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by

Warn Nuarpear Lekfuangfu, Nick Nuttapol Lertmethaphat

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Building Thailand's Beveridge curve: New Insights of Thailand's Labour Markets with Internet Job Platforms

Warn Nuarpear Lekfuangfu (Universidad Carlos III de Madrid, J-PAL),*

Nick Nuttapol Lertmethaphat (Bank of Thailand),

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Abstract

The Beveridge curve, which reflects the relation between unemployment and job vacancies is an important policy-relevant tool for better insights into labour markets. The absence of consistent and reliable data in Thailand, particularly on job postings is a substantial downside. This paper presents a showcase of how the Beveridge curve can be constructed for Thailand by exploiting two, related data sources: (i) the administrative data from the government-run job centre services and (ii) user-generated data from online job portals. We propose a procedure on how vacancy and jobseeker rates can be computed from each database, which may have non-representative coverage of users/stakeholders in the labour market. In effect, we also discuss the extent of the population representation of each database and confirms that each data reflects different segments of Thailand's labour market. Finally, we demonstrate how the Beveridge curve can be plotted as well as re-introduce the measurement of labour market tightness for Thai's labour market.

Keywords: Labour market, Beveridge curve, Labour Market Tightness, Vacancies, Jobseeker, Online job platform, Thailand.

JEL Classifications: J2, J3, E24, N35

* Corresponding Author: Lekfuangfu, Department of Economics, Universidad Carlos III de Madrid, 126 Calle Madrid, Madrid, Spain, 28903, nlekfuan@eco.uc3m.es. Lekfuangfu acknowledges financial support from Puey Ungphakorn Institute for Economic Research (PIER research grant 2022/2). We are grateful to Nada Wasi, Pucktada Treeratpituk, and comments from participants at PIER Research Workshop 2024.

In 1994, Beveridge proposed that movements in unemployment are related to changes in the demand for workers, which can be measured by the volume of job openings (Beveridge 1994). However, as noted in Yashiv (2008), Beveridge himself did not plot the relation between unemployment and vacancies, although he did offer an empirical analysis of both variables that implied a negative association. In fact, the original Beveridge curve plot was instead provided by Dow and Dicks-Mireaux (1958), who additionally demonstrated imbalances in labour supply and demand in the market.

Owing to great efforts in collecting consistent and reliable data on job vacancies as well as the long existing of the statistics on unemployment, the Beveridge curve appears in many countries, including the US and most European countries (Jackman et al. 1990, Blanchard and Diamond 1989, Nickell et al. 2003, Diamond and Sahin 2015, Elsby et al. 2015). And through the long-spanning series of both the vacancies and the unemployment (also of jobseekers) data, not only can researchers empirically observe the elasticity of the Beveridge curve (given its negative-sloping locus), but they are also able to detect some shifts (outward and inward movements) in the curve. For instance, the US's Beveridge curve has persistently shifted outward after the Great Recession, and, again, post the Covid-19 pandemic (Barlevy et al. 2024) – indicating adverse structural changes attributed to a rise in mismatch between labour demand and supply in the market.

Another reason policy-makers have taken a keen interest in the Beveridge curve is that it can provide information about the trade-off between unemployment and inflation (Kocherlakota 2010, Bernanke 2012, Figura and Waller 2022). As central banks decide on raising interest rate, a key concern to what extent a fall in inflation would result in a rise in unemployment. Knowing the shape of the Beveridge curve can provide immense insights to gauge the scale of this trade-off. In other words, policymakers can be better informed with a reliable Beveridge curve.

This paper intends to do such that, for the case of Thailand. We will demonstrate some exercises that gather and exploit available data from various sources and construct some examples of Thailand's Beveridge curve.

In the initial step, we will propose the case for building two key components of the curve, namely unemployed (or jobseekers) and job vacancies, from two alternative data sources. The first source is the monthly report of jobseekers and job vacancies by Thailand's Department of Employment (Ministry of Labour). The summarised data comes from an administrative database of users (jobseekers and employers) of the DOE's job centre services across the country. The report began in January 2014 and has continued until the present date – giving us a 10-year time span. The second source is of an online job platform where we managed to scrap and collect the data more granularly at the jobseeker and at the job-post level. However, the time series of the second dataset is much shorter (1 year but with a higher frequency). In working with both datasets, we must acknowledge that the representativeness of these datasets may be somewhat limited. The data cannot provide much insights into labour markets of the agricultural or rural sectors. Users of the online job platform are more urban, white-collar, and better educated than the national average. While users of the DOE's services are more geographically covered, they are less educated and jobs are largely blue-collar types.

In the next step, we construct some preliminary examples of Thailand's Beveridge curve as well as calculate the measure of labour market tightness (the number of vacancies per a jobseeker). To our knowledge, our paper is the first to attempt to plot and trace Thailand's Beveridge curve. The plotted curve appears to have a negative slope but not a steep one. However, this is not without some serious cautions. While we are more confident in the shape of each plotted Beveridge curve, we urge the readers to interpret the values of the rates much more cautiously as they vary much drastically to the choice of the denominator (labour force size) used in the calculation. We hope that our paper is the first exercise of many more works in the near future.

2. Introduction to the Beveridge curve: A relationship between unemployment and vacancies

2.1. The Beveridge curve

2.1.1. Key components of the Beveridge curve

Generally speaking, the Beveridge curve provides economic explanations for the presence of a relation between two labour market indices: unemployment (U) and vacancies (V). Both of these indices illustrate the degree of efficiency of the labour market and its worker-to-job matching process. On the one hand, the level of unemployment (and jobseekers) reveals the unmet need to find a job, or, in other words, the excess labour supply at a given time for a given market segment. On the other hand, vacancy numbers show the degree of unfilled positions that stem from the excess labour demand and thus less output.

The unemployment is rather well understood as there is a rather clear concept across countries on how to collect the data for unemployment rates. By contrast, the information on vacancies is starkly scarcer and more sporadic. In Section 2.2, we will go over some detailed on how unemployment rates and vacancy numbers are currently constructed in selected countries.

In a simple, frictionless labour market, both unemployment rates and vacancy rates would be low - even if they may not be non-zero - because the matching process works well. However, in reality, labour markets are frictional and positions take time to fill even if there are many people actively seeking jobs (Diamond 1985, Pissarides 1985, Mortensen and Pissarides 1994). Therefore, the empirical relationship between U and V is conventionally found to be a negative one. That is, the Beveridge curve (with U on the horizontal axis and V on the vertical axis) has a negative slope – signifying that unemployment and vacancies cannot be simultaneously reduced (Michaillat and Saez 2021). As Abraham and Katz (1986) point out, the cyclical co-movement along the Curve is a result of business cycles and the changes in aggregate demand for labour.

2.1.2. Interpretation and Implication of the Beveridge curve

In general, policy makers pay attention to both (a) the movement of each 'dot' (i.e., the ratio of V on U at a given point in time) along the curve; and (b) the directional shifting of the locus.

Movements along the curve can be attributed to changes in labour market tightness, driving by changes in the business cycle.

A tight labour market (typically occurring when the economy is booming) is one with low unemployment and many vacancies; labour supply is low and labour demand is high. There are labour shortages and there is upward pressure on wages. On the Beveridge curve, the tightening of the market would be represented by a point on the left-upper part of the curve. On the contrary, when unemployment is high and there are few vacancies (low labour demand, with high labour supply), it is represented by a point on the right-low part of the curve. This is normally associated with recessions and there is downward pressure on wages.

Shifts of the Beveridge curve occur due to events that are more structural and fundamental – typically associated with changes in the matching efficiency between labour supply and demand. Labour economists define matching efficiency as the ease with which unemployed people can find employment at a given job vacancy rate. An inward shift of the curve indicates an improvement in matching efficiency, while an outward shift indicates a decline. For example, Beveridge curve can shift outwards (worse U for worse V) when the economy struggles due to structural shifts (for instance, demographic shifts) (Abraham 1987; Shimer 2001). In contrast, it shifts inwards as the matching efficiency improves. For instance, an improvement in information flow, which reduces frictions in the labour market, can lead to the simultaneous declines in jobseekers and unfilled vacancies. Elsby, Michaels and Ratner (2015) provide a comprehensive review of the Beveridge curve and examples of the Beveridge in various countries.[1] In addition, Michaillat and Saez (2021) demonstrate some examples of the Beveridge curve in the US since 1951. Note that the Beveridge curve can be plotted using the rate in percentage or in the log unit of the rates of unemployment and job vacancies.

[1] The position of the Beveridge Curve in many developed economies had shifted, most notably during the persistent rise in European unemployment in the 1980s, and more recently in the wake of the Great Recession in the United States. See Elsby, Michaels and Ratner (2015) for the review.

2.1.3. Beveridge curve as a slack measure

Typically, the Phillips curve is used as a main framework that links inflation dynamics to unused capacity ("slack") in the economy. The tightening of the market puts pressure on prices and, subsequently, higher inflation. Since the inflation surge in the post-COVID recovery, the Phillips curve is no longer "dormant" (e.g., Ball et al., 2022, Benigno and Eggertsson, 2023, Blanchard and Bernanke, 2023).

Nonetheless, unemployment is not the only measure of slack. Other popular slack candidates include average real marginal cost, the labour share, the output gap (see, e.g., Galí, 2015), the job-switching rate (Moscarini and Postel-Vinay, 2017, Moscarini and Postel-Vinay, 2023, Faccini and Melosi, 2023), and most recently the vacancy–unemployment ratio (Barnichon and Shapiro, 2022, Ball et al., 2022). A recent work of Barnichon and Shapiro (2024) assess the performances of different slack measures at predicting and explaining inflation (i.e., which variable can best explain the movements in inflation caused by changes in aggregate demand). With data from US's labour market (at the Metropolitan level), they show that vacancy-unemployment (V/U) ratio, in particular the shifts of Beveridge curve due to the changes in matching efficiency, outperforms other slack measures, including the unemployment rate. Interested readers should refer to the paper for more extensive details of the model and the estimation methods.

2.2. Measurement: current practices and challenges

Unemployment: This index is a more familiar concept of the two. The unemployment level measures the total number of people estimated to be unemployed. In general, the headline measure of unemployment is the unemployment rate for those of the working ages, that is aged 16 and over. Typically, unemployment rates are calculated, in accordance with international guidelines, as the number of unemployed people divided by the economically active population (those in employment plus those who are unemployed).

Most OECD countries collect the necessary information for unemployment from the Labour Force Surveys (or equivalent, for instance the US's Current Population Surveys). The measurement is usually be constructed monthly and it can also present the pattern at the national as well as some sub-national levels.

Nonetheless, there remains some debates on whether the conventional measure of unemployment captures the fullest extent of worker's unmet demand for jobs. First of all, the standard index of unemployment does not include on-the-job search nor employed workers who work fewer hours than they would prefer. In developing economies where informal or part-time jobs are more prevalent, even their unemployment indicator may be low, it lacks the true reflection of excess supply of under-utilised workforce. An alternative indicator is the job search activities of the workforce who may or may not be in employment currently, which can be measured by the scale of job applicants in the economy.

Overall, the conventional definition of unemployment rate (u) is the number of unemployed (U) divided by the civilian labour force (L).

$$u = 100 \times U / L \qquad \text{(Eq. 1)}$$

Vacancies: Conceptually, Abraham (1983) proposed a definition of a vacancy as unmet labour demand. However, this is no simple concept in practice as idle resources or foregone outputs (for instance, capital or land) are not as easily observable in most production contexts (Elsby, Michaels, and Ratner 2015).

Therefore, in practice, many countries decide to use a simpler definition of vacancies. The US's Job Openings and Labor Turnover Survey (JOLTS), started in December 2000, defines a vacancy as "*(i) a position exists for which work could start within thirty days, and (ii) for which the employer is actively recruiting from outside the establishment*". This is done as a monthly survey that covers around 16,000 establishments.[2] Note that, prior to 2000, the US also utilised the Help-Wanted Index, which was based on counts of help-wanted ads placed in newspapers in fifty-one large US cities[3]. In addition, as job ads are now predominantly on internet platforms, the calculation and monitoring of job vacancies can now incorporate such datasets. The most well-known US-based dataset is from the Burning Glass Institute (BGI).[4] We will discuss the utilisation of online datasets in more details below.

For the UK, vacancies are similarly defined as "*positions for which employers are actively seeking recruits from outside their business or organisation*". The monthly job vacancies come from the Vacancy Survey, which began in 2001. The survey covers all industrial sectors except agriculture, forestry and fishing.[5] It is common practice to exclude these sectors from vacancy surveys in other countries, including the EU. Around 6,000 stratified enterprises from the Business Register database (IDBR) are surveyed monthly where they only reply just one number by telephone data entry using their keypad.[6] Unlike the US, job vacancies can be reported at the industry level (at the 1-digit level).

For the EU countries, Eurostat defines a job vacancy as "*a paid post that is newly created, unoccupied, or about to become vacant: (i) for which the employer is taking active steps and is prepared to take further steps to find a suitable candidate from outside the enterprise concerned; and (ii) which the employer intends to fill either immediately or*

[2] For ease of data collection, the JOLTS do not collect the occupation/industry of a vacancy in exchange of larger samples of firms (National Commission on Employment and Unemployment Statistics 1979; Plunkert 1981).

[3] See Barnichon (2010) for the demonstration of the construction of vacancy proxy in the US during 1951-2000 for the Conference Board's Help-Wanted index.

[4] The Burning Glass Institute scrapes, parses and codes electronic postings from over 40,000 online job boards and company websites on the US-based market to arguably construct the near-universe of jobs that were posted online. See www.burningglassinstitute.org for more details. Selected works that use the dataset to monitor labour demand are Hershbein and Kahn (2018), Forsythe, Kahn, Lange, and Wiczer (2020).

[5] This is because of high administrative costs and the difficulties of measuring vacancies in these selected sectors, which mainly consist of very small firms that do not post vacancies as defined (www.ons.gov.uk).

[6] For the UK, the completion of the survey is legally compulsory.

within a specific period of time".[7] The statistics from the national-level vacancy surveys are available on a quarterly basis and can be broken down by economic activity and by size of enterprise. Moreover, Eurostat also exploits the dataset from online job advertisements, which covers job posts from job search engines and public employment services' websites. Many of the available information, which are initially unstructured data (in particular, text-based data), is processed and classified according to main international classifications.[8]

In summary, the conventional definition of vacancy rate, v, is the number of job openings (V) divided by the civilian labour force (L).

$$v = 100 \times V / L \qquad \text{(Eq. 2A)}$$

Note also that the Eurostat formular adds the number of job openings itself as a component of the denominator.

$$v = 100 \times V / (V+L) \qquad \text{(Eq. 2B)}$$

2.3. Existing data on unemployment, jobseekers, and job vacancies in Thailand

Unemployment:

In the case of Thailand, the data on unemployment has been consistently and reliably collected since early 1980s under the Labour Force Survey (Thailand's National Statistical Office). In effect, the unemployment rate can be summarised annually and monthly at the national level as well as the provincial level.[9] The official statistics defines unemployment as "a person who DOEs not have a job, DOEs not work at least one hour in that week, looking for work and ready for work amongst persons aged 15 to 64 years during the reference week". Moreover, "job seeking" is defined as "a person who has taken specific steps during the four weeks ending with the reference week to find paid work or are self-employed or those seeking employment to start later".

Aside the official statistics from the NSO, Thailand's Ministry of Labour (MoL), via the Department of Employment (DOE) has, in the past years, released the summarised information of jobseekers who utilise the services provided by the DOE's job centres.[10] This monthly dataset is available from January 2014 until present, and it can be disaggregated

[7] See https://ec.europa.eu/eurostat/cache/metadata/en/jvs_esms.htm
[8] At present, the data collection is undertaken by Cedefop and Eurostat. Data are acquired through web scraping, web crawling techniques or direct access using an Application Programming Interface (https://ec.europa.eu/eurostat).
[9] https://catalog.nso.go.th/dataset/0706_02_0016
[10] The services are provided via both physical centres as well as online platforms (http://smartjob.doe.go.th/). Specifically, for recent unemployed workers who register to claim the unemployment benefit, they are obliged to register as an unemployed, and report themselves monthly via https://e-service.doe.go.th where they need to identify and updaste their status as a jobseeker.

by geographical area (province) and certain characteristics of jobseekers (age group, gender, education level), and occupations.[11]

Job vacancies: There had been some efforts to collect comprehensive data on job vacancies in Thailand in the past years. Most notably is the NSO's Labour Demand of Establishment Survey.[12] On the one hand, the Survey provides nationally representative information on labour demand and contains much detailed information on the characteristics of enterprises as well as workers they seek to hire. On the other hand, the survey has some drawbacks. First, there are only three past waves of the survey (2013, 2008, 2006). Secondly, it contains job vacancy information rather unfrequently - at the annual basis. And lastly, the survey covers only selected sectors, namely retails, construction, manufacturing, transportation, hospitals, and services. The lack of temporal frequency of the NSO's Labour Demand Survey makes it unsuitable for tracking temporal variation of job vacancies, and thus for constructing the Beveridge curve.

In fact, a promising dataset of Thailand's job vacancies is vacancies posted by firms and enterprises with the Department of Employment' job centres. Similar to the jobseeker data of the DOE, the data is publicly accessible at the aggregate level since January 2014 until present (amount to 10 years span). Additionally, the data can be disaggregated at the geographical area (province) and certain workers' characteristics (age group, gender, education level), occupations (1-digit ISCO), and sector (1-digit ISIC).[13]

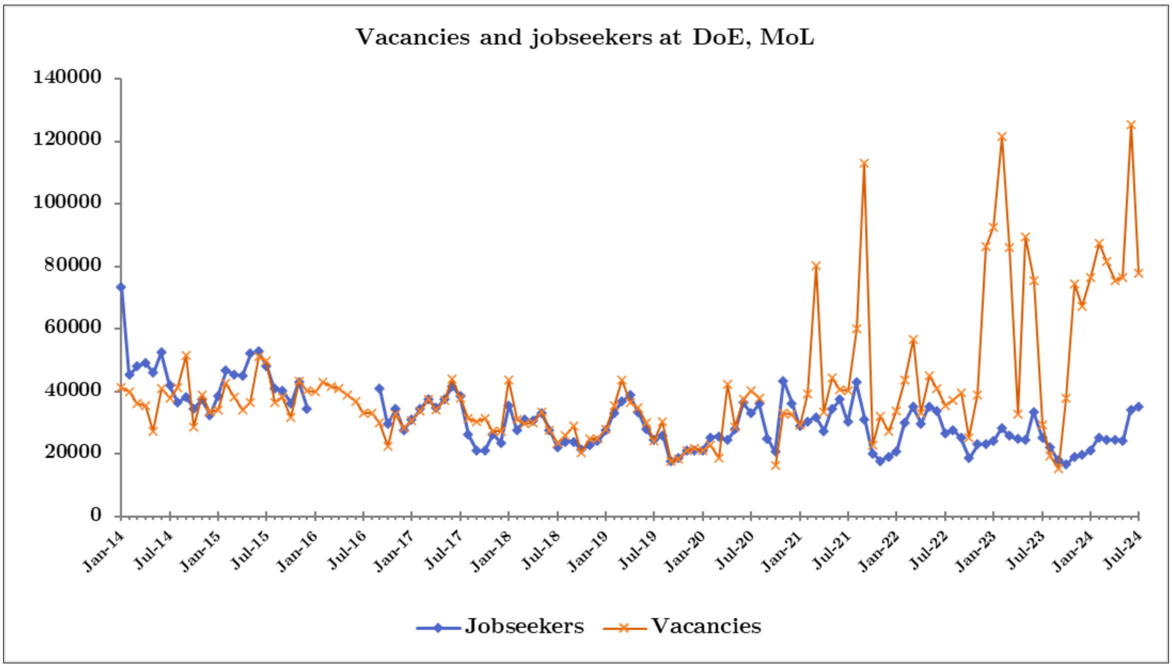
In Figure 1, we plot the time-series of jobseekers and posted vacancies from the DOE (January 2014 to July 2024). Given some extraordinary spikes of the data in some specific dates, we decide to omit reporting those numbers in the figure.[14] Based on worker-job search behaviours of users of the DOE's platform, on average there are approximately 35,000 jobseekers and job postings in a given month, up until the beginning of 2020. Thereafter, the volume of jobseekers has stayed somewhat stable (with minimum at 20,000 and maximum of 40,000 individuals per month seeking a position) whilst the number of posted jobs via the official platform sees a rising trend (with some seasonal fluctuations) – reaching over 100,000 posts for a given month by the first quarter of 2024.

To further demonstration this pattern, Figure 2 plots the labour market tightness, which is the ratio of vacancies to jobseekers in this official job platform. The value of the ratio is above 1 when there are more available jobs than available workers, and below 1 if the reverse is true. Therefore, it is worth noting that, based on labour market activities observed in the DOE's job platform, the tightness ratio fluctuates just below 1 in the years prior to January 2020 – showing that there are relatively more workers seeking jobs than available jobs. However, thereafter, the ratio has continued to rise and reached around 3.6

[11] See https://doe.go.th/lmia for more details of the datasets.
[12] See https://www.nso.go.th/nsoweb/nso/survey_detail/Hy.
[13]https://www.doe.go.th/prd/lmia/statistic/param/site/131/cat/93/sub/0/pull/category/view/list-label
[14] The omitted dates are: January 2016 to August 2016 for the jobseeker data, and September 2020 for job vacancies.

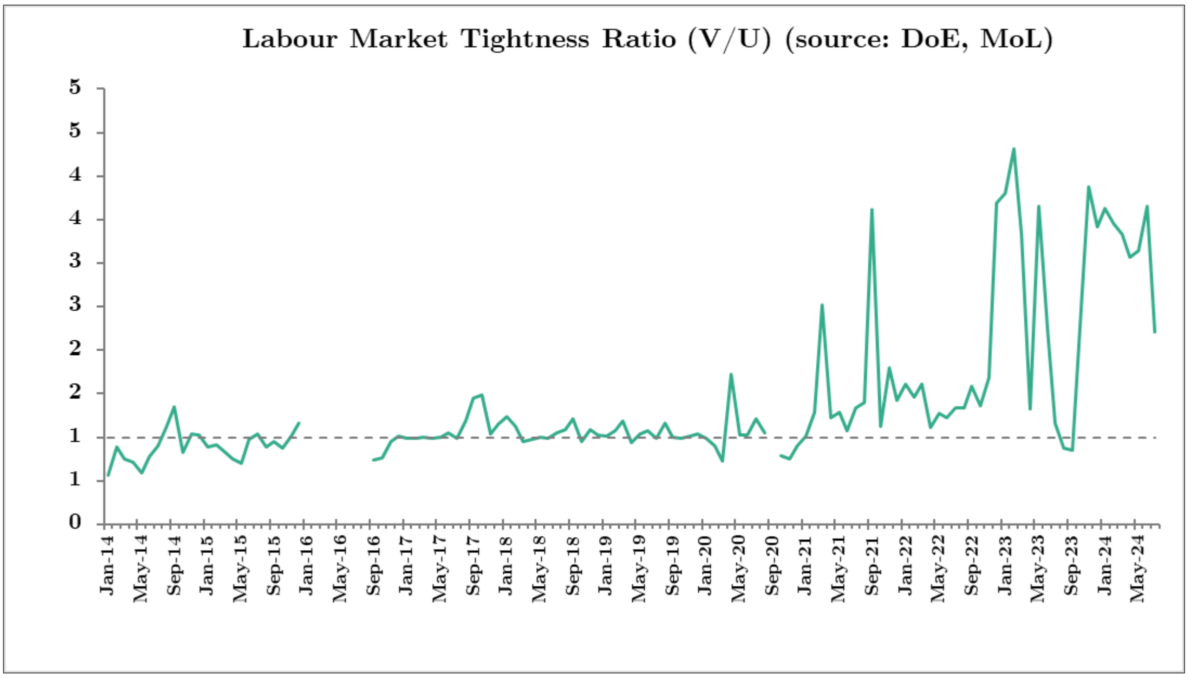
at the last quarter of 2023 - indicating that Thailand's labour market recently has much fewer workers to fill vacancies jobs. Lastly, with the dataset, it is also possible to construct the Beveridge curve for this given labour market segment. However, we will refer to Section 4 for this exercise.

Figure 1. plot of DOE's data



Source: Department of Employment, Thailand's Ministry of Labour

Figure 2. Labour market tightness (V/U) of the DOE's job data



Source: Department of Employment, Thailand's Ministry of Labour. Labour market tightness is calculated as the ratio of vacancies (V) on jobseekers (U) among those who used job centres of the Department of Employment, the Ministry of Labour.

3. Application for Thailand: Statistics on jobseekers and vacancies

In the section, we will demonstrate how the data on jobseekers and vacancies from online job platforms can be utilised to provide further insights into the behaviours and patterns of Thailand's labour market. First, we will introduce the data source and briefly describe the data cleaning process, including the application of machine learning and natural language processing. Then, we will discuss the representative of the data, compare to the well-known Labour Force Surveys (by the NSO) and the DOE's job platform dataset.

3.1. Data from online job platforms in Thailand.

A typical online job platform serves both the users who look for jobs and employers who seek out workers. Jobseekers can create a profile and leave their detailed 'resume' on the platform while firms or employers can post their vacancies. The information on job platforms provides insights into the trends and patterns of jobseekers and job vacancies in this given market segment.

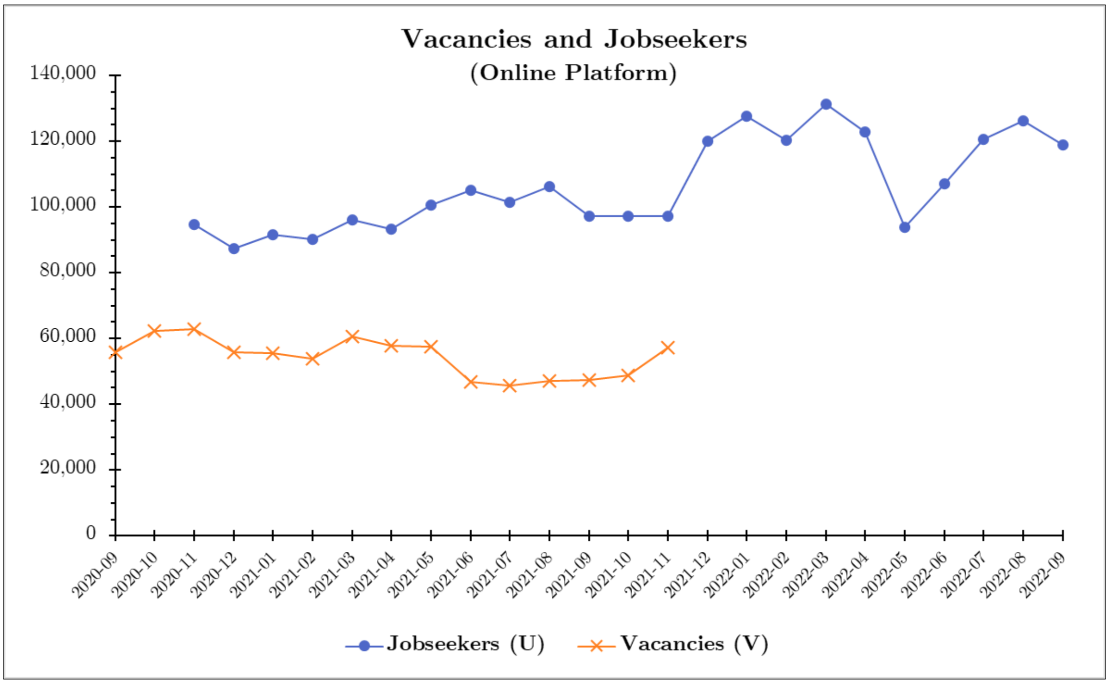
For the purpose of this exercise, we had scrapped detailed data from two main online job platforms (both sides of the market) in Thailand, starting in September 2020 until August 2023. The web-scrapping process was done automatically, with the weekly frequency. The information derived from the raw dataset is a combination of structured and unstructured (natural language) data types. Most crucially, we collect the time stamp of when a job is initially posted, and similarly when a personal profile "resume" is created as well as updated. This works as the time dimension of the dataset (monthly and fortnightly). Further details of the dataset will be described shortly in Section 3.2.

Unfortunately, because of some changes in the structure of the platforms over time, the data quality is optimal only one major platform, and only for the period of November 2020 to November 2021.[15]

Figure 3 plots the number of jobseekers and vacancies that are obtained from a major online job platform. In contrast to Figure 1 (of the DOE database), we observe a higher number of jobseekers than posted vacancies in this platform.

[15] In details, the data of jobseekers is high quality during November 2020 to September 2022; whilst the data of job vacancies are optimal during September 2020 to November 2021. Therefore, the overlapped time period of these two datasets, which is the main requirement for the construction of the Beveridge Curve is from November 2020 to November 2021. The data from the second major job platform (Platform B) is checked but we decided not to utilise it in this paper to avoid duplications of both jobseekers and job posts. The chosen platform (Platform A) contains approximately twice the volume of the user flows of Platform B.

Figure 3. Vacancies and jobseekers from an online platform



Source: Scrapped data from an online job platform in Thailand

3.2. Data construction and cleaning

As mentioned earlier, the data from job websites contain both structured and unstructured data. For jobseekers, we can construct policy-relevant information on their personal characteristics, job history, job preferences. Similarly, for job vacancies, there are useful information on the characteristics of workers that employers require, including their gender (male-only, female-only, no requirement), age range (minimum and maximum age), education, work experience, and offered salary (for some).

Notably, the information on job titles (both jobseeker and vacancies datasets) is also available but it is not presented in a familiar, standard way, and, most of all, they are manually filled information by the users. Therefore, to circumvent this issue, we develop an algorithm that standardise the high-frequency data from job websites, which consists of manually written job titles from major online job posting websites in Thailand (in Thai and English languages) into the International Standard Classification of Occupations (ISCO) codes (up to 4-digit level). Through the integration of advanced Natural Language Processing (NLP) and machine learning techniques, our methodology automates what would otherwise be prohibitively labour-intensive due to the volume and velocity nature of the data. Readers interested in the detail of our methodology can refer to the companion paper by Lertmethaphat, Lekfuangfu, and Treeratpituk (2024).

3.2. Representativeness of the online data

One major noteworthy acknowledge of typical online data is the issue of representativeness of such data. Our online job dataset is no exception. In this sub-section, we transparently outline the extent of the representativeness of our dataset, in comparison to the commonly-used Labour Force Surveys as well as to a closely-related dataset from the Department of Employment's job platform. Overall, we argue that the users (in particular, jobseekers) of online job platforms are predominantly young, better educated, white-collar, and urban. In other words, neither job platforms (DOE's and online-based) reflect labour market behaviours in agricultural and rural sectors. Having said that, in comparison to equivalent datasets of other countries, this pattern is rather common.

Table 1 shows the representativeness of our online data across sector (1-digit ISCO) and compares the finding to that of the contemporaneous Labour Force Survey (2021) and of the DOE's equivalent database. From columns (1) and (2), we can observe that both jobseekers and available jobs on the online platform are highly concentrated in white-collar occupations, namely services/sales, clerical support, and some high-skilled jobs (professional and technical occupations). By contrast, users of the DOE's job centre come from less skilled occupations (sales/services, elementary, machine operators), with fewer skilled jobs (columns 3 and 4).[16] Compare column (1) to the broader workforce (in columns 5-7), we can see that the online users look rather dissimilar to the Thai workforce as a whole (column 5), but appear more comparable to the young and skilled labour force in the Bangkok area (column 7).

Furthermore, Tables 2 and 3 provide the comparison of the characteristics of job vacancies and jobseekers, respectively, between the internet platform, the DOE, and the Labour Force Survey.

According to Table 2, jobs posted on the internet platform target more highly-skilled workers than jobs on the DOE – with a higher proportion of jobs seeking workers with a Bachelor's degree or higher (39% and 14%, respectively) whereby the majority of jobs on the DOE aim at workers with high school diploma or below (86%). Employers on the DOE platform posted jobs that target younger workers – with only 20% of all jobs seek workers above 35 years old. Nevertheless, most jobs posted on both platforms search for relative inexperienced and young workers, with only 14% of jobs posted on the internet platform search for workers with 6 or more years of work experience. In addition, approximately 5% of job vacancies offer the starting salary higher than 30,000 bahts – indicating that these jobs are relatively entry-level positions.

[16] It is worth noting that, there may be a degree of human errors on the DOE's part when classifying jobs into the standard occupational title (ISCO). This is based on our analysis done in our companion work (Lertmethaphat, Lekfuangfu, and Treeratpituk 2024) where in our Machine Learning analysis, we detected that some service occupations, particularly maids, gardeners, cooks in the DOE's database are mis-categorized as ISCO Major Group 9 ("Elementary workers") instead of their appropriate categories of Major Group 5, resulting in an exaggeration in the size of Major Group 9. With this aggregate data of the DOE that is used in this paper, we do not have the information on how non-standard occupational titles are classified into its corresponding ISCO group.

Analogously, based on Table 3, we can see that jobseekers who use the online job platform are relatively young (60% aged 20-29 years old), highly educated (75% with a Bachelor's degree or higher), urban (80% reside in Bangkok areas), and mostly seek entry-level jobs (over 90% seek jobs with offered salary below 25,000 baht). By contrast, the ages of jobseekers in the DOE's database are more dispersed – with 50% of them aged older than 30 years old.

In terms of geographical coverage, vacancies and jobseekers on the internet platform are predominantly from Bangkok areas whilst the DOE's jobs are more dispersed across 5 regions in the country.

Table 1. Proportion of jobseekers and job vacancies by occupation (ISCO 1 digit)

ISCO 1-digit	Internet		DOE		LFS: Labour Force		
	Vacancies	Job seekers	Vacancies	Job seekers	All employed	20-30 yo, BKK	20-30 yo, BKK, college+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Managers	4.4	3.8	2.7	3.0	3.4	3.4	6.6
2. Professionals	13.7	22.9	4.1	5.3	5.8	14.3	29.1
3. Technicians, Associate Professionals	16.6	15.1	13.8	13.6	4.6	12.5	22.3
4. Clerical Support	18.7	25.1	13.2	18.2	4.5	12.0	16.8
5. Service, Sales	38.0	29.4	14.9	14.9	20.7	23.2	17.2
6. Skilled Agricultural, Forestry, Fishery	0.0	0.0	0.4	0.3	28.2	0.5	0.0
7. Craft and Related Trades	3.8	1.3	6.3	4.6	11.4	11.4	2.5
8. Plant/Machine Operators, Assemblers	3.1	1.6	5.8	5.2	9.9	11.1	1.9
9. Elementary	1.7	0.8	38.8	34.9	11.6	11.7	3.6

Note: Columns 1 and 2 show the proportion of job vacancies and jobseekers in a given occupation (1-digit ISCO) of the data from the internet-based platform (dated November 2020 – November 2021), columns 3 and 4 show the equivalent value of the data from the Department of Employment (DOE)'s platform (January 2014-July 2024). Columns 5-7 show the proportion of labour force from the Labour Force Survey (average of 2020 and 2021) for three defined population groups: (5) all employed, (6) employed workforce who aged 20-30 years old and resided in Bangkok plus area, (7) is (6) who also have a university degree or higher.

Table 2. Proportion of job vacancies by selected characteristics

	Internet (1)	DOE (2)
Panel A: Gender requirement		
Female-only	11.1	6.6
Male-only	20.3	15.1
Not Specified	68.6	78.3
Panel B: Age requirement		
Not older than 25	1.7	33.0
26 - 30	12.7	26.0
31 - 35	35.9	21.2
Above 35	49.7	19.8
Not Specified	0	0
Panel C: Education requirement		
PhD	0.0	0.1
Master's Degree	0.2	0.6
Bachelor's Degree	38.1	13.9
High Vocational Certificate	13.4	21.2
High School Diploma	12.9	32.9
Vocational Certificate	10.3	14.4
Below High School	10.5	15.7
Unspecified	14.6	0
Panel D: Location		
Bangkok & Peripheral	84.2	35.8
Central	3.8	25.6
North	2.2	12.6
Northeast	3.1	13.3
South	1.4	12.7
Unspecified	5.3	0
Panel E: Types of companies		
Public Company Limited	14.1	N/A
Company Limited	75.2	N/A
Partnership Limited	0.5	N/A
Unspecified	10.2	N/A
Panel F: Experience requirement		
Up to 1 year	9.2	N/A
2 years	18.2	N/A
3 years	6.3	N/A
4 - 5 years	19.5	N/A
6+ years	14.1	N/A
No minimum	32.8	N/A
Panel G: Salary offered		
Over 50,000 baht	1.3	N/A
30,000 - 50,000 baht	4.6	N/A
25,000 - 30,000 baht	3.4	N/A
20,000 - 25,000 baht	7.6	N/A
15,000 - 20,000 baht	16.1	N/A
12,000 - 15,000 baht	13.9	N/A
Less than 12,000 baht	8.6	N/A
Not Specified	44.5	N/A

Note: Column 1 shows the proportion of job vacancies in each given characteristic of the data from the internet-based platform (dated November 2020 – November 2021). Column 2 shows the equivalent value of the data from the Department of Employment (DOE)'s platform (January 2014-July 2024).

Table 3. Proportion of jobseekers by selected characteristics

<table>
<tr><th rowspan="2"></th><th rowspan="2">Internet</th><th rowspan="2">DOE</th><th colspan="3">Labour Force Survey</th></tr>
<tr><th>All employed</th><th>20-30, BKK</th><th>20-30, BKK, college+</th></tr>
<tr><th></th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th></tr>
<tr><td colspan="6">Panel A: Gender</td></tr>
<tr><td>Female</td><td>60.6</td><td>57.7</td><td>45.8</td><td>49.9</td><td>60.5</td></tr>
<tr><td>Male</td><td>39.4</td><td>42.3</td><td>54.2</td><td>50.1</td><td>39.5</td></tr>
<tr><td colspan="6">Panel B: Age groups</td></tr>
<tr><td>15-19</td><td>1.7</td><td>0.8</td><td>2.3</td><td>0.9</td><td>0.0</td></tr>
<tr><td>20-24</td><td>44.2</td><td>29.1</td><td>10.8</td><td>6.8</td><td>4.3</td></tr>
<tr><td>25-29</td><td>29.4</td><td>20.4</td><td>16.2</td><td>14.6</td><td>18.9</td></tr>
<tr><td>30-34</td><td>12.3</td><td rowspan="2">28.6</td><td>15.8</td><td>19.5</td><td>22.0</td></tr>
<tr><td>35-39</td><td>6.7</td><td>15.9</td><td>19.1</td><td>19.9</td></tr>
<tr><td>40+</td><td>5.5</td><td>21.2</td><td>39.0</td><td>39.2</td><td>35.0</td></tr>
<tr><td colspan="6">Panel C: Education</td></tr>
<tr><td>PhD</td><td>0.1</td><td>0.0</td><td rowspan="3">17.6</td><td rowspan="3">47.1</td><td rowspan="3">N/A</td></tr>
<tr><td>Master's Degree</td><td>2.6</td><td>0.5</td></tr>
<tr><td>Bachelor's Degree</td><td>72.2</td><td>28.1</td></tr>
<tr><td>High Vocational Certificate</td><td>10.3</td><td>10.9</td><td rowspan="2">23.6</td><td rowspan="2">22.8</td><td rowspan="2">N/A</td></tr>
<tr><td>High School Diploma</td><td>7.4</td><td>38.8</td></tr>
<tr><td>Vocational Certificate</td><td>4.0</td><td>6.5</td><td rowspan="2">58.8</td><td rowspan="2">30.1</td><td rowspan="2">N/A</td></tr>
<tr><td>Below High School</td><td>3.5</td><td>14.8</td></tr>
<tr><td colspan="6">Panel D: Location</td></tr>
<tr><td>Bangkok & Peripheral</td><td>79.4</td><td>29.1</td><td>14.2</td><td>15.5</td><td>25.7</td></tr>
<tr><td>Central</td><td>4.7</td><td>23.6</td><td>31.8</td><td>34.2</td><td>30.3</td></tr>
<tr><td>North</td><td>4.8</td><td>14.3</td><td>16.0</td><td>14.9</td><td>14.2</td></tr>
<tr><td>Northeast</td><td>6.3</td><td>17.2</td><td>24.5</td><td>21.8</td><td>17.1</td></tr>
<tr><td>South</td><td>4.8</td><td>15.8</td><td>13.6</td><td>13.6</td><td>12.7</td></tr>
<tr><td colspan="6">Panel E: Salary asked</td></tr>
<tr><td>Over 50,000 baht</td><td>1.2</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>30,000 - 50,000 baht</td><td>5.1</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>25,000 - 30,000 baht</td><td>5.1</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>20,000 - 25,000 baht</td><td>9.4</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>15,000 - 20,000 baht</td><td>30.6</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>12,000 - 15,000 baht</td><td>30.1</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td>Less than 12,000 baht</td><td>18.5</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
</table>

Note: Column 1 shows the proportion of jobseekers in each given characteristic of the data from the internet-based platform (dated November 2020 – November 2021). Column 2 shows the equivalent value of the data from the Department of Employment (DOE)'s platform (January 2014-July 2024). Columns 3-5 show the proportion of labour force from the Labour Force Survey (average of 2020 and 2021) for three defined population groups: (3) all employed, (4) employed workforce who aged 20-30 years old and resided in Bangkok plus area, (5) is (4) who also have a university degree or higher.

3.3. Defining the parameters of the Beveridge curve

Prior to building up Thailand's Beveridge curve(s) from the databases described earlier, let us first define the required parameters as the followings:

- U: the number of jobseekers in a given platform in a given time period (monthly or fortnightly)
- V: the number of posted vacancies in a given platform in a given time period (monthly or fortnightly)
- L: This is the number of labour force in a given market segment. This value is used as the denominator in the calculation of the rates of jobseekers and vacancies subsequently. Based on the representativeness of our internet platform data (see Section 3.2), we decide to narrow the coverage of Thailand's labour market from the entire national segment down to two definitions:
    - L_1: Labour force aged 20-30 years old, lived in Bangkok and surrounding area.
    - L_2: Labour force aged 20-30 years old, lived in Bangkok and surrounding area, *and with a college education or higher.*
    - Furthermore, given that the representativeness of these two datasets is noticeably different, we will use a different value of L when we construct the Beveridge curve from the DOE's database.

In summary, two main components of the Beveridge curve are calculated as shown in Table 4 – with respect to the choice of L (namely, L_1 or L_2) as the denominator.

Table 4. Calculation of the jobseeker rate and job vacancy rate

	L_1 as denominator	L_2 as denominator
Jobseeker rate (u):	$100 \times U/ L_1$	$100 \times U / L_2$
Vacancy rate (v):	$100 \times V/(L_1 + V)$	$100 \times V/ (L_2 + V)$

4. Main results: a showcase of Thailand's Beveridge curve(s)

In the section, we follow the standard approach of the construction of Beveridge curve(s). Recall that, for the case of Thailand, we now have necessary statistics from two available sources: (i) the online job platform (for the period of November 2020 – November 2021), and (ii) the Department of Employment's job platform (January 2014 to July 2024). We also urge our readers to keep in mind that these two databases represent two different segmentations of Thailand's labour market (see Section 3.2), and that, none of them reflect the labour market at the nationally representative level.

4.1. Monthly Beveridge curve using the entire coverage of each database

Recall that we employ two values for the possible size of labour force as the denominator for the calculation of the rates of jobseekers and of job vacancies. Therefore, Table 5 shows how the rates vary directly with whether or not the coverage of appropriate labour force is defined as: (i) as L_1 (employed workforce, aged 20-30, residing in Bangkok areas); or (ii) a more narrowly defined group of L_2 (the sub-group of L_1 who has at least a university degree). Empirically, for the period of 2020-2021 (based on the corresponding Labour Force Surveys), the levels of L_1 and L_2 are approximately 1,000,000 and 500,000, respectively.

Table 5 illustrates the rates correspond to each defined coverage of the labour force, using the online platform database during November 2020 to November 2021. Given that the size of L_2 is approximately a half of L_1, the rates of u and v in columns (4) and (5) are doubled of (1) and (2). It is worth noting that, by construction, the labour market tightness (defined as v/u) in columns (3) and (6) are robust to the choice of labour force coverage. Therefore, under the defined labour market segmentation of the online platform databased, during this 1-year period, there are around 0.5 jobs available for each jobseeker.

Additionally, we knowledge that the period covered by the data overlaps almost the entire episodes of covid-19 pandemic and lockdowns in Thailand. Surprisingly, we observe only a slight contraction of hiring demand, with approximately a 1-2 percentage points increase in the jobseeker rates during Quarter 2 of 2021.

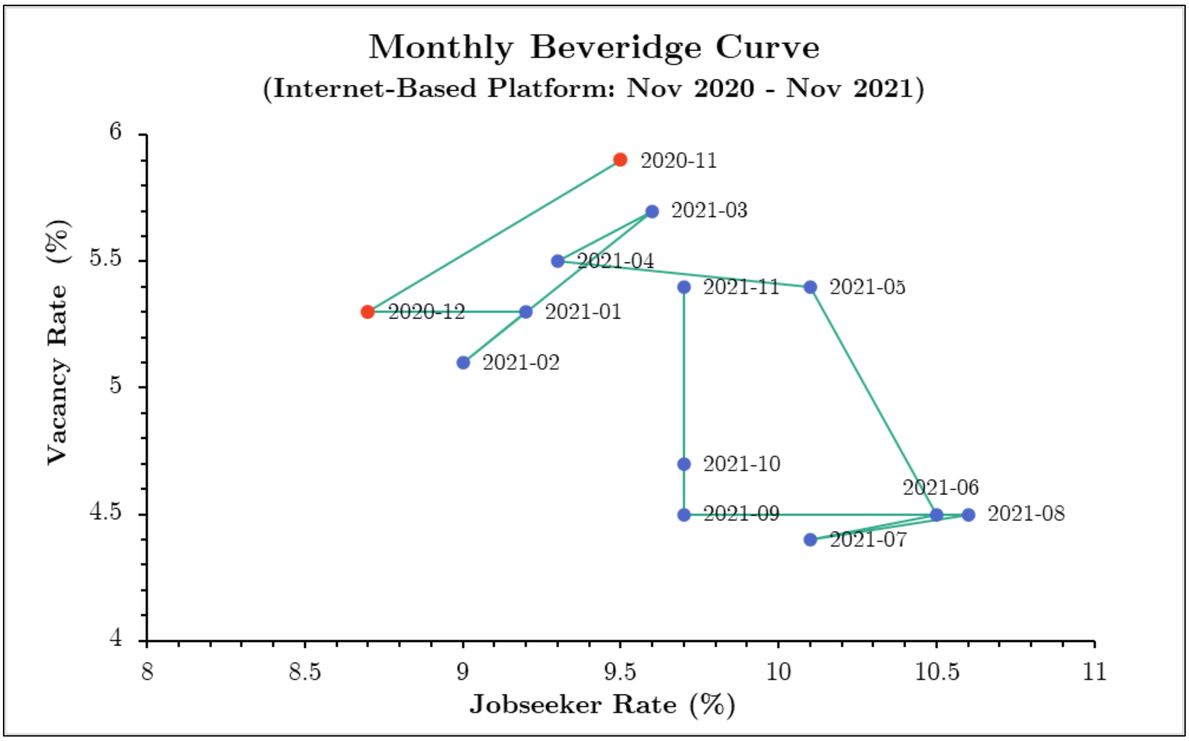
Table 5. The rates of jobseekers and vacancies (internet platform)

	L_1 as LF			L_2 as LF		
	u	v	v/u	u	v	v/u
	(1)	(2)	(3)	(4)	(5)	(6)
2020-11	9.5	5.9	0.62	18.9	11.2	0.59
2020-12	8.7	5.3	0.61	17.5	10.1	0.57
2021-01	9.2	5.3	0.58	18.3	10.0	0.55
2021-02	9	5.1	0.57	18.1	9.7	0.54
2021-03	9.6	5.7	0.59	19.2	10.8	0.56
2021-04	9.3	5.5	0.59	18.7	10.3	0.55
2021-05	10.1	5.4	0.53	20.1	10.3	0.51
2021-06	10.5	4.5	0.43	21	8.6	0.41
2021-07	10.1	4.4	0.44	20.3	8.4	0.41
2021-08	10.6	4.5	0.42	21.3	8.6	0.4
2021-09	9.7	4.5	0.46	19.4	8.6	0.44
2021-10	9.7	4.7	0.48	19.4	8.9	0.46
2021-11	9.7	5.4	0.56	19.5	10.3	0.53

Notes: The data source is the online platform database during November 2020 to November 2021. L1 is the coverage of labour force who are employed workforce, aged 20-30, residing in Bangkok areas; L2 are a more narrowly defined group of the sub-group of L1 who have at least a university degree. The calculation of labour force numbers utilises the Thailand's Labour Force Survey (averaged 2020-2021 surveys).

Now, Figure 4 plots the corresponding Beveridge curve - using the rates in columns (1) and (2) of Table 5 above (with L_1 as the denominator).[17] Broadly speaking, this Beveridge curve appears to have a negative slope, as commonly found in other countries. Starting from period 1 (November 2020), we can track the movement over the coming months of the relationship of u and v along this Beveridge locus. In fact, we observe the downward direction as the vacancy rate (v) continued to decline whilst the jobseeker rate (u) started to expand from April 2021 to July 2021. However, the fluctuation of u and v is somewhat moderate. By comparison, over the same time period, the US' labour market its vacancy and unemployment rates vary by 4 ppt and 10 ppt, respectively.[18]

Figure 4. Monthly Beveridge curve (the online platform, whole coverage)



Notes: The data covers all observations on the online platform database during the period of November 2020 – November 2021. The nominator that is used to calculate the rate here is L1.

Next, Figure 5 plots an equivalent Beveridge curve (November 2020 – November 2021) using the DOE's parameters for a direct comparison. Provided that the labour market coverage of DOE is different from that of the online platform, we employ a different value for the labour force size (L_3) as the denominator when converting the levels to the rates.[19] Curiously, the shape of the DOE-based Beveridge curve DOEs not follow its conventional

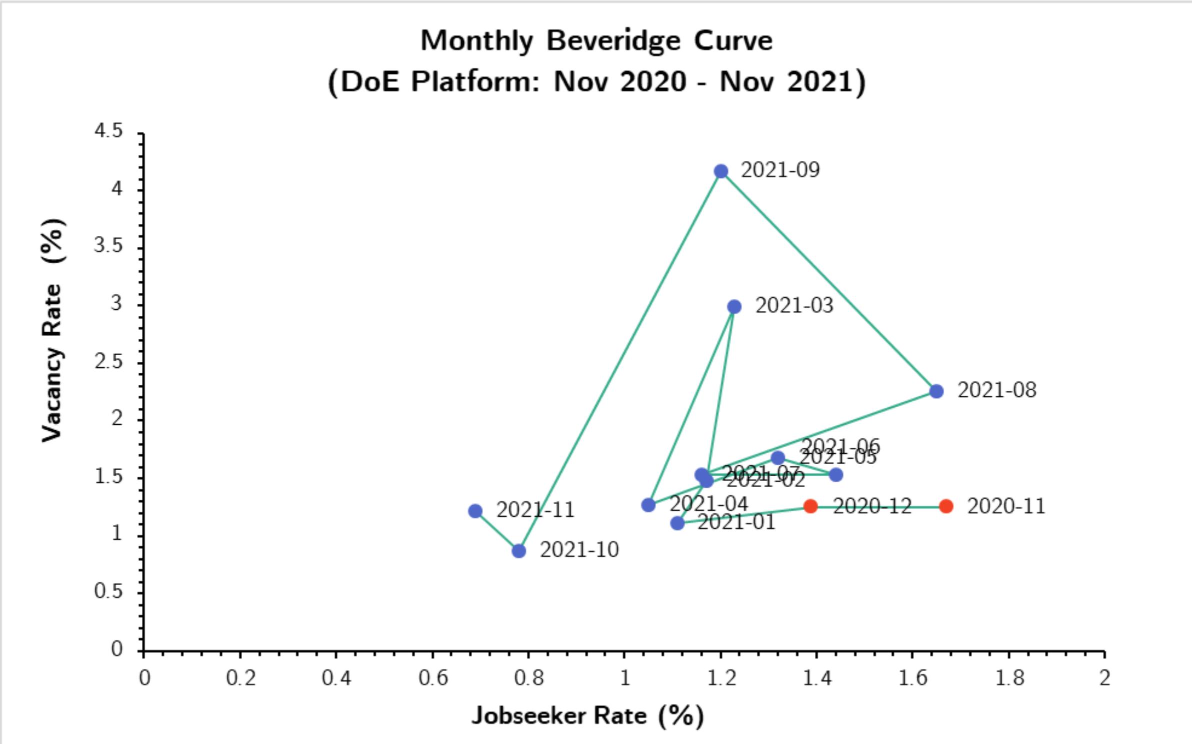
[17] The related Beveridge Curve with the rates being calculated with L2 is available upon request. Its shape should analogously mimic Figure 4.

[18] See Figure 1 in Barlevy et al. (2024).

[19] We approximate the annually average size of the corresponding labour force coverage for the DoE as 2.3 million people. This approximation is based on the representativeness of the DoE's users along the dimension of sector, region, age group and educational group.

shape. The co-movement relationship between DOE's u and v appears to be a positive one. Additionally, there is more volatility than the equivalent statistics from the online platform.

Figure 5. Monthly Beveridge curve (DOE platform)

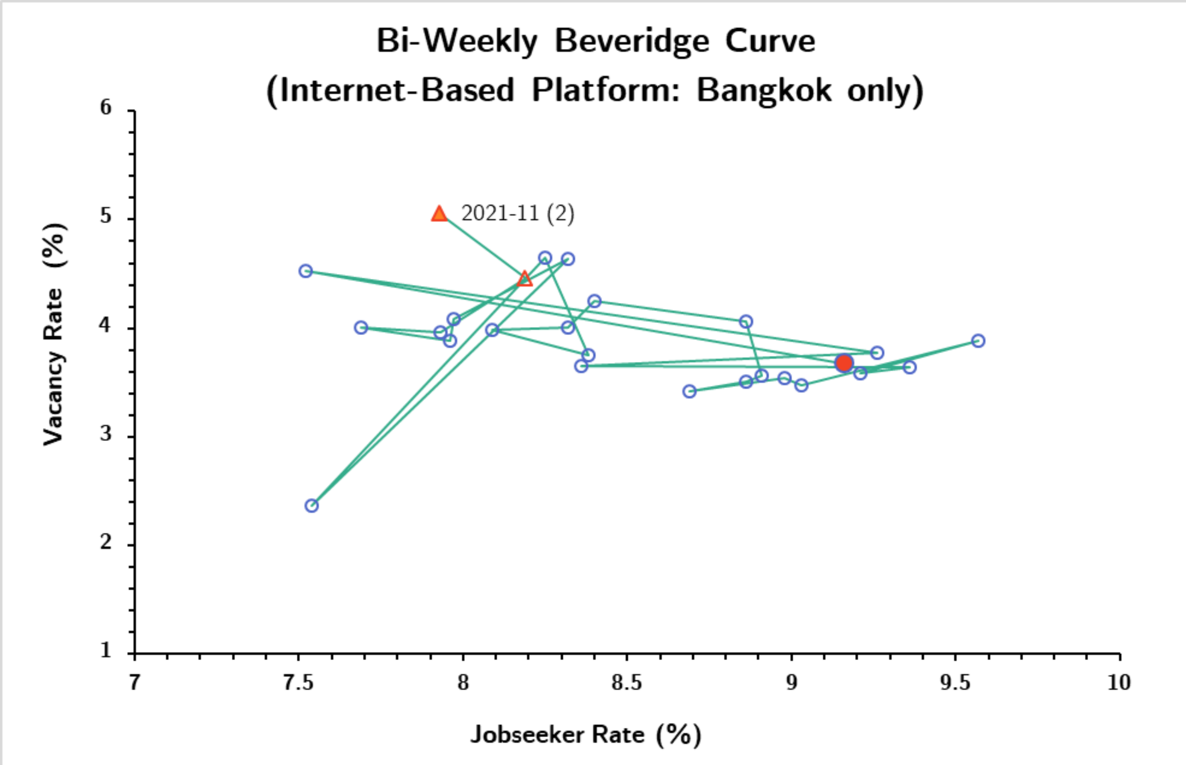


Notes: The data covers all observations on the DOE's job platform database during the period of November 2020 – November 2021. The nominator that is used to calculate the rate here is L3 (at 2.4 million persons).

4.2. Biweekly Beveridge curve (with the online platform)

With the online data, we can also plot the Beveridge curve with a higher temporal frequency. Figure 6 shows the curve using the biweekly flows of jobseekers and vacancies in the database. Compare to the monthly locus (Figure 5), a higher-frequency Beveridge curve shows a relatively higher fluctuation period-to-period. This is partly due to a higher dispersion of the biweekly values of u and v than their monthly counterparts. Overall, the negative sloping locus of a typical Beveridge curve is observed. And as we noticed previously, the labour market appears to have experienced a contraction in vacancies whilst a higher jobseeker rate toward the end of the covid-19 (quarter 3 of 2021).

Figure 6. Biweekly Beveridge curve (the online platform)



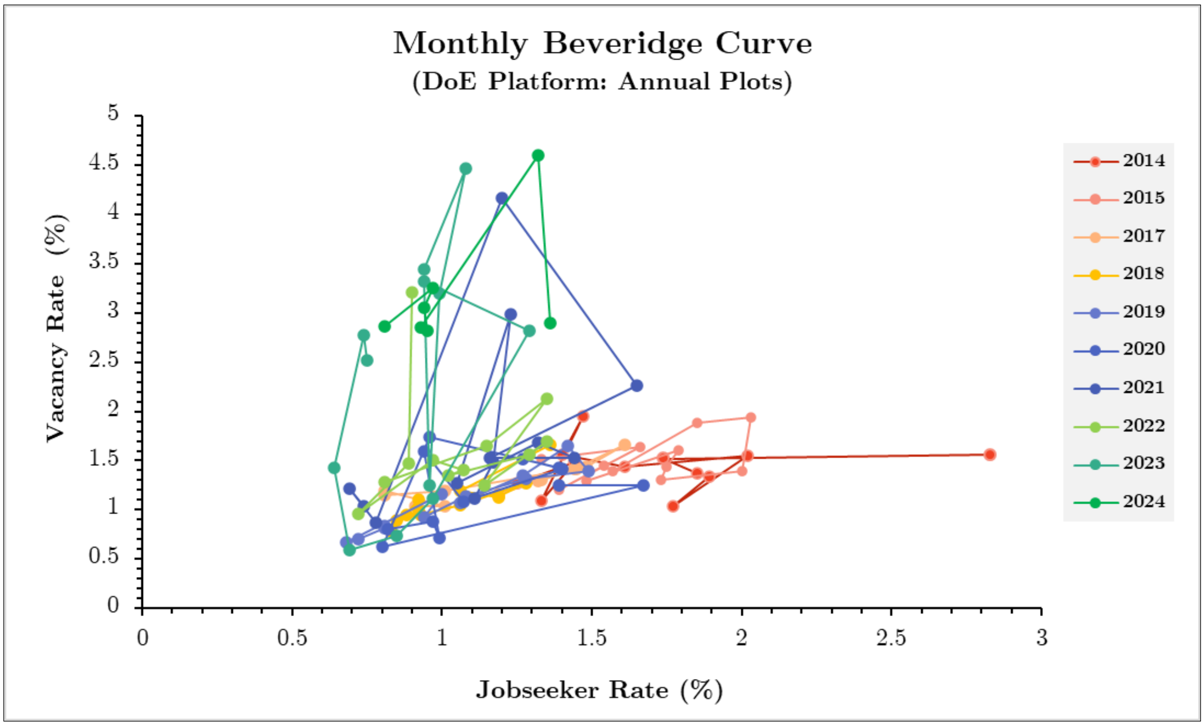
Notes: The data covers all observations on the online platform database during the period of November 2020 – November 2021. The nominator that is used to calculate the rate here is L1. The vertical axis starts at V = 1%, and the horizontal axis starts at U = 7%.

4.3. Exploring Beveridge curve of the past decade.

With the availability of the statistics of u and v of the DOE's job platform since January 2014, we can attempt to plot the Beveridge curve for this segmented market over a long time period.

Figure 7 presents each curve for each associate year from 2014 to 2024. Arguably, we can group the years into (a) pre covid-19 period (2014-2018), (b) covid-19 period (2019-2021), and (c) post covid-19 (2022-2024). Looking across the entire decade, the Beveridge curve looks to demonstrate the typical negative-sloping shape. The period prior to the covid-19 (in red) witnesses a relative flat movement of the vacancy rate (0.5% to 1.5%) but a somewhat fluctuating jobseeker rate (0.5% to 3%). By contrast, since 2022, we began to notice a much volatile movement of the vacancy rate whilst relative minimal movements (and low level) of the jobseeker rate in this market segmentation. During the similar time of post covid-19 period (2022-2023), many developed economies experienced a notable rise in quits and unemployment due to the so-called Great Resignation phenomenon (Barlevy et. al. 2024).

Figure 7. Beveridge curve of 2014-2024 (DOE platform)



Notes: The data covers all observations on the DOE's job platform database during the period of January 2014 – July 2024. The nominator that is used to calculate the rate here is L3 (at 2.4 million persons).

4.4. Beveridge curves for selected labour market segmentations

Finally, this section will demonstrate further possible depictions of Beveridge curve in certain sub-coverage of the labour market. On the one hand, such exercises are viable as there exist necessary statistics (namely, jobseeker and job vacancy levels) for selected segmentation of the labour market. On the other hand, one needs to be highly cautious and carefully select such segmentations where the representativeness of the data is sufficient and meaningful.

In this exercise, we will attempt to plot the Beveridge curve for occupation groups that each of our database well represents the market. We aim to check if (i) each occupation group shares a common slope of its locus of the curve; and (ii) the position of its locus on the diagram. The latter would indicate the relative degree of matching efficiency in each segment of the labour market. The further to the upper-right, the worse the matching mechanism of that market.

First of all, Table 6 shows the labour market tightness measurement for each ISCO 1-digit occupation in the online platform. Group A are occupations with large numbers of job ads and jobseekers (Occupation groups 2,3,4,5) whilst Group B (groups 1, 6, 7, 8) are those with much fewer counts on the platform and thus their statistics are less reliable. We will discuss and later present the curves for only occupations in Group A. At least for this internet job platform, there are more available jobs per jobseeker among Occupation Group 5 (Service and Sales Workers) than others – even if there is fewer than one job per person overall.

Subsequently, to check the shape of the locus of the relationship between u and v in a given sector, Figures 8 presents the Beveridge curve for each occupation in Group A.

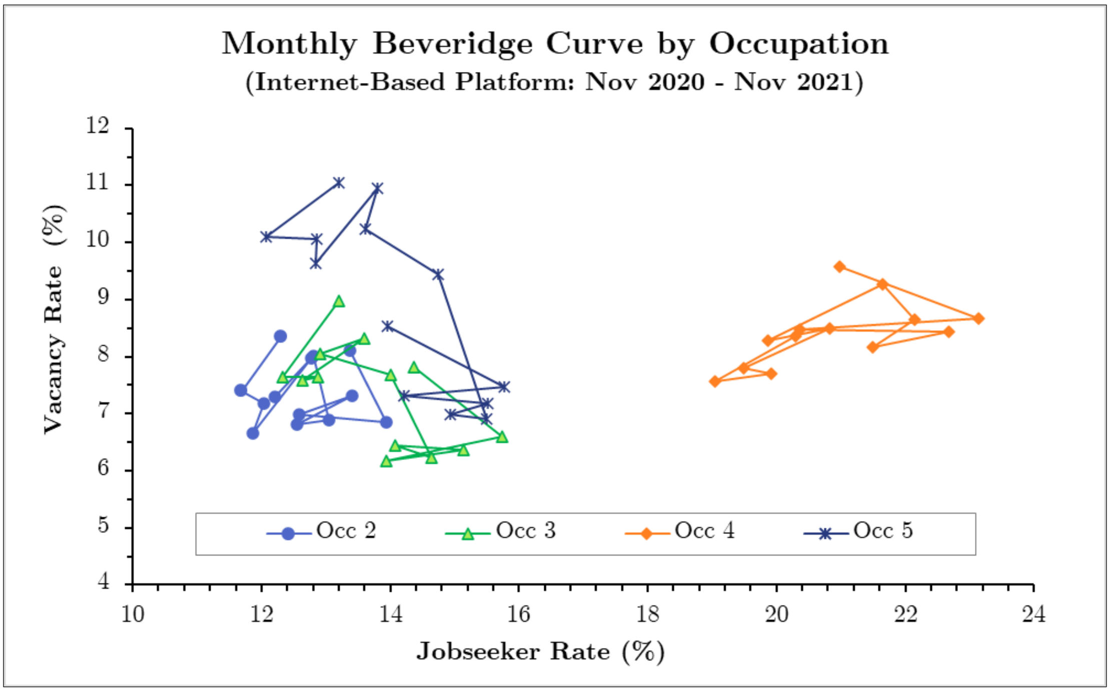
Next, we continue our exercise with the DOE's data and plot the Beveridge curve for occupational groups 4, 5, and 9 as they are occupations that are better represented (Figure 9). For simplicity, we focus only on the period of January 2022 to July 2024 in this exercise.

Table 6. Labour market tightness by ISCO occupational group (online platform)

	Group A				Group B				
	Occ 2	Occ 3	Occ 4	Occ 5	Occ 1	Occ 6	Occ 7	Occ 8	Occ 9
Nov-20	0.35	0.68	0.41	0.84	0.68	N/A	2.03	0.98	1.02
Dec-20	0.33	0.62	0.40	0.84	0.63	N/A	2.04	0.88	1.01
Jan-21	0.32	0.59	0.39	0.78	0.60	N/A	1.90	0.85	0.91
Feb-21	0.32	0.60	0.40	0.75	0.56	N/A	1.94	0.81	0.96
Mar-21	0.34	0.61	0.41	0.79	0.62	N/A	2.04	0.87	1.11
Apr-21	0.32	0.62	0.42	0.75	0.60	N/A	1.94	0.89	1.20
May-21	0.31	0.55	0.43	0.64	0.63	N/A	1.88	1.02	1.26
Jun-21	0.27	0.43	0.39	0.45	0.53	N/A	1.48	0.91	1.20
Jul-21	0.26	0.46	0.38	0.47	0.54	N/A	1.51	0.89	1.12
Aug-21	0.26	0.42	0.37	0.46	0.55	N/A	1.55	0.89	1.13
Sep-21	0.28	0.44	0.42	0.52	0.55	N/A	1.69	0.99	1.43
Oct-21	0.26	0.42	0.37	0.47	0.49	N/A	1.52	1.04	1.41
Nov-21	0.35	0.54	0.46	0.61	0.61	N/A	2.38	1.73	1.91
L*	130,000	110,000	110,000	210,000	30,000	N/A	100,000	100,000	100,000

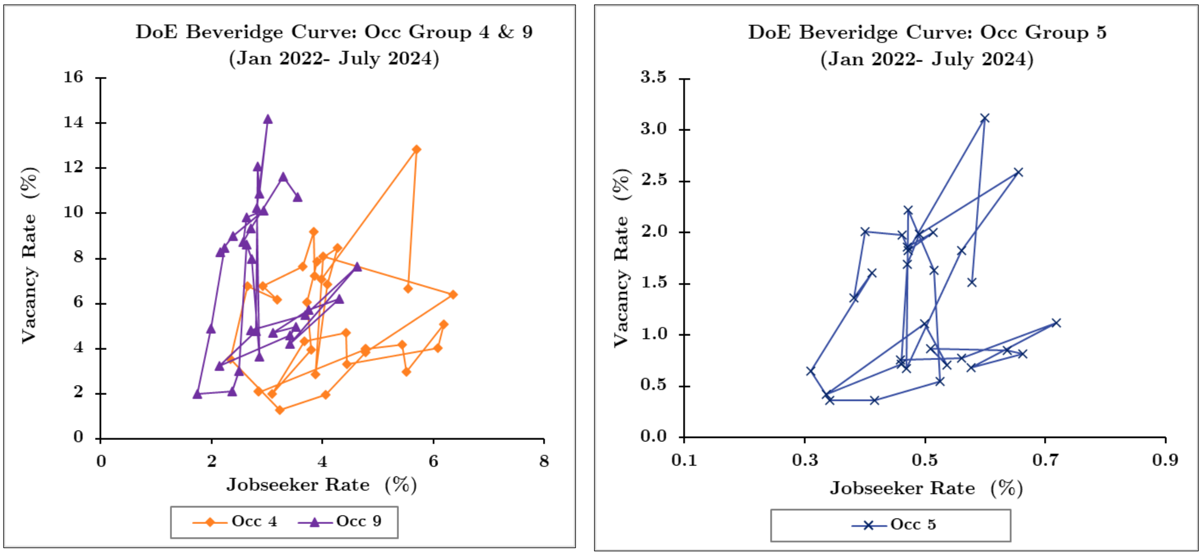
Notes: The data source is the online platform database during November 2020 to November 2021. We first re-calculate the rate of jobseekers and of vacancies for each occupation-month by dividing the total number of the size of the segmented labour force (L*). We denote the corresponding L* for each occupation at the bottom row of the table. The calculation of labour force numbers utilises the Thailand's Labour Force Survey (averaged 2020-2021 surveys). The data for ISCO Major Group 6 is not available in the database.

Figure 7. Beveridge curve by occupation (the online platform)



Notes: The data covers all observations on the online platform database during the period of November 2020 – November 2021. The nominator used to calculate the rates is the size of labour force that is specific for each occupation (see L* in Table 6). The vertical axis starts at V = 4%, and the horizontal axis starts at U = 10%.

Figure 8. Beveridge curve by occupation (DOE's platform)



Notes: The data covers all observations in occupation groups 4, 5 and 9 on the DOE's job platform database during the period of January 2022 – July 2024. The nominator used to calculate the rates is the size of labour force that is specific for each occupation. On the right panel, the vertical axis starts at V = 0%, and the horizontal axis starts at U = 0.1%.

5. Going forward and conclusions

Overall, this paper initially addresses the importance of Beveridge curve in decision making for policies regarding the labour market and beyond. The absence of consistent and reliable data in Thailand, particularly on job postings has posed a significant disadvantage. This is because the comprehension of labour market behaviours was able to rely only on limited indices, particularly unemployment rates. In the case of Thailand, this index has always remained low (around 1-3 %) and its changes is rather inelastic – with highly limited reaction to other surrounding economic drivers.

This paper presents a showcase of how the Beveridge curve can be constructed for Thailand by exploiting two, related data sources: (i) the administrative data from the government-run job centre services and (ii) user-generated data from online job portals. We have presented a procedure on how vacancy and jobseeker rates can be computed from each database. On the other hand, we also discuss the extent of the population representation of each database and cautiously confirm that each data reflects different segments of Thailand's labour market. Online job platforms attract posted jobs and jobseekers from relatively higher skilled of the young and urban population. By contrast, the government job centre services have drawn more users of blue-collar jobs, and also their database has better regional coverage. Since both databases do not overlap much, we believe that it is more insightful for policy-makers to continue to pay attention to information arising from both market segments. Finally, we note that it is of the high interest for central banks or related agencies to continue collect and monitor these databases in order to better track and comprehend the behaviour of Thailand's labour market above and beyond the few conventional, less informative indices.

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