	(112)	(66)	(226)	(122)	(104)
Architecture	10.2	6.8	4.1	10.0	12.4	7.0	16.2
	(226)	(89)	(49)	(40)	(137)	(57)	(80)
Civil Engineering	4.6	4.2	2.9	9.3	4.8	0.9	10.5
	(779)	(216)	(173)	(43)	(563)	(334)	(229)
Agriculture	41.1	41.0	26.8	50.0	41.1	33.1	44.6
	(1,797)	(588)	(228)	(360)	(1,209)	(369)	(840)
Health Sciences	21.5	11.2	11.3	11.2	34.7	22.2	36.8
	(558)	(313)	(71)	(242)	(245)	(36)	(209)
Welfare	91.6	98.8	100.0	98.2	89.1	93.6	87.6
	(333)	(85)	(31)	(54)	(248)	(63)	(185)
Domestic Science	52.4	50.0	46.2	51.2	53.2	36.4	57.1
	(227)	(54)	(13)	(41)	(173)	(33)	(140)
Hotel & Travel & Tourism	64.0	69.6	51.8	73.6	60.9	60.0	61.1
	(1,248)	(450)	(83)	(367)	(798)	(155)	(643)
Sports Science	27.4	40.0	35.5	55.6	20.6	11.9	32.3
	(113)	(40)	(31)	(9)	(73)	(42)	(31)
Community Sanitation	21.6	27.5	20.0	29.3	21.0	20.9	21.0
	(536)	(51)	(10)	(47)	(485)	(67)	(418)
Occupational Health/Safety	2.2	25.0	-	25.0	1.4	2.6	1.1
	(225)	(8)	(0)	(8)	(217)	(38)	(179)
Transportation and Logistics	43.9	68.2	75.0	65.2	41.3	28.3	49.2
	(691)	(66)	(20)	(46)	(625)	(237)	(388)

Note: The table is presented in the same way as Table 4.

We should now go back to the selection bias mentioned earlier. From the table, graduates from Education, Humanities, Political Science, Psychology, Library Science, and Welfare are consistently having very high mismatch rate. Consider carefully, we can see all these are majors intended for public sector, not private. As the market has no public-sector jobs, graduates from these majors presenting in this market are likely having selection bias, participate with intention to choose mismatch occupation, just as analyzed before. I will thus exclude these majors from estimation and later analyses.

Chapter 5: Empirical Method

5.1 Econometric model

I adopt conditional logit model in this study as it does not change parameters interpretation. Using McFadden's logit transformation, the model in equation (4) turns into:

$$\ln\left(\frac{P_{ijk_2}}{P_{ijk_1}}\right) = (\rho_{0jk_2} - \rho_{0jk_1}) + \rho_{1j}(W_{ijk_2} - W_{ijk_1}) + \mathbf{X_{ij}}(\boldsymbol{\omega}_{jk_2} - \boldsymbol{\omega}_{jk_1}) \quad (5)$$

where P_{ijk} is probability that individual *i* who graduated from college major *j* will opt for occupation *k*. However, this model requires normalization in order to estimate its parameters. One alternative k_0 must be used as a comparison reference, that is parameters ρ_{0jk_0} and $\boldsymbol{\omega}_{jk_0}$ are considered zero. As I am interested in comparison between mismatch alternatives and the match one, I choose the match as a reference. The model is simplified into:

$$\ln\left(\frac{P_{ijk}}{P_{ijk_0}}\right) = \beta_{0jk} + \beta_{1j}(W_{ijk} - W_{ijk_0}) + \mathbf{X_{ij}}\boldsymbol{\theta}_{\mathbf{jk}} \quad (6)$$

where $k \neq k_0$. k_0 indicates the match occupation which depends on graduated major *j*. See **Table A2** in **Appendix A** for the defined match occupation for each college major. W_{ijk} and W_{ijk_0} is initial earnings expectation for mismatch occupation *k* and the match occupation k_0 respectively. $\mathbf{X_{ij}}$ consists of characteristic variables that relate to mismatch decision, in this context GPA and gender. All parameters are utility gain from choosing mismatch occupation over the match one given respective variable.

In the dataset, however, the maximum of one W_{ijk} is observed for all *k*. To overcome this problem, I estimate the missing values using earnings expectations reported by other individuals from the same major who apply to that missing occupation. Following ***Assumption 2***, graduates from the same college major will also form earnings expectation for a particular occupation in the same way. Thus, this method would yield consistent estimation. Missing expectations are then estimated using Mincer-type earnings equation, specified as:

$$\ln(W_{ijk}) = \alpha_{0k} + \alpha_{1k}\mathrm{MWL} + \mathbf{Z_{ijk}}\boldsymbol{\lambda}_{\mathbf{k}} + \varepsilon_{ijk} \quad (7)$$

where MWL is binary variable equals to unity if the new minimum wage law is in effect at the time of creating resume. $\mathbf{Z_{ijk}}$ is vector of characteristic variables for both the individual and the job and ε_{ijk} is error term. As we focus on new college graduates, there is no experience variable in the model. MWL is used to capture an exogenous effect of the enacted minimum wage law on college graduate's expectations as it would lead to expectation revision, the same way as the experiment conducted in Wiswall and Zafar (2015) where external information is provided to students and they revised their expectations accordingly. $\mathbf{Z_{ijk}}$ is practically $\mathbf{X_{ij}}$ with characteristic variables of the applied position, such as year of application, intended province of work, availability to work abroad, etc. These are variables likely to have effect on earnings expectation but not on mismatch decision.

5.2 Identification strategy

The process consists of two steps. Firstly, unobserved earnings expectation is estimated for all pair of k and k_0, using model in equation (7). To preserve normality, only pairs with 30 or more observations are considered. The model is estimated separately for each occupation choice because effect of the law depends on job. Also, in this scenario, control variables implicitly interact with the occupation. However, I do not estimate the model separately for male and female, even though many have suggested there exists difference between men and women in expectations, as it seems not an issue in this case. **Table 6** presents regression results from the model controlling for all variables and interactions. Column 1 are results using all sample. Column 2 and 3 regressed only for male and female respectively. We can see results for male and female are almost indifferent. There are two interesting results worth mention. First, negative effect caused by being female is approximately equal to difference in parameter of GPA between women and men. This likely tells us that gender difference only reflects different weight put on GPA when forming earnings expectations. As such, instead of regress separately for each gender, estimation using gender as control variable seems valid in this case. This is contrary to actual earnings found between gender. Second, mismatch has no effect on earnings expectation for both male and female, which means graduates do not expect to earn less in the chosen occupation compared to those graduated from the match major. Again, this contradicts to actual earnings found in previous works on major-occupation mismatch. These implies graduates think that all individuals are equivalent regardless of major and gender.

Table 6: OLS Regression for Earnings Expectations

VARIABLES	(1) All	(2) Male	(3) Female
Year	2.46***	2.25***	2.62***
	(0.0829)	(0.141)	(0.103)
Mismatch	5.65	4.89	-35.3
	(16.2)	(16.6)	(33.7)
Female	-1.39***		
	(0.211)		
Abroad	4.12***	4.18***	4.09***
	(0.270)	(0.467)	(0.333)
GPA	4.42***	5.38***	3.93***
	(0.223)	(0.400)	(0.270)
Observations	34,852	11,935	22,917
R-squared	0.538	0.550	0.545
Major-Job interaction	YES	YES	YES
Major-Law interaction	YES	YES	YES

Notes: Column displays regression results for each type of subsample by gender: all samples, male samples only, and female samples only respectively. Results are presented in percentage. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Secondly, the obtained estimates are used to regress occupational choice model.[1] Similar to the first step, I estimate the model separately for each college major. The first reason is to avoid selection problem as graduates from different major may have different taste on jobs. For example, graduates from Mathematics major may not fond of memorization tasks so they would avoid Law and Biology jobs. The second reason is the match occupation for each major differs. Estimation by college major makes the process more convenient. Unusually though, there are only two control variables here: GPA and gender. There are findings that students underperformed in their own major will either shift or dropout. See e.g. (Stinebrickner & Stinebrickner, 2012), (Stinebrickner & Stinebrickner, 2014), and (Avery, Gurantz, Hurwitz, & Smith, 2017). There are also large number of evidence documented regarding gender role and gender preferences in occupations. See e.g. (Hunt, 2016) and (Lordan & Pischke, 2016). Other observed variables are unlikely to affect decision to choose mismatch occupation so they are not included. Age is automatically excluded because of studying scope that focuses on new college graduates, thus their age has too small range. Nevertheless, due to availability of data, I cannot rule out the possibility of omitted variable problem which could lead to overestimation of parameters, but the model will still yield consistent estimates.

[1] The bottom 1 percent of accepted gaps in each major are excluded to prevent negative outliers, that is those choose the job even if it gives extremely lower earnings.

Chapter 6: Results

Out of original 39 majors in the dataset, 23 majors are excluded from the estimation so there are only 16 majors reported. From the descriptive analysis section, 6 majors are excluded because of likeliness of market selection bias. Another 17 majors, from their predicted mismatch probability, I cannot reject that their mismatch rate is significantly different from zero. Therefore, we should make another summary statistics to see if the exclusion changes characteristics of overall samples significantly.

Table 7: Summary Statistics of Estimable Samples

VARIABLES	(1) All	(2) Male	(3) Female
Mismatch	0.42	0.37	0.45
	(0.49)	(0.48)	(0.50)
Female	0.69	-	-
	(0.46)	(0)	(0)
Abroad	0.12	0.12	0.12
	(0.32)	(0.32)	(0.32)
GPA	2.75	2.66	2.79
	(0.42)	(0.41)	(0.42)
Age	23.80	24.08	23.67
	(2.50)	(2.64)	(2.42)
Graduation Age	22.41	22.57	22.33
	(1.01)	(1.07)	(0.98)
Observations	26,291	8,059	18,232

Notes: The table presents results in the same way as Table 1

Table 7 presents summary statistics of this estimable samples. Even though some portion of samples is excluded, overall results are still almost identical to that of overall samples shown in **Table 1**. Portion of mismatch and female increases slight by 2 percent and 5 percent respectively. Rate of willingness to work abroad, GPA, age, and age at graduation remain unchanged. These results tell us that natural characteristics of overall sample is still the same and that the exclusion will not alter our main findings.

Table 8 presents regression results of the conditional logit model for each major, ranking by size of effect from largest to smallest and separately by (perceived) specificity of skills trains. The table shows that earnings expectation has positive and significant effect on probability for occupation choice to be chosen. This applies to graduates from every college major. The results imply that when earnings expectation of the choice rises, whether match or mismatch, individual will be more likely to choose the choice. This is straightforwardly intuitive because higher earnings mean higher utility to gain compared to other choices. Size of effect between majors training general skills and specific skills are quite distinct with specific skill majors has larger size of effect. This means changes in earnings expectation has larger impact on choice probability for graduates from specific skill majors than from general skill majors.

Table 8: Parameter Estimates of Earnings Expectation

Panel A: General Skills		Panel B: Specific Skills	
Majors	Earnings Expectation	Majors	Earnings Expectation
Agriculture	0.192*** (0.029)	Manufacturing	0.231*** (0.063)
Computer Use	0.175*** (0.016)	Finance & Banking	0.207*** (0.055)
Management	0.156*** (0.015)	Accounting	0.178*** (0.032)
Transportation and Logistics	0.148*** (0.045)	Health Sciences	0.170*** (0.045)
Marketing	0.122*** (0.020)	Software Development	0.164*** (0.023)
Languages	0.105*** (0.015)	Mathematics and Statistics	0.164*** (0.079)
Hotel, Travel, and Tourism	0.085*** (0.025)		
Economics	0.076* (0.041)		
Arts	0.073*** (0.016)		
Journalism	0.055* (0.032)		

Notes: Standard errors in parentheses. Unit of earning expectation is thousand Baht.
*** p<0.01, ** p<0.05, * p<0.1

To give further picture on scale of effect, and also to prevent problem of variable's measurement unit, I will next present results in term of elasticity of mismatch probability to changes in earnings expectation. I will focus on effect from changes in W_{ijk_0} for a couple reasons. First, students are more well informed about information related to their field of study, as mentioned in (Dominitz & Manski, 1996) and (Bettes, 1996). In this case, they are more likely to recognize changes in their match occupation. Second, effect from changes in other W_{ijk} are smaller than from W_{ijk_0}. Consider a case when W_{ijk_1} rises while all other W_{ijk} remain stable as an example. P_{ijk_1} definitely will increase while other P_{ijk}, including P_{ijk_0}, must decrease. However, as all probability must add up to one, each will then decline at smaller degree than the increase in P_{ijk_1}. That is, change in probability to choose match occupation P_{ijk_0} will be smaller, hence also mismatch probability $1-P_{ijk_0}$.

From equation C.I in **Appendix C**, elasticity of probability to choose mismatch occupation $1-P_{ijk_0}$ when earnings expectation of the match choice W_{ijk_0} changes is $-\beta_{1j}P_{ijk_0}W_{ijk_0}$. **Table 9** reports elasticities of mismatch probability when earnings expectation of the match occupation varies. All elasticities are negative in value, implying that mismatch probability will decline when earnings expectation of the match occupation rises. Not surprisingly, increase in earnings expectation of the match choice means the choice gives higher returns compared to mismatch choices. As such, individual will be more likely to choose the match choice and hence lowering mismatch probability. Size of elasticities are mostly one or higher which means college graduates are quite elastic to earnings expectation. Compared between type of major, range of the elasticity is clearly distinct. Elasticity for graduates from majors training specific skills are larger in size, roughly 2 or higher, than that of graduates from majors training general skills. Ranking of size is also similar to ranking in parameter estimate in **Table 8**. This could possibly mean size of the elasticity may positively correlated specificity of skills trained in major.

Table 9: Elasticities of Mismatch Probability to Changes in Earnings Expectation of the Match Occupation

Panel A: General Skills		Panel B: Specific Skills	
Majors	Earnings Expectation	Majors	Earnings Expectation
Agriculture	-1.58 (0.49)	Manufacturing	-2.46 (0.79)
Computer Use	-1.32 (0.61)	Finance & Banking	-2.33 (0.56)
Management	-0.90 (0.35)	Accounting	-1.93 (0.53)
Transportation and Logistics	-1.39 (0.40)	Health Sciences	-2.37 (0.61)
Marketing	-0.97 (0.34)	Software Development	-2.05 (0.55)
Languages	-0.62 (0.26)	Mathematics and Statistics	-1.92 (0.47)
Hotel, Travel, and Tourism	-0.43 (0.14)		
Economics	-0.43 (0.14)		
Arts	-0.55 (0.14)		
Journalism	-0.43 (0.12)		

Notes: Standard errors in parentheses.

Though the above results seem fascinating at first, we must interpret them with care. If we look back at the elasticity equation $-\beta_{1j}P_{ijk_0}W_{ijk_0}$, we will see that elasticity depends on current match probability P_{ijk_0}, the counterpart of mismatch probability. The smaller mismatch probability, the larger elasticity will be. Therefore, we should also analyze behavior of mismatch probability before making such conclusion. **Table 10** illustrates predicted mismatch probability of graduates from each major. As expected, mismatch probability is clearly lower for graduates from specific skill majors, implying higher match probability than graduates from general skill majors. At this point, we see that both parameter estimates and match probability for specific skill majors are larger than general skill majors which explains why elasticity for the former is clearly larger than the latter. Therefore, we should not yet make the conclusion on responsiveness of graduates from each type of major.

Table 10: Predicted Mismatch Probability

Panel A: General Skills		Panel B: Specific Skills	
Majors	Earnings Expectation	Majors	Earnings Expectation
Agriculture	36.4*** (12.1)	Manufacturing	22.9** (10.1)
Computer Use	43.1** (19.2)	Finance & Banking	14.5** (6.6)
Management	53.6*** (12.9)	Accounting	13.7** (6.1)
Transportation and Logistics	36.9*** (13.2)	Health Sciences	12.4* (7.1)
Marketing	39.4*** (12.4)	Software Development	13.3* (8.0)
Languages	58.0*** (9.7)	Mathematics and Statistics	19.0*** (6.6)
Hotel, Travel, and Tourism	60.5*** (7.3)		
Economics	57.5*** (8.4)		
Arts	48.4*** (7.2)		
Journalism	40.4*** (7.6)		

Note: Probabilities are presented in percentage. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

To actually see how responsive graduates are to changes in earnings expectation, we should also look at how mismatch probability changes when earnings expectation of the match choice changes by percentage instead. The way to do so is by multiplying their elasticity with their current mismatch probability. From equation C.II in **Appendix C**, probability change in percentage point when earnings expectation of the match occupation increases by 1 percent is $-\beta_{1j}P_{ijk_0}(1-P_{ijk_0})W_{ijk_0}$. **Table 11** reports mismatch probability change when earnings expectation for the match occupation increases by 1 percent for each major. Results are presented in percentage point. In general, increases the earnings expectation by 10 percent can reduce mismatch rate by 2.5 to 5 percentage point. Ranking in size of probability change is almost identical to parameter estimates in **Table 8** for both types of major. When examine separately between type of major, percentage point change of mismatch probability for general skill majors spans wider. Specific skill majors have size of change concentrates between 2.5 and 3.5 for 10 percent increase in the earnings expectation. At this point, we can conclude that graduates from majors training general skills are generally more responsive to changes in earnings expectation than those from majors training

occupation specific skills. Raising earnings expectation by 10 percent would reduce likelihood of mismatch by at least 2.5 percentage point and may be more depends on the major applicants graduated from.

Table 11: Mismatch Probability Changes to Percent Change in Earnings Expectation of the Match Occupation

Panel A: General Skills		Panel B: Specific Skills	
Majors	Earnings Expectation	Majors	Earnings Expectation
Agriculture	-0.53 (0.12)	Manufacturing	-0.51 (0.15)
Computer Use	-0.47 (0.13)	Finance & Banking	-0.31 (0.11)
Management	-0.44 (0.10)	Accounting	-0.24 (0.08)
Transportation and Logistics	-0.46 (0.09)	Health Sciences	-0.26 (0.09)
Marketing	-0.35 (0.08)	Software Development	-0.24 (0.11)
Languages	-0.34 (0.08)	Mathematics and Statistics	-0.34 (0.09)
Hotel, Travel, and Tourism	-0.25 (0.06)		
Economics	-0.24 (0.05)		
Arts	-0.26 (0.04)		
Journalism	-0.17 (0.03)		

Notes: Probability changes are presented in percentage point. Standard errors in parentheses.

If we analyze characteristics of each major further, even though subjectively, we would reach additional conclusion regarding size of responsiveness. Looking at each panel in **Table 11** majors with low responsiveness are likely to represent very strong trait of the group. Arts, Journalism, and Hotel majors are very general in nature. Languages, Transportation, and Computer Use seems to have more specific skills trained in major. On the other hand, Accounting, Software Development, and Health Sciences are very specific in occupation while skills trained in Finance, Mathematics, and Manufacturing majors seems more portable. Given these, we may add that responsiveness to changes in earnings expectation will be larger for graduates from

majors that train appropriate portion of general and specific skills. The major must neither be too general nor too specific in skills trained.

In term of policy implication, these results suggest that raising earnings of an occupation can be an effective solution to reduce major-occupation mismatch for majors which train specific skills at an appropriate level. As shown in **Table 10**, graduates from these majors are having moderate mismatch probability. Intervention on earnings can reduce these intentions significantly. For majors training very specific skills, such as science/engineering-related fields, their graduates will already have small intention to mismatch so it is not very much of concern. Shifting is likely caused by something else unrelated to personal profile, such as actual job pay being much lower than expected. For majors training very general skills, their mismatch rate would be too large while their responsiveness to changes in earnings is small. The amount of earnings increase required may be too much to intervene.

Chapter 7: Conclusion

In this article, I have demonstrated that earnings expectation consistently affect decision for major-occupation mismatch among recent graduates. Rise in earnings expectation of the occupation choice increases the chance it will be chosen. Also, specificity of skills trained in the major plays role in determining whether the size of effect will be large or small. From the estimation result, sizes of effect are quite distinct between general and specific skills majors with earnings expectation has smaller impact on the former. When further consider percentage point of probability change, the distinction becomes blurred. Rise in earnings expectation of the match occupation by 10 percent will reduce mismatch probability by at least 2.5 percentage point and could be larger depends on major. Graduates from majors training specific skills at a moderate portion are those most affected by changes in earnings expectation. Raising their respective match occupation earnings by 10 percent can reduce mismatch rate up to 5 percentage point, double of the minimum. Graduates from majors training very general and very specific skills have the smallest level of responsiveness to changes in earnings expectation. Both groups have comparable size of responsiveness, with the latter slightly more than the former. Additional analysis shows that academic performance consistently has negative impact on mismatch decision.

For policy maker interested in reducing major-occupation mismatch, results imply that increase earnings in an occupation of interest is effective if the occupation requires appropriate level of specific skills. Mismatch intention among graduates from very specific majors is already small so there is no need to worry. For graduates from very general majors, there is little to none that the policy maker can do. Actual mismatch rates in job market may be higher if actual earnings offers are lower than graduates' expectation.

7.1 Discussion and Suggestion

The research has four caveats need to be addressed. The first is a problem of omitted variable. Due to availability of data, I cannot rule out the possibility of omitted variable problem which could lead to overestimation of parameters. As seen in the model, there are only two control variables: GPA and gender, which is quite low in number, so the problem is likely.

Second, specificity of skills used in this research are all "perceived" as I cannot find any numerical measure of specificity of skills trained in major. These specificities are based on normative intuition. In the future, if the measure become available and further evidence is found, this conclusion may be disputable. For now, these specificity perceptions will remain useful for the conclusion.

The third is that I cannot observe true behavior of graduates from majors intended for public sector. Due to market bias discussed in analysis section, their behavior observed here is distorted and I excluded them from the analyses. These majors are primarily member of general skill major. Therefore, I need to leave some room in the conclusion in case that, if found, these majors have some unexpected characteristics.

The last point is regarding mismatch rates. Predicted mismatch rates presented are “intention”, not “actual” mismatch occurred in the market. Real mismatch in the market will be equal to the result presented here if earnings offers are equal to graduate’s expectation. If the actual mismatch rate is higher or lower, then it could mean the actual pay structure is lower or higher respectively. Nevertheless, this fact of mismatch rates will not interfere with mismatch behavior. Graduate’s responsiveness to changes in earnings expectation analyzed will remain the same regardless. Actual mismatch rates are only results from these behaviors given actual earnings offers in the market.

These limitations suggest at least three venues for further research that could improve results in this thesis.

1) Find other potential variables that may have effect on major-occupation mismatch decision. With only two control variables in this research, results may be overestimated. Finding additional variables could help ensure that the problem would be less severe.

2) Find numerical measure of specificity of skills trained in each major and include it in the model and analyses. Specificity of skills trained analyzed in this thesis are only intuitively perceived. In the future, if numerical measure of the specificity is found, it should give us more

3) Find other market that contains jobs from every sector so we can observe behavior of graduates from majors aiming for public sector.

REFERENCES

Altonji, J. (1993). The Demand for and Return to Education when Education Outcomes are Uncertain. *Journal of Labor Economics, 11*, 48-83.

Altonji, J., Blom, E., & Meghir, C. (2012). Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers. *Annual Review of Economics, 4*, 185-223.

Altonji, J., Kahn, L., & Speer, J. (2016). Cashier or Consultant? Entry Labor Market Condition, Field of Study, and Career Success. *Journal of Labor Economics, 34*, S361-S401.

Arcidiacono, P. (2004). Ability Sorting and the Returns to College Major. *Journal of Econometrics, 121*, 343-375.

Arcidiacono, P., Hotz, V. J., & Kang, S. (2012). Modeling College Major Choices using Elicited Measures of Expectations and Counterfactuals. *Journal of Econometrics, 166*, 3-16.

Avery, C., Gurantz, O., Hurwitz, M., & Smith, J. (2017). Shifting College Majors in Response to Advanced Placement Exam Scores. *Journal of Human Resources, Forthcoming*.

Baker, G., Gibbs, M., & Holmström, B. (1994). The Wage Policy of a Firm. *Quarterly Journal of Economics, 109*, 921-955.

Beaudry, P., & DiNardo, J. (1991). The Effect of Implicit Contracts on the Movement of Wages over Business Cycle: Evidence from Micro Data. *Journal of Political Economy, 99*, 665-688.

Beffy, M., Fougère, D., & Maurel, A. (2012). Choosing the Field of Study in Postsecondary Education: Do Expected Earnings Matter? *Review of Economics and Statistics, 94*, 334-347.

Berger, M. (1988). Predicted Future Earnings and Choice of College Major. *Industrial and Labor Relations Review, 41*, 418-429.

Bettes, J. (1996). What do Students Know about Wages? Evidence from a Survey of Undergraduates. *Journal of Human Resources, 31*, 27-56.

Bordon, P., & Fu, C. (2015). College-Major Choice to College-Then-Major Choice. *Review of Economic Studies, 82*, 1247-1288.

Chao, R., & Tseng, V. (2002). Parenting of Asians. *Handbook of Parenting, 4*, 59-93.

Dominitz, J., & Manski, C. (1996). Eliciting Student Expectations of the Returns to Schooling. *Journal of Human Resources, 31*, 1-26.

Gathman, C., & Schönberg, U. (2010). How General is Human Capital? A Tasked-Based Approach. *Journal of Labor Economics, 28*, 1-49.

Grogger, J., & Eide, E. (1995). Changes in College Skills and Rise in College Wage Premium. *Journal of Human Resources, 30*, 280-310.

Hunt, J. (2016). Why do Women leave Science and Engineering? *Industrial and Labor Relations Review, 69*, 199-226.

Keane, M., & Wolpin, K. (1997). The Career Decisions of Young Men. *Journal of Political Economy, 105*, 473-522.

Kinsler, J., & Pavan, R. (2015). The Specificity of General Human Capital: Evidence from College Major Choice. *Journal of Labor Economics, 33*, 933-972.

Lemieux, T. (2014). Occupations, Fields of Study and Returns to Education. *Canadian Journal of Economics, 47*, 1047-1077.

Long, M., Goldhaber, D., & Huntington-Klein, N. (2015). Do Completed College Majors Respond to Changes in Wages? *Economics of Education Review, 49*, 1-14.

Lordan, G., & Pischke, J.-S. (2016). Does Rosie like Riveting? Male and Female Occupational Choices. *NBER Working Paper 22495*.

Loury, L., & Garman, D. (1995). College Selectivity and Earnings. *Journal of Labor Economics, 13*, 289-308.

Malamud, O. (2011). Discovering One' Talent: Learning from Academic Specialization. *Industrial and Labor Relations Review, 64*, 375-405.

Miller, R. (1984). Job Matching and Occupational Choice. *Journal of Political Economy, 92*, 1086-1120.

Montmarquette, C., Cannings, K., & Mahseredjian, S. (2002). How do Young People Choose College Major? *Economics of Education Review, 21*, 543-556.

Nordin, M., Persson, I., & Rooth, D.-O. (2010). Education-Occupation Mismatch: Is There Income Penalty? *Economics of Education Review, 29*, 1047-1059.

Paglin, M., & Rufolo, A. (1990). Heterogeneous Human Capital, Occupational Choice, and Male-Female Earnings Differences. *Journal of Labor Economics, 8*, 123-144.

Robst, J. (2007). Education and Job Match: The Relatedness of College Major and Work. *Economics of Education Review, 26*, 397-407.

Silos, P., & Smith, E. (2015). Human Capital Portfolios. *Review of Economic Dynamics, 18*, 635-652.

Stinebrickner, R., & Stinebrickner, T. (2012). Learning about Academic Ability and the College Dropout Decision. *Journal of Labor Economics, 30*, 707-748.

Stinebrickner, R., & Stinebrickner, T. (2014). A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout. *Review of Economic Studies, 81*, 426-472.

Turner, S., & Bowen, W. (1999). Choice of Major: The Changing (Unchanging) Gender Gap. *Industrial and Labor Relations Review, 52*, 289-313.

Willis, R., & Rosen, S. (1979). Education and Self-Selection. *Journal of Political Economy, 87*, S7-S36.

Wiswall, M., & Zafar, B. (2015). Determinants of College Major Choice: Identification using an Information Experiment. *Review of Economic Studies, 82*, 791-824.

Zafar, B. (2013). College Major Choice and the Gender Gap. *Journal of Human Resources, 48*, 545-592.

APPENDIX

Appendix A: Data cleaning

The original dataset consists of 306,884 resumes. However, due to organization of data of the website, intensive cleaning is needed. The first step is data completeness. I start by dropping occupation groups that are uninterpretable or ambiguous: Executive Officer, Part-Time, Other Technicians, Others and those unspecified. 2,763 observations were dropped in the process. Also, I limit samples to students graduating at the age between 21-25 to prevent the case that student took on some occupation before finishing their college study. This range comes from the fact that, in Thailand, children can start their elementary school at the age of 3. Years of schooling is 3 for elementary school, 6 for primary school, 6 for middle and high school, and 4 to 6 for college with most major being 4 years. If college graduates have no full-time work experience, they will then graduate at the age of 22 to 24. I allow for 1 year range extension, give me a range of 21 to 25 years old at graduation with expected age of 22-23.[2] The reason for this limitation is higher education in Thailand is heavily supported by the government, makes it very accessible. Financial constraints are also less likely because students can enroll in compulsory schooling for free and in college at no more than 36,000 Baht yearly. Even if financial constraints exist, there is Student Loan Fund which is the government agency to provide loan with interest rate as low as 1 percent. From all these, most students can then obtain college degree before start working. Under this scope, another 5,815 observations were excluded. I then use ISCED-2013 as college major categorization standard. After dropping observations with incomplete qualitative data such as college major, institution, and intended province of work, the first dataset consists of 42,363 resumes with 52 majors and 69 occupation categories.

The next step is data reliability. I first truncate extreme data to prevent estimation from going crazy. I exclude those declared log earnings expectation further than 1 percent level of the distribution, dropping 348 observations in the process. Secondly, I merge some majors that can be grouped up to increase number of observation in the group. In major categorization, I initially follow ISCED-2013 "Detail" standard. However, I observed later that some majors have too small number of observation. To mitigate this problem, I merge them into a larger group, either "Narrow" or "Broad" level, where it is possible. Majors that can be merged are those in the same larger group and have the same matching occupation category. For example, "Mathematics" and "Statistics" majors are in the same Narrow group: "Mathematics and Statistics". They have the same matching category: "Economics/Mathematics/Statistics". Therefore, these two majors can be merged into Narrow level of "Mathematics and Statistics". See tables in **Appendix B** for list of major before and after being merged. Majors with lower than 30 observations and cannot be merged into a larger group will be dropped. Third, I exclude occupation

[2] There are only small number of degree that requires 5 or 6 years of study. Five-year majors are generally Education and Architecture. Six-year majors are Medicine, Dentistry, and Pharmaceutical Science.

categories with less than 120 applicants and is not any major's matching group. Intuition behind this rule is that dataset consists of resumes from the past 120 months. Occupations with average of less than one applicant per month are likely not well-known occupation. But if it is some major's matching group, I have to keep it for using as a reference category. At this point, the number of resumes becomes 40,396 with 40 majors and 40 occupations.

Nevertheless, in the estimation step, one major: Music & Performing Arts will automatically disappear, count for 139 observations. Then, the job Performer/Singer/Musician/MC will no longer have its match major, along with the fact that it is already under 120 applicants, so it is dropped, 60 observations. Another job eliminated is Beauty Health/Spa/Fitness: 159 observations with no match major. To simplify tasks in estimation, I drop all of them here so that the Arts major can now be grouped up and merging process repeat. Therefore, the cleaned dataset consists of 40,038 resumes with 39 majors and 38 occupations.

Appendix B: Major-Occupation matching

In categorizing college major, I follow International Standard Classification of Education 2013 (ISCED-2013).

It classifies majors in 3 levels: Broad, Narrow, and Detail. Broad category, as its names, is the most widely used in previous works. There are 10 Broad majors: Education, Arts & Humanities, Social Sciences and Journalism & Information, Business and Law, Natural Sciences and Mathematics & Statistics, ICT, Engineering & Manufacturing & Construction, Agriculture and Veterinary, Health and Welfare, and Services. Narrow and Detail categorization are in more details with Detail is the smallest one such as Accounting, Finance, Management, and Marketing. I then classify each observed major into each Detail class in ISCED-2013. Since there are so many unusually name, such as Sustainable Cultural Tourism or Applied Financial Mathematics, they will not be listed here. But in general, majors are classified following its last word. For example, Applied Financial Mathematics is classified as Mathematics.

There are several modifications should be noted here. First, I add one category into Engineering group: Industrial Engineering. The reason is there are so many similarly technology-related majors in Thailand, but they are completely different in occupation aspects. One of the most widely-seen is Industrial Engineering and Industrial/Manufacturing Technology. The former is classified as Engineering and able to obtain Certificate of Engineer from Engineering Council of Thailand while the latter cannot. Working as engineer in Thailand always requires Certificate of Engineer. But in ISCED-2013, both are grouped up in Manufacturing and Processing. Therefore, I need to separate them into a different group.

Second, I merge Hotel & Restaurants & Catering with Travel & Tourism & Leisure. From observed data, majors defined as Hotel always include Tourism in its name. Hotel & Tourism is the most widely seen. In addition, occupation category provided in the online job market also group these jobs up. Therefore, in this context, they can be merged without any problem, reduce complexity in categorization.

Third, I define match occupation for Management major as Administrator/Procurement/Coordinator/Typist. The nature of management jobs, such as supervisor and manager, always require experience before applicant can apply. Consistent with data observed, over 40 percent of graduates from Management major apply to this occupation group instead of General Management occupation group. Also, when looking at jobs categorized as Management group, less than 10 percent that do not require experience. As this study focuses on new college graduates, that is no experience, it is natural that General Management occupation group will not be applied to, less than 3 percent observed. However, I still do not count that those applied to General Management jobs being mismatched. Rather, for graduates from Management major, I re-specify their intended occupation of General Management into

Administrator/Procurement/Coordinator/Typist instead. This way, they will remain counted as being matched.

Fourth, some majors have more than one match occupation group. Marketing & Advertising and Languages majors have 2 match occupation group. Fashion & Interior & Industrial Design major has 3 match occupation group. To reduce complication, I treat graduates in each major applying to their match groups as applying to some specific match group. Marketing & Advertising graduates applying to either Marketing or Advertising are treated as applying to Marketing. Languages applying to Tourism or Language Teacher occupation are considered applying to Languages/Liberal Arts job. Fashion & Interior & Industrial Design graduates applying to any of their three are counted as applying to Arts/Computer Graphic/Industrial Design.

Table B1 and **Table B2** illustrates major-occupation matching prior and after merge respectively. There are 6 Narrow-level merged majors and 1 Broad-level merged major. Narrow-level majors are Arts, Humanities, Physical Sciences, Mathematics & Statistics, and Health Sciences. The Broad-level merged major is Agriculture.

Table B1: Pre-merge Major-Occupation Matching Table

Broad	Narrow	Detail	Major	Job
1	11	111	Education	Lecturer/Teacher/Academic/Liberal Arts/English Teacher
2	21	211	Audio-visual techniques and media production	Arts/Computer Graphic/Industrial Design
		212	Fashion, interior, and industrial design	Arts/Computer Graphic/Industrial Design
		213	Fine arts	Arts/Computer Graphic/Industrial Design
		215	Music and performing arts	Performer/Singer/Musician/MC
	22	221	Religion and theology	Language/Liberal Arts/Writer/Editor
		222	History and archeology	Language/Liberal Arts/Writer/Editor
	23	231	Languages	Language/Liberal Arts/Writer/Editor
3	31	311	Economics	Economics/Mathematics/Statistics
		312	Political science	Political Science/Government
		313	Psychology	Psychologist/Social Worker
	32	321	Journalism and reporting	Mass Communication - Radio/Television
		322	Library science	Language/Liberal Arts/Writer/Editor
4	41	411	Accounting and taxation	Accountant
		412	Finance, banking and insurance	Finance/Banking
		413	Management and administration	Administrator/Procurement/Coordinator/ Typist
		414	Marketing and advertising	Marketing
	42	421	Law	Law
5	51	511	Biological sciences	Science/Chemistry/Biology/Food Technology
	52	521	Environmental sciences	Science/Chemistry/Biology/Food Technology
	53	531	Chemistry	Science/Chemistry/Biology/Food Technology
		532	Earth science	Earth Science/Mining
		533	Physics	Science/Chemistry/Biology/Food Technology
	54	541	Mathematics	Economics/Mathematics/Statistics
		542	Statistics	Economics/Mathematics/Statistics
6	61	611	Computer Use	Computer/IT/Programmer
		613	Software Development	Computer/IT/Programmer
7	71	710	Industrial engineering	Mechanical Engineer/Metallurgical Engineer/Industrial Engineer
		711	Chemical engineering	Chemical Engineer/Petrochemical Engineer/Polymer Engineer
		712	Environmental technology	Environmental Engineer
		713	Electricity and energy	Electrical Engineer/Electronics Engineer

		714	Electronics and automation	Electrical Engineer/Electronics Engineer
		715	Mechanics and metal trades	Mechanical Engineer/Metallurgical Engineer/Industrial Engineer
	72	721	Food processing	Science/Chemistry/Biology/Food Technology
		722	Materials manufacturing	Production Engineer/Production Line/QA/Factory
	73	731	Architecture and town planning	Engineering Drawing/Architecture/Interior Design
		732	Civil engineering	Foreman/Civil Engineer
8	81	811	Agriculture	Agriculture/Horticulture/Fishery/Irrigation
	82	821	Forestry	Agriculture/Horticulture/Fishery/Irrigation
	83	831	Fisheries	Agriculture/Horticulture/Fishery/Irrigation
	84	841	Veterinary	Veterinary
9	91	913	Nursing and midwifery	Doctor/Nurse/Pharmacist/Public Health
		914	Medical diagnostic and treatment technology	Doctor/Nurse/Pharmacist/Public Health
		915	Therapy and rehabilitation	Doctor/Nurse/Pharmacist/Public Health
		916	Pharmacy	Doctor/Nurse/Pharmacist/Public Health
		917	Traditional and complementary medicine	Doctor/Nurse/Pharmacist/Public Health
	92	923	Welfare	Psychologist/Social Worker
10	101	1011	Domestic services	Food and Beverage/Chef
		1013	Hotel, travel, and tourism	Hotel/Tourism/Ticket
		1014	Sports	Sports Science
	102	1021	Community sanitation	Doctor/Nurse/Pharmacist/Public Health
		1022	Occupational health and safety	Occupational Safety
	104	1041	Transport services	Warehousing/Logistics

Table B2: Post-merge Major-Occupation Matching Table

Broad	Narrow	Detail	Major	Job
1			Education	Lecturer/Teacher/Academic/Liberal Arts/English Teacher
2	21		Arts	Arts/Computer Graphic/Industrial Design
	22		Humanities	Language/Liberal Arts/Writer/Editor
	23		Languages	Language/Liberal Arts/Writer/Editor
3	31	311	Economics	Economics/Mathematics/Statistics
		312	Political science	Political Science/Government
		313	Psychology	Psychologist/Social Worker
	32	321	Journalism and reporting	Mass Communication - Radio/Television
		322	Library science	Language/Liberal Arts/Writer/Editor
4	41	411	Accounting and taxation	Accountant
		412	Finance, banking and insurance	Finance/Banking
		413	Management and administration	Administrator/Procurement/Coordinator/ Typist
		414	Marketing and advertising	Marketing
	42	421	Law	Law
5	51		Biological sciences	Science/Chemistry/Biology/Food Technology
	52		Environmental sciences	Science/Chemistry/Biology/Food Technology
	53		Physical sciences	Science/Chemistry/Biology/Food Technology
	54		Mathematics and statistics	Economics/Mathematics/Statistics
6	61	611	Computer Use	Computer/IT/Programmer
		613	Software Development	Computer/IT/Programmer
7	71	710	Industrial engineering	Mechanical Engineer/Metallurgical Engineer/Industrial Engineer
		711	Chemical engineering	Chemical Engineer/Petrochemical Engineer/Polymer Engineer
		712	Environmental technology	Environmental Engineer
		713	Electricity and energy	Electrical Engineer/Electronics Engineer
		714	Electronics and automation	Electrical Engineer/Electronics Engineer
		715	Mechanics and metal trades	Mechanical Engineer/Metallurgical Engineer/Industrial Engineer
	72	721	Food processing	Science/Chemistry/Biology/Food Technology
		722	Materials manufacturing	Production Engineer/Production Line/QA/Factory

	73	731	Architecture and town planning	Engineering Drawing/Architecture/Interior Design
		732	Civil engineering	Foreman/Civil Engineer
8			Agriculture	Agriculture/Horticulture/Fishery/Irrigation
9	91		Health sciences	Doctor/Nurse/Pharmacist/Public Health
	92		Welfare	Psychologist/Social Worker
10	101	1011	Domestic services	Food and Beverage/Chef
		1013	Hotel, travel, and tourism	Hotel/Tourism/Ticket
		1014	Sports	Sports Science
	102	1021	Community sanitation	Doctor/Nurse/Pharmacist/Public Health
		1022	Occupational health and safety	Occupational Safety
	104	1041	Transport services	Warehousing/Logistics

Appendix C: Derivation of elasticity and probability change

Elasticity of mismatch probability to change in earnings expectation of the match choice is:

$$E_{Mismatch,W_{ijk_0}} = \frac{\partial(1-P_{ijk_0})}{\partial W_{ijk_0}} \cdot \frac{W_{ijk_0}}{1-P_{ijk_0}} = \frac{-\partial P_{ijk_0}}{\partial W_{ijk_0}} \cdot \frac{W_{ijk_0}}{1-P_{ijk_0}} \quad (C.1)$$

From our objective equation (C.1), we will see that we can find the elasticity through marginal effect of earnings expectation change on match probability P_{ijk_0}. The following derivation will be for that purpose.

Consider equation (6) in case of occupation k_1 and k_2, given $P_{ijk} \neq 0$ for all k:

$$\ln\left(\frac{P_{ijk_1}}{P_{ijk_0}}\right) = \beta_{0jk_1} + \beta_{1j}(W_{ijk_1} - W_{ijk_0}) + \mathbf{X_{ij}\theta_{jk_1}} \quad (C.2)$$

$$\ln\left(\frac{P_{ijk_2}}{P_{ijk_0}}\right) = \beta_{0jk_2} + \beta_{1j}(W_{ijk_2} - W_{ijk_0}) + \mathbf{X_{ij}\theta_{jk_2}} \quad (C.3)$$

Subtract equation (C.3) by equation (C.2):

$$\ln\left(\frac{P_{ijk_2}}{P_{ijk_1}}\right) = (\beta_{0jk_2} - \beta_{0jk_1}) + \beta_{1j}(W_{ijk_2} - W_{ijk_1}) + \mathbf{X_{ij}(\theta_{jk_2} - \theta_{jk_1})} \quad (C.4)$$

Total differentiate equation (C.4) by W_{ijk_0} using chain rule would yield:

$$\frac{P_{ijk_1}}{P_{ijk_2}} \cdot \left(\frac{\partial\left(\frac{P_{ijk_2}}{P_{ijk_1}}\right)}{\partial P_{ijk_0}} \cdot \frac{\partial P_{ijk_0}}{\partial W_{ijk_0}}\right) = 0 \quad (C.5)$$

We already know that $P_{ijk} \neq 0$. Also, as we will easily see that $\frac{\partial P_{ijk_0}}{\partial W_{ijk_0}} \neq 0$, then:

$$\frac{\partial\left(\frac{P_{ijk_2}}{P_{ijk_1}}\right)}{\partial P_{ijk_0}} = 0 \quad (C.6)$$

which implies fraction $\frac{P_{ijk_2}}{P_{ijk_1}}$ is unaffected by changes in P_{ijk_0}, straightforwardly intuitive. When W_{ijk_0} changes, only earnings expectation gaps between W_{ijk_0} and other W_{ijk} change. Thus, only proportions between P_{ijk_0} and other P_{ijk} that changes while of other pairs remain unchanged as their earnings expectation gap is not altered.

Now consider basic property of choice probabilities. For any individual *i* who graduated from college major *j*, probability for choosing each occupation choice *k* must add up to one. Given that *n* is number of alternatives observed,:

$$1 = P_{ijk_0} + P_{ijk_1} + P_{ijk_2} + \ldots + P_{ijk_{n-1}} \qquad (C.7)$$

Divide both sides of equation (C.7) by any P_{ijk} where $k \neq 0$. Here, I choose P_{ijk_1}:

$$\frac{1}{P_{ijk_1}} = \frac{P_{ijk_0}}{P_{ijk_1}} + \left(1 + \frac{P_{ijk_2}}{P_{ijk_1}} + \frac{P_{ijk_3}}{P_{ijk_1}} + \ldots + \frac{P_{ijk_{n-1}}}{P_{ijk_1}}\right)$$

For ease of writing, I will use variable *C* to represent terms in parentheses:

$$\frac{1}{P_{ijk_1}} = \frac{P_{ijk_0}}{P_{ijk_1}} + C$$

$$P_{ijk_1} = \frac{1 - P_{ijk_0}}{C} \qquad (C.8)$$

Substitute equation (C.8) back into (C.2) yields:

$$\ln\left(\frac{1 - P_{ijk_0}}{C \cdot P_{ijk_0}}\right) = \beta_{0jk_1} + \beta_{1j}(W_{ijk_1} - W_{ijk_0}) + \mathbf{X_{ij}\theta_{jk_1}} \qquad (C.9)$$

From equation (C.6), we already know that fractions of probabilities without P_{ijk_0} are independent of P_{ijk_0}. As variable *C* is total addition of such fractions, then *C* must also be independent of P_{ijk_0}. When differentiate with P_{ijk_0}, the variable *C* is equivalent to constant.

We will then total differentiate equation (C.9) by W_{ijk_0} using chain rule:

$$\frac{C \cdot P_{ijk_0}}{1-P_{ijk_0}} \cdot \frac{-C}{(C \cdot P_{ijk_0})^2} \cdot \frac{\partial P_{ijk_0}}{\partial W_{ijk_0}} = -\beta_{1j}$$

$$\frac{\partial P_{ijk_0}}{\partial W_{ijk_0}} = \beta_{1j} P_{ijk_0}(1 - P_{ijk_0}) \qquad \textit{(C.10)}$$

Now that we got marginal effect of earnings expectation on match probability, substituting equation (C.10) into our objective equation (C.1) yields:

$$E_{Mismatch, W_{ijk_0}} = -\beta_{1j} P_{ijk_0} W_{ijk_0} \qquad \textit{(C.I)}$$

The equation tells us how many percent of current mismatch probability would the probability changes when the earnings expectation increases by 1 percent. If we would like to know in term of real probability change, all needs to do is multiplying the elasticity by current mismatch probability $1 - P_{ijk_0}$. The equation of real probability change is then:

$$\Delta(1 - P_{ijk_0}) = -\beta_{1j} P_{ijk_0}(1 - P_{ijk_0}) W_{ijk_0} \qquad \textit{(C.II)}$$

VITA

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