COVID-19 and the Intentions to Migrate from Developing Countries: Evidence from Online Search Activities in Asian Countries

by Nobuyuki Nakamura and Aya Suzuki

COVID-19 and the Intentions to Migrate from Developing Countries: Evidence from Online Search Activities in Asian Countries

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COVID-19 has had an enormous effect on labor markets globally. Economic restrictions, notably strict border controls and lockdowns, have led many workers to lose their jobs and forced many migrants to return to their homes or change their migration plans. While adverse effects on labor mobility are expected, variations in the prevalence of COVID-19 and governmental responses to the pandemic across countries are likely to influence workers' intentions to migrate in different ways. To understand the effects of pandemics on the international labor supply, we explore the impact of COVID-19 and the various economic restriction policies on job search behavior by considering cases from Southeast Asian countries using the difference-in-differences (DID) approach with data from Google Trends Index (GTI). We find that the search volume of queries related to the labor market dramatically increased over time following the outbreak of COVID-19. However, we do not observe any positive impact on the search volume related to emigration, regardless of the infection control measures in the host countries. Our results imply that the job insecurity increases after the imposition of lockdown in the respective countries. On the other hand, the expectation to migrate outside of the country, which requires preparation time and incurs high costs, does not seem to have increased in developing countries.

Keywords: COVID-19, Migration, Google Trends, Unemployment

JEL: C55, I18, J61, O15, O53

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I. Introduction

Cross-border labor mobility has recently surged, and labor interdependency has escalated in the global market. In December 2019, a novel coronavirus (COVID-19) was firstly reported, which dramatically spread and wreaked havoc on the global market. As of December 15, 2020, more than 72 million people have been infected, and approximately 1.6 million patients have died because of this pandemic. To curb the spread of the virus among their respective citizens, each government has implemented strict lockdowns or social distancing measures. Although these implementations are helpful for averting the epidemic of the novel coronavirus, economic restrictions to mitigate the spread of the virus have made many workers redundant and forced countless migrants to return to their homes (Khanna 2020) as the economy and labor market in each country has been heavily and negatively affected. While the full impact of this pandemic on the world economy and labor markets is yet to be determined, recent studies have provided quantitative evidence of its negative impact. Gupta et al. (2020) suggest that the employment rate decreased after the stay-at-home mandate in the U.S., while Couch et al. (2020) and Montenovo et al. (2020) imply that there have been heterogeneous effects of this pandemic on unemployment in the U.S., and these effects have impacted minorities with particular severity. In addition, Borjas and Cassidy (2020) explain that unemployment has severely affected immigrants in the United States.

These adverse effects have expanded globally, not only in industrialized countries but also in developing countries, where the impact is more severe. According to IMF (2020), there have been substantial and negative effects on low-income households, causing severe unemployment and crowding out the effort to reduce extreme poverty around the world that has been in progress since the 1990s. This recession of the economy and industry will lead to food insecurity and nonattainment of the Sustainable Development Goals (SDGs) in developing countries (Barbier & Burgess 2020; Elleby et al. 2020; Sumner et al. 2020). Moreover, border controls have prohibited the entry of foreign workers into host countries. As the early estimates, World Bank (2020) suggests that international remittances will be expected to decrease by approximately 20% in 2020 because the income and employment of migrant workers will be lost, although remittances are a crucial source of income for developing countries. Therefore, the adverse effects on both domestic and international labor markets will impact the livelihood of households in developing countries.

While adverse effects on labor mobility are expected in general, variations in the prevalence of COVID-19 and governmental responses to the pandemic across countries are likely to influence workers' intentions to migrate in different ways. If the situation has worsened in their home countries, workers may seek jobs in other countries that are in better condition. Above all, high unemployment or job instability in the living areas plays a key role for one of push factors of international migration (Pissarides & Wadsworth 1989; Mihi-Ramírez et al. 2014). As for this pandemic, for example, it has been reported that the number of people seeking information about emigrating to New Zealand, which has been relatively successful in containing the virus, increased by 65% in the U.S. and by 18.5% in the U.K. in May 2020 compared to the same month one year ago (Guardian 2020). On the other hand, workers may not consider migration during the pandemic because most countries have implemented strict border control policies. A survey of nationals in Central America and Mexico, who had the intentions of migrating in the past year, reveals that COVID-19 has affected their immigration plans, and 10% of those who had intended to migrate no longer wished to do so (IOM 2020). While some studies have examined the effects of past pandemics on labor markets (Lee & Cho 2017; Yu et al. 2020), the unprecedented scale of COVID-19 suggests the need for further investigation, especially in regard to the international labor market. Moreover, among the emerging studies on the effects of COVID-19, there is still limited evidence from developing countries.

To understand the immediate effects of pandemics on the cross-border labor supply, we explore the impact of COVID-19 and various economic restriction policies on job search behavior using the difference-in-differences (DID) approach to consider cases from Asia, where we witness a substantial influx and outflux of migration within the region (IOM 2017). We examine how the search volume of job- or migration-related queries was affected by COVID-19 and the resulting lockdowns using panel data with daily online search trends based on the Google Trends Index (GTI) in the

Southeast Asian countries. The GTI reflects the search intensities of queries submitted to the Google search engine worldwide (Choi & Varian 2012). Relying on big data such as the GTI has several advantages. First, the big data are available in real time. Collecting data for effective policymaking is difficult while this pandemic continues around the world. Even if household data could be collected, there is a considerable lag in regard to when the published data are available to the public. In developing countries, these costs and lags regarding data collection commonly occur in survey-based research, even in ordinary times, and data relating to job security or to migration intentions are often unavailable (Böhme et al. 2020). Therefore, when needed to implement sound policy frameworks immediately, real-time big data become a powerful tool for research and policymaking (Varian 2014). Second, the use of big data has been shown to predict economic outcomes more accurately than traditional benchmark models. Above all, researchers can obtain economic trends or contemporary demands among Internet users using online search data. Recent literature implies that the GTI can be used to predict economic outcomes such as unemployment rate (D'Amuri and Marcucci 2017; Mihaela 2020), employment growth (Borup & Schütte 2020), real GDP (Narita & Yin 2018), stock price (Da et al. 2011), and migration flows (Böhme et al. 2020). Many models using the GTI outperform the benchmark model with only the traditional economic measures, which are collected by the physical survey, because the Google searches reflect the revealed and timely demands for information with related queries[3]. The GTI trends will capture the stream about interest of people and forecast the future outcomes of the related activities.

In our research, in addition to GTI data, we use data from a daily index on the strictness of government policy measures imposed to combat COVID-19 published by the University of Oxford, the confirmed cases of COVID-19 as provided by Johns Hopkins University, and GDP per capita and unemployment rates for each country from the World Bank and the IMF. We select data on Indonesia, the Philippines, and Vietnam, where many nationals travel overseas for work, while we also collect

[3] Google holds the top search engine share globally, with a share of 70.43% from desktop devices and 93.29% from mobile devices in August 2020 (retrieved from https://netmarketshare.com/ on September 29, 2020).

policy- and COVID-19-related data for Taiwan and Japan. Taiwan and Japan are selected for the potential destinations of the bilateral migration in our research because the numbers of migrant workers from Indonesia, the Philippines, and Vietnam to two host countries are rapidly increasing in recent years, and the prevalence of COVID-19 and the government measures enacted were different between these destinations. We collect data from December 2, 2018, to August 3, 2019, as the ex-ante period, and from December 1, 2019, to August 1, 2020, as the ex-post period, with 1,470 daily samples in total (245 days for each period and each country); using this information, we construct the daily panel data. We obtain the GTI data of queries in the native languages given the local job market situations and then adjust the index to compare the trends. To explore the impact of the pandemic and lockdown measures on daily job-related search activities, we employ the DID approach to compare same-date samples over the respective periods, following some literatures which explore the impacts of COVID-19 (e.g., Leslie et al. 2020; Ming et al. 2020). We examine whether the search outcomes are systematically different across these periods before and after the announcement of the emergency by the World Health Organization (WHO) and the consequent lockdown announcement in the capital of each country, during the assigned time frame.

The results suggest that the search volume of queries related to employment stability, such as "job," which is strongly correlated with the unemployment rate as the extant literature implies, dramatically increased after the outbreak of COVID-19 in the three Southeast Asian countries in question. Such trends have intensified over time, and we find that the volume dramatically increased after the release of the lockdown restriction. On the other hand, the search queries related to remittance decreased after the lockdown, and this tendency was reinforced after the lockdown was lifted. Moreover, we observe that bilateral queries to capture the migration intentions (Böhme et al. 2020), which are labor-related queries with the host country's name (e.g., "job Japan"), are affected either negatively or insignificantly regardless of prevalence control. In addition, we perform an event study approach to check the validity of the parallel trend assumption in the DID approach, and we demonstrate that our results satisfy this assumption.

These results imply that job insecurity increased for an unexplained reason, possibly unemployment or facility closures, after the virus became an epidemic; however, interest in remittance decreased. Moreover, we confirm that the solid expectation of migrating outside the country has not been enhanced in these countries, although the general concern for work or common interest in other countries seems to have increased dramatically. Thus, the priority among workers in developing countries is maintaining their livelihood during the pandemic. Even though migrating to developed countries may increase income, relocating to other countries becomes less of an option among their solutions after a large adverse shock.

This study contributes to the existing literature in two ways. First, it provides insight into the economic and social impact of epidemics, and specifically, COVID-19 in developing countries. After the outbreak of COVID-19, researchers in empirical economics have explored the effects of this pandemic and the related social distancing policies. Some studies explain the adverse effects in labor markets in industrialized countries such as the U.S. (Forsythe et al. 2020; Montenovo et al. 2020; Coibion et al. 2020; Bartik et al. 2020) or Japan (Kikuchi et al. 2021). As for studies in developing countries, researchers have explored the effects of the pandemic and the consequent recessions on households' livelihoods (Murakami et al. 2021; Lustig et al. 2020; Sumner et al. 2020), business performance (Anh & Gan 2020; Campos-Vazquez et al. 2020), and macro economies (IMF 2020; Suryahadi et al. 2020). However, because of data limitations, the literature in the context of developing economies is still scarce, especially in labor-supply research. This study is the first to examine the change in job search behaviors following the appearance of COVID-19 in these developing countries using timely response data. Our estimates will help understand the response to lockdown restrictions on laborers in developing countries.

Second, this research adds to the body of literature on the use of big data in economic research in emerging and developing countries. Narita and Yin (2018) explain the benefits of using big data, especially the GTI, for policymaking and economic or development research because timely data are often not available in low- and middle-income countries, and this may solve the problem of time lags in obtaining datasets. Some studies using GTI data explore economic behavior after the outbreak of COVID-19 during this time when it is difficult to collect data directly, including consumer behavior (Abay et al. 2020), job-related activities (Aaronson et al. 2020; Gupta et al. 2020), mental health (Brodeur et al. 2021), and information gathering about the pandemic (Chundakkadan & Ravindran 2020). Although some studies have utilized the GTI to predict economic outcomes in emerging and developing countries, such as the unemployment rate in Turkey (Chadwick & Sengul 2015) or in Romania (Mihaela 2020), the number of existing works using GTI in developing countries is much more limited than that in industrialized countries, as Narita and Yin (2018) suggest. While the online-based job-hunting process has been flourished in developing countries (Nomura et al. 2017), we need to beware that the Internet usage rates in developing countries are relatively lower than those in developed countries; thus, such research using online data may only produce biased results from a minority group of people who have access to the Internet (Shahiri & Osman 2015). In our context, however, the digital infrastructure in the three targeted countries has undergone a massive transformation during the current decade, and between 2009 and 2019, the Internet usage rate among the entire population in each country has dramatically increased (6.9% to 47.7% in Indonesia, 9.0% to 43.0% in the Philippines, and 26.6% to 68.7% in Vietnam)[4,5]. We believe that the increase in internet availability allows us to estimate the causal effects on the concerns for working and migration in the general population in the countries before and after this pandemic using big data.

The remainder of this paper is organized as follows. Section II describes the context of the study. Section III reports the data, and Section IV discusses the estimation strategies employed. Section V presents the estimation results, and Section VI concludes the paper.

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[4] Source: World Development Indicators

[5] We select the three target countries based on the considerations of the economic size, the magnitude of out-migration and the internet-usage rate. For instance, while the net migration population (the number of immigrants - the number of emigrants) of Myanmar represents the most negative value (-816,564 people) in Southeast Asian countries in terms of followed by Indonesia (-494,477 people), Vietnam(-399,999 people) and the Philippines (-335,758 people) in 2017. However, the internet usage of Myanmar in 2017 (the most recent record) is relatively low (23.6%). (Source: World Development Indicators)

II. Context

Recently, the global dependence on labor supply has become immense, and international labor mobility is a noteworthy phenomenon. The instance of immigrants from developing countries seeking temporary jobs in industrialized countries has been increasing to earn higher incomes or achieve higher standards of living. According to the World Bank, it is estimated that more than 250 million people who migrate to developed countries from developing countries remit more than US$ 6 trillion to their home countries (World Bank 2018). The amount of remittance is four times greater than that of official development aid from developed countries and is one of the crucial engines for economic growth and improvement of living standards in developing countries. On the other hand, for developed countries, inflows from developing countries are expected to satisfy labor demand because of their lower salaries. Thus, the international labor supply is a crucial productive resource for both developing and developed countries. International immigrants from Asian countries number 4.4 billion in total, accounting for over 40% of the world's international migrants in 2015 (IOM 2017). We select Indonesia, the Philippines, and Vietnam for our case study because we observe an increase in the migration outflows from these countries to developed countries as well as expansions of the availability of Internet usage, which we explained in the introduction. These countries have recently witnessed international labor exportation, especially to Japan and Taiwan, which are popular destinations in the region. Figures 1 and 2 show the number of immigrant stocks from the three countries in Japan and Taiwan, respectively. Over the course of five years beginning in 2013, the number of immigrants in each destination has gradually increased because the industries of host countries, in the face of labor shortages, are experiencing increased dependence on foreign workers, and host governments have shifted to allow for these tentative immigrants to enter and stay longer in their respective countries. For example, in 2014, the Japanese government concluded economic partnership agreements with the governments of Indonesia, the Philippines, and Vietnam and allowed candidates for nursing and certified care work from three countries to enter and stay in Japan for periods of up to three years and four years, respectively (Ministry of Foreign Affairs in Japan 2020).

Moreover, approximately 60% of Technical Intern Trainees (TIT) in Japan (typically low-skilled foreign workers) are from three countries, and the government has permitted these TITs to renew their visas since 2018[6]. As for Taiwan, dependence on foreigners has escalated as the ratio of foreign workers in the productive industry increased from 8.3% in 2009 to 15.4% in 2019. Among them, the population of workers from our target countries occupies a large share, rising rapidly from 115,000 (33% of foreigners) to 400,000 (55% of foreigners)[7]. Therefore, Japan and Taiwan have experienced an enormous increase in the demand for labor from Indonesia, the Philippines, and Vietnam.

Moreover, we found that these countries vary in terms of the prevalence of COVID-19 and the timing or strictness of infection control. The WHO declared a public health emergency of international concern, the highest level of alarm under international law, on January 30, 2020. In response to the announcement, citizens have had to comply with the “new normal,” such as maintaining social distancing or wearing masks in public. Although some countries implemented stricter border control measures immediately after the first report of positive cases of a novel coronavirus, the governments of our target countries only implemented lockdown measures several months after the declaration once positive cases of novel coronaviruses had been confirmed. Figure 3 shows the timelines for the targeted countries after the first report worldwide of COVID-19. These countries implemented lockdown measures in their respective capital city by mid-April, although the implementation duration differed among them. Figure 4 shows the cumulative number of confirmed cases in each country. Although the first patients were confirmed at an earlier time in Vietnam than in the other two countries, the Vietnamese government succeeded in infection control. On the other hand, the number of confirmed cases has exponentially increased in Indonesia and the Philippines, although lockdown measures have been implemented. These restrictions on economic activities and the countries’ epidemics have negatively affected economic projections by governments, economists, and international organizations. According to Park et al. (2020), in a report by the Asian Development

[6] Source: Ministry of Justice in Japan (2017)
[7] Source: Ministry of Labor in Taiwan (2020)

Bank, the regional GDP will decrease from 6.2% to 9.3% depending on the containment scenarios, which would be the lowest regional growth outcome since 1961. The impacts on employment and income will also be dramatically negative because somewhere from 109.1 million to 166.7 million jobs will be lost in the region, accounting for approximately 70% of the total employment losses in the world, and $359 billion to $550 billion will be deprived, about 30% of world income. In addition, the total remittance to Asian countries would also be expected to drop by between $31 billion and $54 billion. As for the targeted countries, each country is expected to experience a decrease in economy-wide remittance by 21.4% in Indonesia, 20.2% in the Philippines, and 18.1% in Vietnam (Kikkawa Takenaka et al. 2020).

Some studies have already discussed the adverse effects of epidemics and their mechanisms on the national economy and the labor market. The World Bank (2014) discusses two channels by which epidemics adversely affect national economies. One is defined as the direct effects of infection spread among laborers, leading to the labor supply being temporarily or permanently lost. The other is the behavioral changes caused by people's fear of contagion, which leads to the reduction of contact with other people or the closure of the workplace. Past epidemics, such as the SARS epidemics in 2003 and the H1N1 epidemic in 2009, caused the behavioral effects that occupy 80–90% of the total actual impact of the diseases on the economy. Mesnard and Seabright (2009, 2016) theoretically explain strategic migration behavior following the outbreak of epidemics. They imply that individuals will consider migrating to other places with low prevalence if the perceived costs of migration are relatively lower than their benefits. Additionally, some studies have empirically examined the effects of past epidemics on labor markets. Lee and Cho (2017) investigate the impact of the MERS epidemic in Korea on employment and find that there were spillover effects in the rural labor market due to behavioral changes. Yu et al. (2020) conduct a cross-country analysis and explicate how past epidemics affected the labor force participation. They find that the outbreak of an epidemic negatively affects the labor force participation rate, typically robust in low-income countries. However, in the contexts of immigration and international labor markets, the empirical literature is limited.

III. Data

GTI

The GTI represents the volume of queries searched in Google within a given geographic area and a given time-frame. This index is not the absolute number of search queries but, rather, is converted to the standardized relative index scaling from 0 to 100 during the selected period, which is assigned as 100 for the day with the highest number of searches for the search terms and 0 if there is not sufficient search volume for these terms. Therefore, we can elucidate the trends of interest in the related topic regarding query words using this index. IP addresses searching for each query contribute to the information of geographical data in the GTI, and repeated queries from the same IP address in the short term are disregarded because of the risk of internet bots. Moreover, Google does not release the GTI if the number of searches is below the minimum threshold, although the threshold value is not public. When we obtain GTI data, the time interval of the GTI differs depending on the specified time range. Daily GTI data are provided if we specify a time range shorter than nine months. If the specified duration is between nine months and five years, we can obtain weekly GTI data. Recently, the economic literature using big data has grown such that online search-based big data can predict economic and social outcomes in many fields. For example, Choi and Varian (2012) imply that the GTI can forecast economic indicators, such as automobile sales or unemployment claims. In migration research, Böhme et al. (2020) suggest that the predictions using the GTI for international migration flows outperform the traditional gravity model. Moreover, Narita and Yin (2018) discuss that GTI is beneficial for macroeconomic research for developing countries, where we always face time lags in the availability of such data.

This article focuses on changes in search behavior regarding query keywords related to the local and international labor markets in the targeted countries as reflected in data from the GTI. First, we must select keywords to focus on that are used in Google Trends. We follow Böhme et al. (2020) for keyword selection. They retrieve 67 keywords related to migration decisions and apply the GTI of these keywords into the prediction model for international migration flows[8]. Moreover, this literature suggests that the combination of the keywords and the name of the destination country allows us to capture the bilateral migration intentions; therefore, we obtain the bilateral GTI, i.e., the keywords with destination name (*"Japan"* / *"Taiwan"*), in this research. However, some keywords that Böhme et al. (2020) selected, such as "Schengen" or "asylum," are not appropriate for our research context, so we need to choose the keywords which fit with the context. Of 67 keywords, this research assigned the following four labor-related keywords as our interest: *"job," "recruitment," "business,"* and *"income."* There are several reasons why we choose these keywords. First of all, these keywords are usually used for job searches. According to ILO (2021), the incentives of migration in Asian countries are often financial benefits, and they transfer to the destination under temporary migration regimes, which do not expect to live permanently. Moreover, the online job-portal websites recently have been provided for searching the jobs in the local or the international labor market in developing countries (Nomura at al. 2017), and the potential immigrants are likely to use these websites with submitting the keywords into search engines. Secondly, we conduct the robustness check to examine whether these selected keywords are relavant to the prediction of international migration flows, and find that the workhorse model including the GTI of our assigned keywords has a stronger predictive power than the benchmark model using only the traditional parameters of the gravity model (see the details in Appendix A). Finally, these job-related keywords alone are beneficial for understanding concerns for working or job security in the countries. D'Amuri and Marcucci (2017) suggest that the term *"jobs"* is strongly correlated with unemployment rates in the U.S. Additionally, Fondeur and Karamé (2013) imply that the term *"EMPLOI"* (which means "jobs" but also "employment" in French) have strong predictive power regarding unemployment in

[8] Using the website which analyzes and identifies the semantically related pairs of keywords, Böhme et al. (2020) calculated the semantic links of keywords from the text of the English language Wikipedia, and they extracted 100 keywords that were strongly related to the keyword "immigration." Furthermore, immigrants determine whether or not to migrate for economic reasons; therefore, they chose another 100 keywords related to the keyword "economics." Of total 200 related keywords, they obtain 67 keywords to apply the prediction model, which captures the intentions to migrate.

France. Other literature (Chadwick & Sengul 2015 in Turkey; Mihaela 2020 in Romania; Pavlicek & Kristoufek 2015 in the Czech Republic and Hungary; Mulero & García-Hiernaux 2021 in Spain) also suggest that the job-related keywords show predictive power on the model of national unemployment or employment stability. These single job-related keywords will be expected to capture the general interest in working or in maintaining livelihood; thus, we collect the GTI of the single keywords together with the bilateral keywords[9]. Also, because of a broad concern on the decrease of remittance following COVID-19 (Kikkawa Takenaka et al. 2020; World Bank 2020), we also search for the GTI of keywords such as *"remittance"* and *"bank account."* We translate these keywords into native languages as they are commonly used in domestic job hunting (Bahasa Indonesia for Indonesia, English for the Philippines, and Vietnamese for Vietnam)[10]. Finally, we request the country-level daily GTIs of the queries related to labor activities and migration intentions, such as "job," "remittance," or "business Japan" from each within the selected periods (December 2, 2018, to August 3, 2019, as the ex-ante period and December 1, 2019, to August 1, 2020, as the ex-post period) through an Application Programming Interface (API)[11].

The daily GTI data are provided when we set the time-range for less than nine months, as previously mentioned. Thus, we can obtain the daily data in ex-ante and ex-post periods separately. However, the scaling factors of the GTI differ between these periods; that is, the search volume that maximum GTI (100) is recorded for in ex-ante periods may not be the same as that in ex-post periods, making them difficult to compare. There are cases in which the search volume representing the figure of the GTI as 40 in one term is much lower than that of the figure of 30 in the other term. Following

[9] While many literature suggest that the term "job" and other work-related keywords are strongly correlated with the unemployment rate, Borup and Schütte (2020) imply that the job-related word has predictive power on the employment growth rate. Although these indicators have opposite directions, they share a common view to capture "the interest to the job" among the internet users using these keywords. Moreover, the searching behavior on these keywords is motivated by feeling "insecure about their jobs," which does not directly indicate unemployment. Even when people are still employed, these keywords are often searched if they feel anxious about continuing the current work (Shahiri and Osman 2015). This behavior may be strengthened with the Internet relative to the traditional job-searching methods because of lower communication costs involved. Considering these cases and the situation under this pandemic, we believe that these keywords reflect "concerns for work" or "job insecurity" in this research.

[10] Even when searching for jobs in Japan or Taiwan, the job-seekers in three countries commonly exploit the local intermediary companies or local web portal sites, and receive job offers at home countries.

[11] We retrieve the GTI data through the API using the codes written in Python (*pytrends*).

Brodeur et al. (2021), we also collect weekly GTIs within the selected periods (December 2, 2018, to August 1, 2020) and rescale them to the adjusted index for comparability. The procedure for processing the GTI data is as follows:

1. Collect the daily GTI from each ex-ante and ex-post period of the *i*th day in week τ for each country *c* ($GTI_{i,c,\tau,2019}$, $GTI_{i,c,\tau,2020}$) and the weekly GTI data from all periods ($\overline{GTI_{\iota,c,\tau,2019-2020}}$)

2. Calculate the average weekly GTI from the daily GTI data

$$\overline{GTI_{\iota,c,\tau,2019}} = \frac{1}{7}\sum_{i=1}^{7} GTI_{i,c,\tau,2019} \quad for\ \tau\text{'}s\ week\ in\ 2019$$

$$\overline{GTI_{\iota,c,\tau,2020}} = \frac{1}{7}\sum_{i=1}^{7} GTI_{i,c,\tau,2020} \quad for\ \tau\text{'}s\ week\ in\ 2020$$

3. Divide the weekly GTI data by the average weekly GTI = **Weights *w***

$$w_{c,\tau,2019} = \frac{\overline{GTI_{\iota,c,\tau,2019-2020}}}{\overline{GTI_{\iota,c,\tau,2019}}}$$

$$w_{c,\tau,2020} = \frac{\overline{GTI_{\iota,c,\tau,2019-2020}}}{\overline{GTI_{\iota,c,\tau,2020}}}$$

4. Multiply the daily GTI with the calculated weights

$$GTI_{i,c,2019-2020} = GTI_{i,c,\tau,2019} * w_{c,\tau,2019} \qquad \textit{for } 2019$$

$$GTI_{i,c,2019-2020} = GTI_{i,c,\tau,2020} * w_{c,\tau,2020} \qquad \textit{for } 2020$$

5. Normalize the index by dividing the daily weighted GTI by the maximum daily weighted GTI to obtain figures 0 to 100, replacing $GTI_{i,c,2019-2020}$

$$GTI_{i,c,2019-2020} = \frac{GTI_{i,c,2019-2020}}{max(GTI_{i,c,2019-2020})} * 100$$

Other Variables

Moreover, we collect daily data on the index of policy measures related to the pandemic and confirmed cases with the macroeconomic indicators for each country. Among the featured data is the Oxford COVID-19 Government Response Tracker (OxCGRT), collected by the Blavatnik School of Government, University of Oxford[12]. OxCGRT is the index of several common policy responses that governments implemented after the outbreak of COVID-19, such as school closures and travel restrictions, reporting a number between 0 and 100 to reflect the level of government action on the relevant topics. We assume that not only the lockdown of the capital cities but also other implementations such as income support or health investment will affect the job security for nationals. Another feature is the daily confirmed cases of COVID-19 in each country, which is provided by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)[13]. We believe that infection status in the country also affects people's search behavior because of its prevalence and the related announcement effects. Regarding GDP per capita and the unemployed in 2019, we obtain data on GDP per capita, the labor force, and the unemployment rate from the World Bank Open Data for each series[14]. We attribute the 2020 forecast to the data that the IMF used to report its economic prediction of real growth and the unemployment rate in each country in April 2020[15]. From the World Bank data and IMF predictions, we calculate each GDP per capita and the unemployed for 2020.

Table 1 presents the summary statistics for each parameter. We find that the GTI of some keywords we requested has no observation or has missing values because the search volume of these keywords is below the threshold Google Inc. has set for data to be made public. The mean value of single keywords is approximately 50, so we assume that these queries are searched constantly during

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[12] Retrieved from https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker
[13] Retrieved from https://coronavirus.jhu.edu/map.html
[14] Retrieved from https://data.worldbank.org/
[15] Retrieved from https://www.imf.org/external/pubs/ft/weo/2020/01/weodata/index.aspx. For the unemployment prediction in 2020 in Vietnam, we refer to the General Statistics Office of Vietnam (https://www.gso.gov.vn/)

the period; on the contrary, we find that the mean search volumes of the bilateral queries are not particularly large. This trend is the same as shown by the descriptive statistics of Böhme et al. (2020). The results of the t-test show that there are statistical differences in some GTI keywords as the search volume of the terms “income” and “remittance” increased in the ex-post period; on the other hand, the terms “recruitment” and “Japan” are less frequently searched in the ex-post period. As for each country’s economic indicators, significant adverse effects on the labor force are forecasted, although real economic growth is predicted to be insignificant. Regarding prevalence level in the host countries, we observe that the confirmed cases in Japan are more extensive than those in Taiwan. The Taiwanese government has addressed the emerging outbreak early and has undertaken an adequate public health response in the early stage of the pandemic (Wang et al. 2020).

IV. Estimation methods

To explore the impact of the pandemic on daily search activities, we employ difference-in-differences (DID) technique using the sample year and phase as a grouping basis following the pieces of literature to explicate the immediate impacts of COVID-19 (Rousseau and Deschacht 2020; Leslie et al. 2020; Brodeur et al. 2021; Ming et al. 2020). This procedure circumvents the effects of seasonal changes on searching behavior. We set the period from December 2, 2018, to August 3, 2019, as the ex-ante period (hereafter *Year2019)* and the period from December 1, 2019, to August 1, 2020, as the ex-post period (hereafter *Year2020*). Thus, we have 245 collections of daily data for each period in each country, that is, 1,470 in total. The period before the declaration of emergency by the WHO is set as “the control period” (Day 1–Day 60). The phase on and after the day of the declaration of emergency by WHO is allocated as “the COVID-19 (treatment) period” (Day 61–Day 245).

Before DID estimation, we start by estimating an event study model to check the common/parallel trend during the control period. When we apply the DID model to examine causal effects, several conditions are required. First, the treatment should be exogenous and should not be related to the outcome at baseline. For our study, this is not an issue as the outbreak of COVID-19 could not be predicted in the ex-ante period (*Year2019*) and we can consider it as exogenously given. Another important assumption in DID estimation is the common/parallel trend assumption (Angrist & Pischke 2009). In our context, in the absence of COVID-19, the change of GTI on the queries of interest in the treatment phase (the period after the declaration of emergency by the WHO) should be parallel to the change in the control phase, conditional on the set of some characteristics and fixed effects. If our data satisfy this assumption, we can yield unbiased DID estimates of the effects of the COVID-19 outbreak. To check for the parallel trend during the control period, we perform a weekly event study model as follows:

$$GTI_{i,c,y} = \delta_1 COVID_i + \delta_2 2020_{i,y} + \sum_{\tau=1}^{17} \delta_{3\tau}\, Week\tau_i * 2020_{i,y} + \delta_4 X_{i,c,y} + \rho_c + \sigma_i + \varphi_d + \pi_m + \mu \qquad (1)$$

where $GTI_{i,c,y}$ denotes the adjusted daily GTIs on the *i*th day, in the *c*th country and in the *y*th year. $COVID_i$ is a dummy variable that represents 1 if the *ith* day sample is included in the COVID-19 period (treatment period). $2020_{i,y}$ is also the dummy variable for whether the ith day sample in year *y* is in the ex-post *Year2020*. The indicator $Week\tau_i$ takes one if the ith day is in the week τ. The weekly GTI starts every Monday. The sample is restricted to Day 1 (Monday in Week 1) through Day 119 (Sunday in Week 17). The vector of control variables $X_{i,c,y}$ include the daily OxCGRT, daily confirmed cases of COVID-19 by CSSE, log annual GDP per capita, and log annual number of unemployed persons in each country. Regarding the model on the adjusted bilateral GTI (e.g., "job Japan"), we also include the variables that indicate situations in the destinations (i.e., OxCGRT and the confirmed number of cases in Japan and Taiwan) because the pull and push factors will influence the flow of the immigrants (Beine et al. 2015; Böhme et al. 2020). With reference to the fixed effects, the search trend would vary by countries because of the national policy or the domestic economic trends. In addition, we obtain each country-level GTI, as we mentioned. Furthermore, the search behavior on job-related activities would be affected by some time effects such as the seasonal trends, the contracts by the time period or the day of week. Therefore, following some literature (e.g., Ming et al. 2020; Brodeur et al. 2021), the model contains the country-fixed effects (ρ_c), the time fixed effects by month (π_m), the day of the week (Monday to Sunday; φ_d), and the day (σ_i). μ captures the error term. We use country-specific day-level clustered robust standard errors. In this model, we are able to examine the dynamic effects of weekly changes on the GTI $\delta_{3\tau}$ in the pre-declaration period up to eight weeks and in the post-declaration period up to eight weeks. Our reference week is the 8th week, which is one week before the declaration of emergency by the WHO. From the 9th week, when the WHO declared the public emergency of COVID-19, onward, some governments have strengthened border controls, or the news media has increased reports on the pandemic, both of which are likely to cause behavioral changes in people. When the coefficients of the dynamic effects $\delta_{3\tau}$ are insignificant before the outbreak of COVID-19, the parallel trend assumption is satisfied (Ming et al. 2020).

Next, we estimate a difference-in-differences model to quantify the average effects of this pandemic on the search volume of the assigned GTIs. We demonstrate the following difference-in-differences equation:

$$GTI_{i,c,y} = \beta_1 COVID_i + \beta_2 2020_{i,y} + \beta_3 COVID_i * 2020_{i,y} + \beta_4 X_{i,c,y} + \rho_c + \sigma_i + \varphi_d + \pi_m + \mu \qquad (2)$$

The interaction dummy variable $COVID_i * 2020_{i,y}$ is the treatment effect of the pandemic and its following lockdown measures. Our interest β_3 represents the changes in the GTI of our assigned words on and after the day at the declaration of this pandemic by WHO (Day 61) in ex-post period (*Year2020*). We include the same set of control variables and a suite of fixed effects as in Eq. (1). Under the parallel trend assumption, the Google Trend would have maintained the same trend after Day 61 if the pandemic had not occurred.

Finally, we conduct the "sub-group" analysis, in which we explicate the effects of each phase regarding the policy intervention on searching behavior. As for the treatment period, we categorized the three phases (Figure 5). The phase on and after the day of the declaration of emergency by WHO until the declaration of lockdown measures is allocated as “WHO declaration period (Phase I)” (Day 61–Day 128 in Indonesia, Day 61–Day 102 in the Philippines, and Day 61–Day 121 in Vietnam). “Lockdown period (Phase II)” denotes the term of the lockdown in each capital (Day 129–Day 187 in Indonesia, Day 103–Day 184 in the Philippines, and Day 122–Day 144 in Vietnam). The start date of lockdown implementation in our research is set as when the governments officially announced the implementations because the public announcement is considered to affect search behavior immediately. Lastly, the day of the declaration of the lifting of the lockdown and afterward represent “Post-lockdown period (Phase III)” (Day 188–Day 245 in Indonesia, Day 185–Day 245 in the Philippines, Day 145–Day 245 in Vietnam)[16]. We model as follows.

$$GTI_{i,c,y} = \theta_1 PhaseI_{i,c} + \theta_2 PhaseII_{i,c} + \theta_3 PhaseIII_{i,c} + \theta_4 2020_{i,y} + \theta_5 PhaseI_{i,c} * 2020_{i,y} + \theta_6 PhaseII_{i,c} * 2020_{i,y} + \theta_7 PhaseIII_{i,c} * 2020_{i,y} + \theta_8 X_{i,c,y} + \rho_c + \sigma_i + \varphi_d + \pi_m + \mu \quad (3)$$

We adopt the control variables and a series of the same fixed effects as those in Eqs. (1) & (2). The coefficients θ_5, θ_6 and θ_7 allows us to distinguish the time effects during the pandemics in *Year2020* and to understand the different effects of each policy intervention on the behavior of web searches.

Note that since the daily policy index, the confirmed cases and our interested DID estimators respond to the COVID-19 severity in the country in question, they are, by nature, correlated. In particular, the correlation between OxCGRT and COVID-19 period in *Year2020* was 0.91, and those between OxCGRT and Phases I to III in *Year2020* were 0.13, 0.62, and 0.57, respectively, while the correlation between the confirmed cases and COVID-19 period in *Year2020* was 0.42, and those between COVID-19 cases and Phases I to III in *Year2020* were -0.11, 0.11, and 0.58, respectively.

[16] Regarding the information on the date for announcing and lifting lockdown in each capital, we refer to the government’s press release, the news articles, and the Japanese embassy information in each country.

The correlation between COVID-19 cases and the OxCGRT is 0.46 (Table 2). While some of these may be high, we use them together in the models as these variables indicate different factors relating to COVID-19 such as other policy interventions and the infection status, and they are essential elements to examine search behavior. We report whether they are jointly statistically significant in the results.

V. Results

Event study

To verify the parallel trend assumption for DID approach, we demonstrate an event study approach. Based on equation (1), we estimate and plot the weekly coefficients of the dynamic events with 95% confidence intervals within 17 weeks before and after the WHO's declaration of the public health emergency. For brevity, we show the figures of the coefficients on the queries "job," "remittance," "job Japan," "job Taiwan," "Japan," and "Taiwan" (refer to the figures in Appendix B for other queries). Figure 6 shows the weekly time-window event study plots for the selected queries[17]. We find that almost all the coefficients of the dynamic effects before the week of the declaration by the WHO are insignificant in the models of the queries: "job," "remittance," "job Japan," and "Taiwan." Above all, the remarkable difference of the queries "job" and "remittance" is observed in the coefficients after the declaration compared to pre-declaration. Therefore, we conclude that the control and treatment groups of the sample in this study satisfy the assumption of these queries. The exceptions were the query on "job Taiwan" and "Japan," in which we find that the coefficients of the dynamic effects in more than half of the weeks in the pre-declaration period of the event study are statistically significant ($p<0.05$), implying the presence of differential trends in the control phase. This suggests that the effects of the declaration of the public health emergency, that is, the outbreak of COVID-19, on the search volume in the queries "job Taiwan" and "Japan" may be partly explained

[17] We use *eventdd* package in Stata for event study analysis.

by unobservable non-parallel trends. To address this concern and check robustness, we employ a daily event study approach using the same controls and fixed effects for these two queries within the same period. In the daily event study approach, our reference day was one day before the declaration of the public emergency by the WHO. We confirm that the days with significant coefficients in the control phase are small in the daily event approach and assume that the analyses of the terms satisfy the parallel trend assumption (Figure 7). Taken together, we satisfy the parallel trend assumption in this context, and conclude that our DID estimates would produce valid results.

DID Estimation

Next, we move to the results of DID estimations. Table 3 shows the results that estimate the impact of the outbreak of COVID-19 on the GTI for the single keywords of interest in this study. The results suggest that after the appearance of COVID-19, the search volume of queries related to the concerns for job security, such as "job," "business," "recruitment," and "income," dramatically increased in the three Southeast Asian countries (Columns (1) to (4)). As queries for a term such as "job" are found by many studies to be strongly correlated with the national unemployment rate (e.g., D'Amuri & Marcucci 2017 in the U.S.; Chadwick & Sengul 2015 in Turkey; Mihaela 2020 in Romania; Pavlicek & Kristoufek 2015 in the Czech Republic and Hungary), the positive significance of COVID-19 on these terms indicates that the concerns for working and the interest in income-earning are enhanced among people in those countries due to unemployment or job insecurity. Further, the coefficient of the OxCGRT index indicates how daily policy strictness affects search volume. The results show that it is negative and statistically significant in affecting job-related words, suggesting that individuals do not search job-related keywords when policy strictness is more intense. Regarding the number of confirmed COVID-19 cases, it is insignificant for "income" but negative and statistically significant for "job," "recruitment," and "business." These results show that the higher the number of confirmed cases, the more people refrain from searching for these words, probably due to restrictions on economic activities.

On the other hand, the queries related to remittance show negative and statistically significant impacts or insignificant impacts (Columns (5) and (6)). Even though job-related search activities increased, those related to remittances decreased. Note that the keyword “remittance” may also include the concern for domestic remittance. Thus, the results suggest that concerns regarding remittance, regardless of the border, decreased after the outbreak of COVID-19. For policy strictness, we observe that the remittance-related keywords increased during the COVID-19 pandemic when governments implemented strict policies for infection prevention, contrary to the job-search activities mentioned earlier. This may suggest that with stricter government policies that restrict economic activities, people’s concern regarding remittances has increased.

We also examined whether search activities for the country names “Japan” and “Taiwan” increased due to COVID-19 (Columns (7) and (8)). We find the coefficients positive and statistically significant at the 5% level. It is difficult to consider these positive coefficients as evidence for an increase in the interest of people visiting these countries because these searches may merely reflect people’s rising interest in knowing the COVID-19 situation in Japan and Taiwan. However, it is interesting to note that the government policy variable (OxCGRT) for the models in both countries and the confirmed cases in Japan’s model are negative and statistically significant in these models. On the other hand, the confirmed cases in Taiwan’s model (Column (8)) show substantial and positive results.

Moreover, we explicate the impact on the bilateral keywords, which measure the intentions to migrate, in Tables 4 and 5. Both tables show the results of the models including the policy strictness and prevalence status of the host country. Surprisingly, almost all of the bilateral words with Japan (Table 4) have not been affected by the pandemic, although the general interest in jobs and the country dramatically increased. On the contrary, the search volume of the query “job Japan”’ decreased at 5% significance. We also obtained bilateral GTIs in Taiwan for each country (Table 5). Taiwan has been more successful in controlling infections than Japan; however, we again found no significant or modest adverse effects on the bilateral GTI. Therefore, we observe no significant positive changes in people's search behavior regarding the direct intentions to migrate after the outbreak of COVID-19 in these countries. To the models in Tables 4 and 5, we add the OxCGRT index and the confirmed cases in the host countries; however, we did not detect any significant results except for the model on "job Japan," which shows that policy strictness in home countries led to fewer searches on "job Japan," while policy strictness in Japan led to more searches on the same term.

Next, we decompose the COVID-19 effects into three different phases, as explained earlier. Tables 6–8 present the results[18]. Regarding the terms related to the job market, we observe significant positive results in all phases (Columns (1) to (4) in Table 6). Primarily, we find that the increase in the search volume for all variables magnified as the phase progressed from the WHO declaration period to lockdown and then to the post-lockdown period in 2020. This likely suggests that the economic situations in these countries have worsened over these phases during the pandemic, which led to increase the number of people looking for jobs increasing. The policy strictness index and the number of confirmed cases were negative and statistically significant in all models, suggesting that the stricter the policy and the greater the number of confirmed cases, the fewer concerns among people to engage in job-related search activities.

On the other hand, the phase effects were almost all negative and statistically significant for the terms "remittance" and "bank account" (Columns (5) and (6) in Table 6). Further, the magnitude of the decrease grew over the course of the phases, indicating that people's interest in remittance declined more and more as the phases progressed from the WHO declaration period to the post-lockdown period in 2020. Although the interest in job-related words multiplied over the course of the phases, we observe that interest in remittances gradually declined. Regarding the search words "Japan" and "Taiwan," we also find that all phase dummies were positive and statistically significant. The magnitude increased over the phases for Japan, while the effect on the lockdown phase was the greatest for Taiwan, showing as if people were interested in determining how Taiwan successfully

[18] We run the regression on the models that use the OxCGRT and confirmed cases variables as a moving average of three days' status to consider the time trends as the robustness check and find similar results with the main analysis. The results are available upon request.

contained the virus. Moreover, the increase in magnitude for the query "Taiwan" was greater than that of "Japan." The policy strictness and the number of confirmed cases show a similar tendency as seen in Table 3, which showed that strict policies in these countries lead to fewer searches for "Taiwan" and "Japan," and more COVID-19 cases in these countries lead to fewer searches for "Japan" but more for "Taiwan."

Although each query related to the job market and the country's name has increased since the declaration and release of lockdown measures, the combination of job queries with the country's name provides almost entirely insignificant results (Tables 7 and 8). These results are also the same even for job-related queries in Taiwan, where the infection prevalence is low. We do not observe a shift in the intentions to migrate after the lockdown because of behavioral effects (World Bank 2014) on online search behavior. The OxCGRT indexes and confirmed cases of COVID-19 were not statistically significant in most of these models except for the model on "job Japan," similar to our results shown in Tables 4 and 5. We observe that while policy strictness in home countries negatively affects the search for "job Japan" and, to a lesser extent, for "job Taiwan," policy strictness in Japan positively affects queries for "job Japan." This result is understandable if we consider that policy strictness in home countries reduces the possibility of going abroad and dampens the desire to search outside job markets, while policy strictness overseas likely signals that the pandemic situation is under control in those economies and attracts people to search for job opportunities in those countries. While we cannot be certain about the mechanism, the findings suggest that the policy strictness of both home and destination countries will affect search behaviors differently.

VI. Conclusion

We explore the impact of COVID-19 and the consequent lockdown measures on job-related search behavior in Southeast Asian countries using timely big data. The findings after employing the DID approach based on the intervention phase grouping basis show that the eruption of COVID-19 has had no apparent positive effects on the search volume of queries related to migrating intentions within the region. This result is also consistent for the destination which has a lower prevalence of the coronavirus and successful government policy. In short, the behavior of job-seeking in other countries remains unaltered even after the pandemic. On the other hand, we find that the search volume of job-related queries in general dramatically increased after the outbreak of COVID-19. As we broke down the COVID-19 effect into several phases, we observe that the magnitude of the COVID-19 effects grows to its largest after the lockdown measures in the capital cities are lifted. Furthermore, we demonstrate the impact on the search volume of the remittance-related queries. The search intensities decreased following the outbreak, and the magnitude of the decrease escalated over the course of the phases.

Our results imply that the job instability intensified after the lockdown measures were imposed because it seems that severe unemployment or cuts in salary payment occurred in these countries, as some international organizations had predicted. Several studies suggest that the search volume for the term “job” is strongly correlated with the national unemployment rate, which means that unemployed or workers who in employment instability seek jobs online. Furthermore, interest in remittance also decreased after the pandemic set in, which is consistent with the predictions of other studies. As the World Bank (2014) discusses, which we previously introduced in the context section, the behavioral changes due to people’s fear of contagion during the epidemic have caused the recession because these people could not participate in economic activities as usual. Indeed, Abay et al. (2020) suggest that the demand for face-to-face services, including in the lodging and restaurant industries, declined as COVID-19 surged according to the GTI data. We assume that the lockdown measures and the downslide of demand for goods and services due to behavioral changes hit the labor demands in the national job market, and the number of potential job-seekers increased after the outbreak of COVID-19 in developing countries.

On the other hand, the direct expectation to migrate outside of the country, which takes time for preparation and incurs high costs, does not seem to have increased in these countries, regardless of the prevalence of COVID-19 or the strictness of government measures. The theoretical consideration from Mesnard and Seabright (2009, 2016) suggests that individuals will intend to migrate to a low-prevalence city if the migration benefit exceeds the migration cost. In our context, the prevalence levels of the host countries, including Japan and Taiwan, were relatively lower than those of the home countries, although Vietnam's prevalence level was lower than that of Japan. However, we do not confirm the growth of interest in working overseas from online search activities during and after the lockdown measures in these countries. Although high unemployment rate in the local region or employment instability sometimes causes the mobility to other area (Pissarides & Wadsworth 1989; Mihi-Ramírez et al. 2014), we assume that migration costs are relatively higher among developing countries in contrast to such cases from developed countries including the increase in migration intentions to New Zealand, which we introduced in the introduction. Thus, immigration to other countries would not include the option for seeking jobs during the pandemic because they must first secure employment for their livelihood.

This study provides several implications for research and policy design. First, big data is beneficial for explicating the demands in developing countries, even if collecting the data is difficult. According to preliminary research and reports by international organizations (e.g., Park et al. 2020), many workers are becoming redundant in their jobs or losing income by the COVID-19. Our results from online search data coincide with these projections. It is suggested that urgent job seeking is the highest priority for people to maintain their livelihoods after the pandemic, and they require income subsidies or labor protection programs in these countries following the imposition of strict government policy measures. We recognize that online search-based big data allows us to capture customers' insights in developing countries with well-equipped IT infrastructure.

In addition, although this study focus on the short-term and immediate effects of the pandemic, our results anticipate the persistent imbalance caused by this pandemic in the international labor market. Even after the pandemic is over, our results suggest that migration flows from developing countries are not expected to immediately and dramatically increase, and employers in developed countries will face a shortage in the labor force during and immediately following the pandemic. When we consider the cost of migration from the home countries, including immigration control, stabilizing the balance of supply and demand in the international labor market requires a longer time frame. Moreover, international remittance, a crucial financial source for developing countries, would not increase immediately following the stagnation of migration flows; thus, the adverse effects on economies in both developed and developing countries are expected to continue globally.

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Tables & Figures

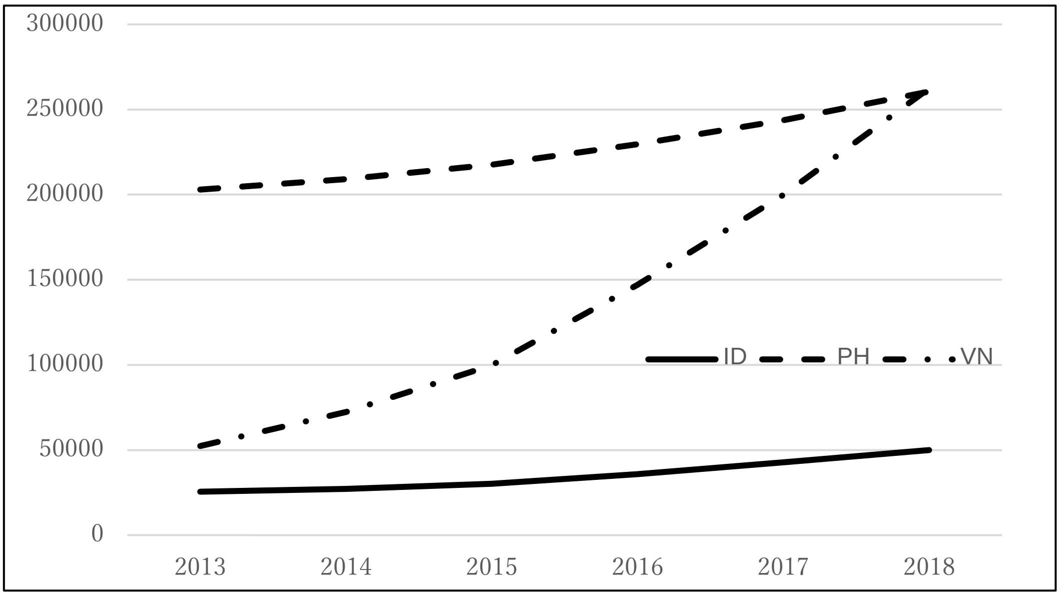

Figure 1. Stock of immigrants in Japan
Source: Ministry of Justice-Immigration Services Agency, Japan

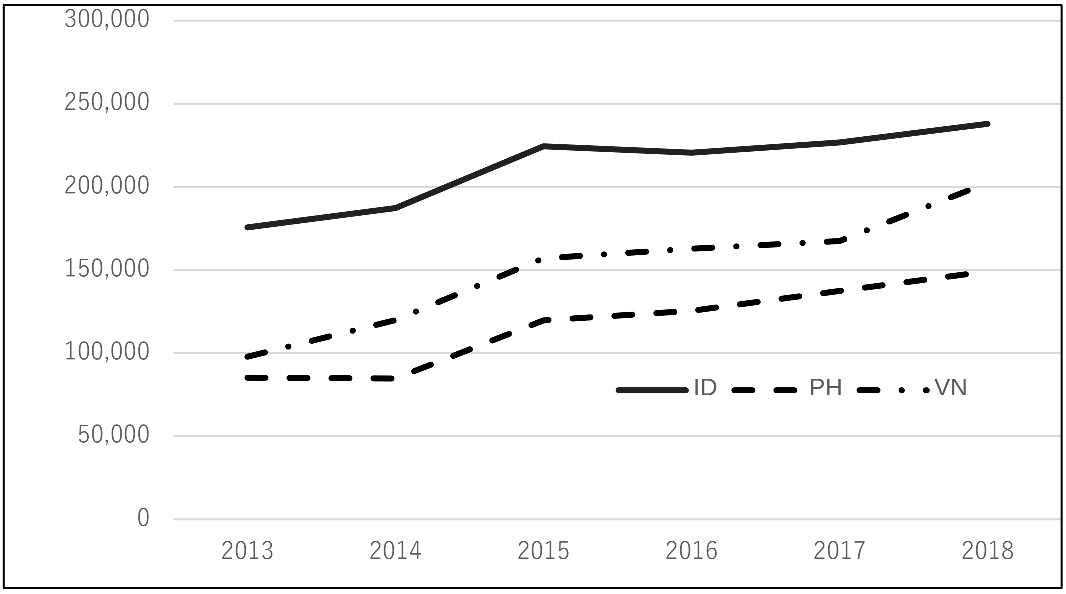

Figure 2. Stock of immigrants in Taiwan

Source: Ministry of the Interior-National Immigration Agency, Republic of China (Taiwan)

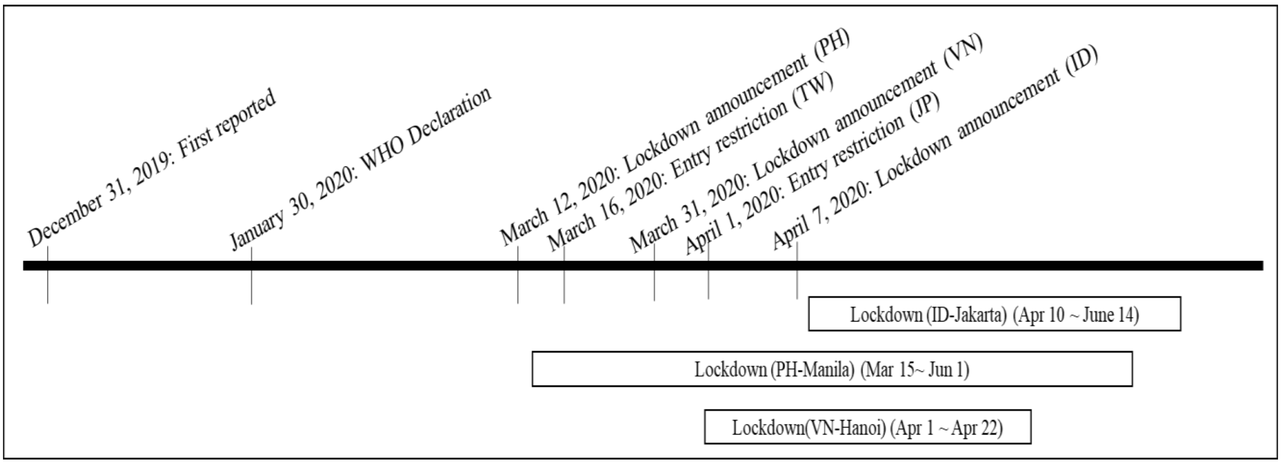

Figure3. Timeline of COVID-19

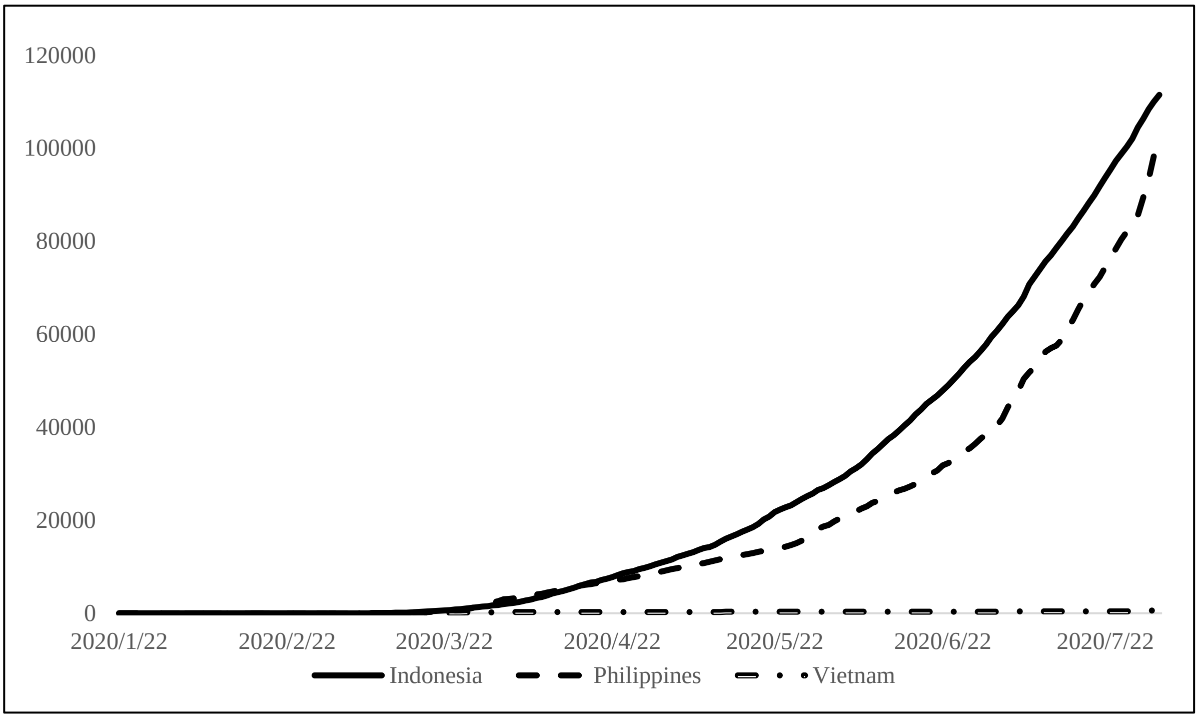

Figure4. Cumulative confirmed cases of COVID-19 in the three countries

Source: Johns Hopkins University- the Center for Systems Science and Engineering
(Retrieved November 11, 2020)

Table 1. Summary statistics

Variable	Obs	2018-2019 (N=735 days) (245 days per country) Mean	Std. Dev.	2019-2020 (N=735 days) (245 days per country) Mean	Std. Dev.	P-value
GTI(Job)	1470	50.88304	22.25182	51.33913	20.09491	0.6801
GTI(Recruitment)	1470	42.98764	21.52056	37.79248	23.2503	0.0000***
GTI(Income)	1470	35.77241	17.66614	40.82532	18.27422	0.0000***
GTI(Business)	1470	61.01716	16.01296	63.30609	17.16159	0.0083**
GTI(Remittance)	1470	35.36776	17.75821	43.00695	19.08508	0.0000***
GTI(Bank Account)	1470	35.03316	15.39398	46.66237	17.44512	0.0000***
GTI(Japan)	1470	47.2538	27.86517	43.54656	22.98174	0.0055**
GTI(Taiwan)	1470	39.92306	10.2534	40.98377	20.70406	0.2135
GTI(Job Japan)	1470	19.90949	15.31758	17.92466	15.16253	0.0126*
GTI(Recruitment Japan)	980	13.63303	19.64872	9.237482	14.90478	0.0001***
GTI(Income Japan)	1470	2.950193	10.21148	4.843819	12.65484	0.0016**
GTI(Business Japan)	1470	11.46632	16.34245	9.764967	14.74516	0.0363*
GTI(Remittance Japan)	980	1.948148	11.24508	5.12664	15.47043	0.0002***
GTI(Job Taiwan)	1470	9.849808	15.58357	6.668834	13.51519	0.0000***
GTI(Recruitment Taiwan)	490	5.998542	16.84583	3.870262	13.56277	0.1241
GTI(Income Taiwan)	0	0	0	0	0	.
GTI(Business Taiwan)	1470	3.636666	14.24186	3.098413	12.17457	0.4362
GTI(Remittance Taiwan)	490	4.668367	15.65703	3.941326	11.53088	0.5587
Log(GDP per capita)	1470	8.130099	0.1728726	8.142636	0.1636217	0.1535
Log(Unemployers)	1470	14.82401	0.7197559	15.0731	0.7842657	0.0000***
OxCGRT	1470	0	0	43.30657	29.6626	.
Confirmed cases	1470	0	0	281.8531	569.8602	.
Log(GDP per capita)(JP)	1470	10.60279	0	10.54939	0	.
Log(Unemployers)(JP)	1470	14.31206	0	14.53521	0	.
OxCGRT(JP)	1470	0	0	29.51045	17.67408	.
Confirmed cases(JP)	1470	0	0	146.249	239.8502	.
Log(GDP per capita)(TW)	1470	10.16173	0	10.12091	0	.
Log(Unemployers)(TW)	1470	13.04717	0	13.19377	0	.
OxCGRT(TW)	1470	0	0	27.29012	13.31755	.
Confirmed cases(TW)	1470	0	0	1.946939	4.643845	.

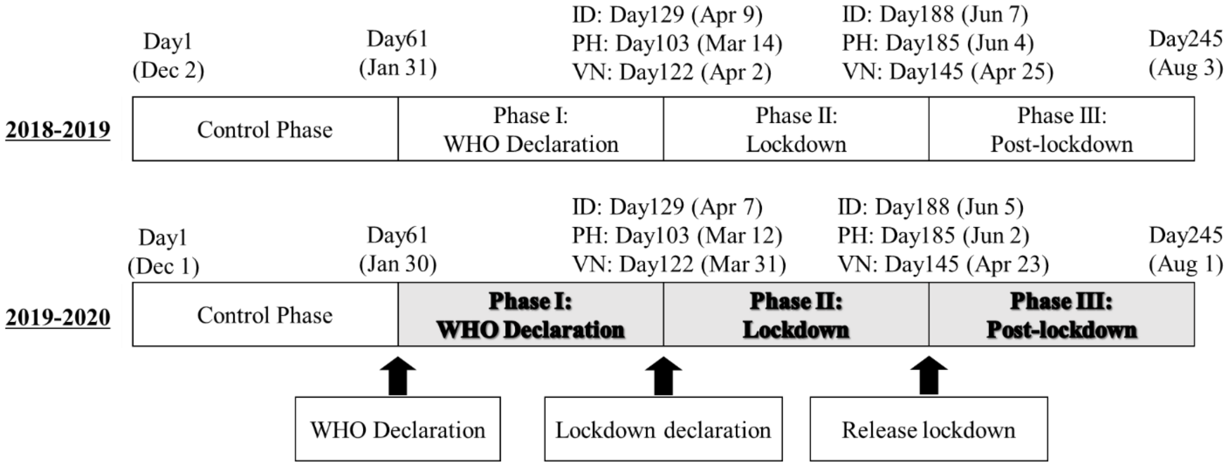

Figure5. Estimation strategy

Table 2. Pairwise correlation

Panel-A	COVID-19 *2020	Log GDP per capita	Log Unemp.	OxXCGRT	Confirmed cases
COVID-19*2020	1.0000				
Log GDP per capita	0.0290	1.0000			
Log Unemployed	0.1272	0.9476	1.0000		
OxCGRT	0.9121	-0.0204	0.0432	1.0000	
Confirmed cases	0.4241	0.2243	0.2439	0.4626	1.0000

Panel-B	WHO *2020	Lockdown *2020	Post *2020	Log GDP per capita	Log Unemp.	OxCGRT	Confirmed cases
WHO Declaration*2020	1						
Lockdown*2020	-0.1286	1					
Post-lockdown*2020	-0.1522	-0.1487	1				
Log GDP per capita	0.0256	0.1157	-0.0857	1			
Log Unemployed	0.0923	0.1262	-0.0214	0.9476	1		
OxCGRT	0.1327	0.6182	0.5747	-0.0204	0.0432	1	
Confirmed cases	-0.1063	0.1078	0.5767	0.2243	0.2439	0.4626	1

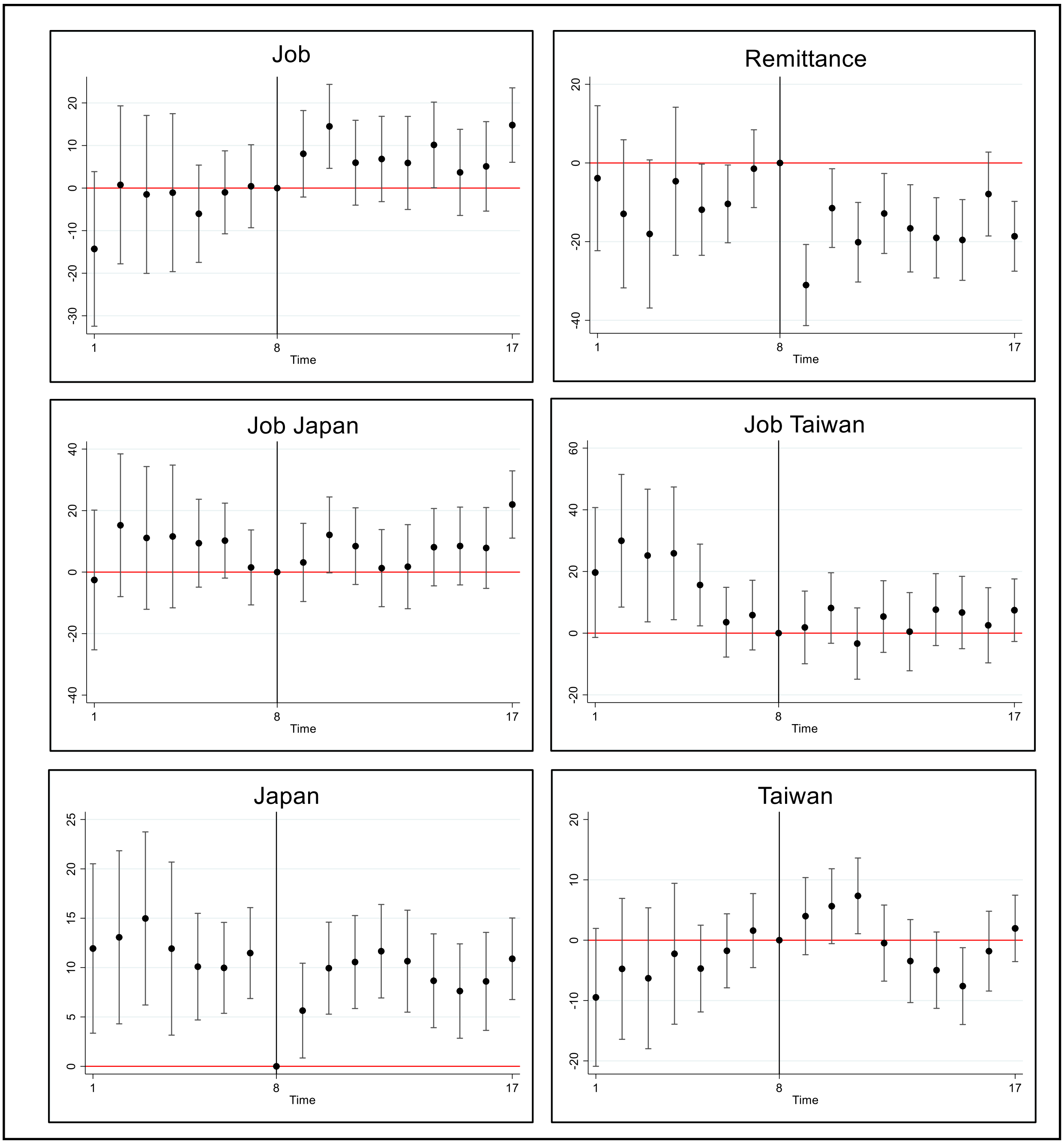

Figure 6. Event study plots (Selected queries: Weekly time window)

Note: The black dots are the coefficients of the event study; the gray lines refer to the bounds of the 95% confidence interval of the coefficients.

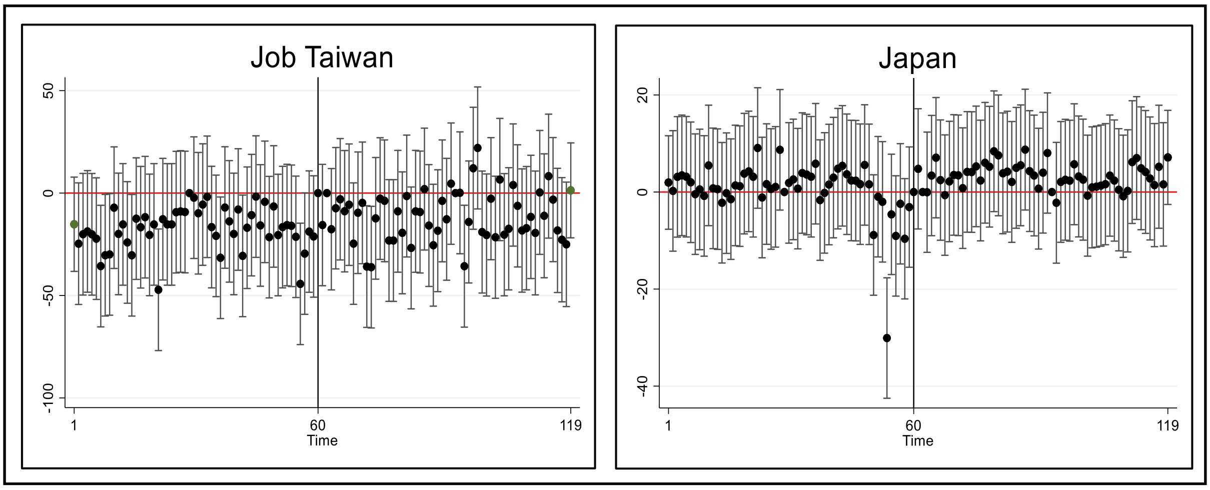

Figure 7. Event study plots (Selected queries: Daily time window)

Note: The black dots are the coefficients of the event study; the gray lines refer to the bounds of the 95% confidence interval of the coefficients.

Table 3. COVID-19 effects (Queries)

	Job-related queries			
	Job	Recruitment	Business	Income
	(1)	(2)	(3)	(4)
COVID-19 period	15.769***	7.644*	13.180***	12.960***
* 2020	(1.854)	(2.997)	(1.807)	(2.053)
	[12.132,19.406]	[1.764,13.523]	[9.635,16.725]	[8.933,16.988]
OxCGRT	-0.238***	-0.203***	-0.108***	-0.132***
(Origins)	(0.031)	(0.046)	(0.031)	(0.035)
	[-0.299,-0.177]	[-0.293,-0.114]	[-0.169,-0.048]	[-0.200,-0.064]
Confirmed Cases	-0.002**	-0.006***	-0.003***	-0.001
(Origins)	(0.001)	(0.001)	(0.001)	(0.001)
	[-0.004,-0.001]	[-0.009,-0.004]	[-0.005,-0.002]	[-0.003,0.001]
Constant	-1.09e+04***	-6021.288***	-1806.875**	-2226.128***
	(583.267)	(741.249)	(564.102)	(643.813)
	[-1.20e+04,-9726.42]	[-7475.57,-4567.01]	[-2913.60,-700.15]	[-3489.244,-963.013]
F-test of 3 vars	0.0000	0.0000	0.0000	0.0000
R-squared	0.264	0.129	0.055	0.038
Obs	1470	1470	1470	1470

	Remittance-related queries		Country name queries	
	Remittance	Bank Account	Japan	Taiwan
	(5)	(6)	(7)	(8)
COVID-19 period	-9.099***	0.515	2.774*	5.044*
*2020	(2.665)	(2.819)	(1.082)	(2.199)
	[-14.327,-3.870]	[-5.015,6.045]	[0.652,4.897]	[0.729,9.359]
OxCGRT	0.275***	0.123**	-0.030+	-0.167***
(Origins)	(0.040)	(0.041)	(0.016)	(0.034)
	[0.196,0.354]	[0.042,0.205]	[-0.062,0.003]	[-0.234,-0.100]
Confirmed Cases	0	0.001	-0.002***	0.006***
(Origins)	(0.001)	(0.001)	(0.000)	(0.002)
	[-0.003,0.003]	[-0.001,0.004]	[-0.003,-0.001]	[0.002,0.009]
Constant	1168.103+	1738.961*	2529.340***	-4277.115***
	(673.126)	(724.334)	(336.083)	(566.441)
	[-152.522,2488.729]	[317.870,3160.051]	[1869.971,3188.71]	[-5388.43,-3165.798]
F-test of 3 vars	0.0000	0.0000	0.0000	0.0000
R-squared	0.069	0.048	0.337	0.31
Obs	1470	1470	1470	1470

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people, as well as country, month, day of week and day fixed effects.

Table 4. COVID-19 effects (Queries with Japan)

	Job-related queries				Remittance-related
	Job Japan	Recruitment Japan	Business Japan	Income Japan	Remittance Japan
	(1)	(2)	(3)	(4)	(5)
COVID-19 period	-7.949*	2.881	1.89	2.457	3.134
*2020	(3.976)	(6.390)	(4.516)	(2.214)	(3.997)
	[-15.750,-0.147]	[-9.665,15.427]	[-6.969,10.750]	[-1.887,6.801]	[-4.712,10.981]
OxCGRT	-0.200**	0.012	-0.103	0.03	0.032
(Origins)	(0.074)	(0.093)	(0.073)	(0.055)	(0.084)
	[-0.346,-0.054]	[-0.171,0.194]	[-0.247,0.041]	[-0.079,0.138]	[-0.132,0.196]
Confirmed Cases	-0.001	-0.002	0	0.003+	-0.002+
(Origins)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
	[-0.003,0.001]	[-0.005,0.001]	[-0.003,0.003]	[-0.000,0.006]	[-0.005,0.000]
OxCGRT(Japan)	0.522***	-0.195	0.156	0.023	0.034
	(0.141)	(0.226)	(0.155)	(0.102)	(0.161)
	[0.245,0.799]	[-0.638,0.249]	[-0.147,0.460]	[-0.178,0.223]	[-0.281,0.350]
Confirmed	0.002	0.008	0.004	-0.007*	0.003
Cases(JP)	(0.004)	(0.006)	(0.005)	(0.003)	(0.004)
	[-0.006,0.011]	[-0.003,0.020]	[-0.006,0.013]	[-0.014,-0.000]	[-0.006,0.011]
Constant	-6189.585***	-44.906	-788.624	-1800.883*	435.692
	(965.056)	(987.885)	(1110.959)	(740.410)	(811.682)
	[-8082.96,-4296.21]	[-1984.39,1894.58]	[-2968.25,1391.0]	[-3253.51,-348.25]	[-1157.86,2029.24]
F-test of 5 vars	0.0044	0.5564	0.5583	0.1972	0.2403
R-squared	0.094	0.000	0.002	0.017	0.011
Obs	1470	980	1470	1470	980

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people in home countries in Columns (1) – (5) and those in both home and host countries in Columns (6)-(10), as well as country, month, day of week and day fixed effects. For Columns (2) & (5), we obtain the GTI data only from the Philippines and Viet Nam.

Table 5. COVID-19 effects (Queries with Taiwan)

	Job-related queries			Remittance-related
	Job Taiwan	Recruitment Taiwan	Business Taiwan	Remittance Taiwan
	(1)	(2)	(3)	(4)
COVID-19 period	2.615	8.171	-9.534+	11.1
*2020	(5.048)	(17.195)	(5.146)	(16.361)
	[-7.289,12.520]	[-25.709,42.051]	[-19.629,0.562]	[-21.136,43.336]
OxCGRT	-0.038	0.054	0.004	-0.02
(Origins)	(0.045)	(0.200)	(0.042)	(0.139)
	[-0.127,0.051]	[-0.340,0.447]	[-0.078,0.085]	[-0.294,0.254]
Confirmed Cases	-0.001	0.23	0.001	-0.195
(Origins)	(0.001)	(0.424)	(0.001)	(0.238)
	[-0.003,0.001]	[-0.606,1.065]	[-0.001,0.003]	[-0.663,0.273]
OxCGRT(Taiwan)	-0.034	-0.184	0.311+	-0.231
	(0.174)	(0.587)	(0.163)	(0.615)
	[-0.375,0.307]	[-1.340,0.972]	[-0.009,0.631]	[-1.443,0.981]
Confirmed Cases(TW)	-0.2	-0.537	0.005	0.337
	(0.190)	(0.370)	(0.134)	(0.480)
	[-0.572,0.173]	[-1.267,0.193]	[-0.257,0.267]	[-0.609,1.284]
Constant	-4175.645***	3.443	-1294.41	3.592
	(947.910)	(2.410)	(836.107)	(2.694)
	[-6035.379,-2315.912]	[-1.306,8.193]	[-2934.794,345.974]	[-1.717,8.900]
F-test of 5 vars	0.361	0.8583	0.1632	0.7982
R-squared	0.028	0.013	0.002	0.004
Obs	1470	490	1470	490

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people in home countries in Columns (1) – (4) and those in both home and host countries in Columns (5)-(8), as well as country, month, day of week and day fixed effects. For Columns (2) & (4), we obtain the GTI data only from Viet Nam.

Table 6. Phase effects (Queries)

	Job-related queries			
	Job	Recruitment	Business	Income
	(1)	(2)	(3)	(4)
WHO declaration period *2020	14.795***	5.363	15.623***	11.874***
	(2.161)	(3.398)	(2.252)	(2.220)
	[10.555,19.034]	[-1.303,12.029]	[11.204,20.041]	[7.519,16.230]
Lockdown period *2020	24.197***	11.976*	34.506***	15.845***
	(4.430)	(5.230)	(4.810)	(4.019)
	[15.507,32.888]	[1.714,22.237]	[25.070,43.942]	[7.961,23.729]
Post-lockdown period *2020	34.614***	27.244***	36.682***	18.875***
	(3.426)	(4.163)	(3.835)	(3.486)
	[27.892,41.336]	[19.076,35.413]	[29.159,44.206]	[12.036,25.714]
OxCGRT (Origins)	-0.382***	-0.316***	-0.382***	-0.173**
	(0.054)	(0.069)	(0.059)	(0.054)
	[-0.489,-0.275]	[-0.452,-0.180]	[-0.498,-0.266]	[-0.280,-0.066]
Confirmed cases (Origins)	-0.007***	-0.012***	-0.007***	-0.002*
	(0.001)	(0.002)	(0.001)	(0.001)
	[-0.009,-0.005]	[-0.015,-0.009]	[-0.009,-0.004]	[-0.004,-0.000]
F-test of 5 vars	0.0000	0.0000	0.0000	0.0000
R-Squared	0.378	0.262	0.174	0.063
Obs	1470	1470	1470	1470

	Remittance-related queries		Country-related queries	
	Remittance	Bank Account	Japan	Taiwan
	(5)	(6)	(7)	(8)
WHO declaration period *2020	-9.978***	-1.885	3.138**	11.159***
	(2.921)	(3.000)	(1.136)	(2.614)
	[-15.709,-4.248]	[-7.771,4.002]	[0.910,5.366]	[6.032,16.287]
Lockdown period *2020	-16.509**	-9.716+	4.117*	27.239***
	(5.226)	(5.112)	(1.941)	(4.831)
	[-26.762,-6.256]	[-19.746,0.314]	[0.309,7.925]	[17.760,36.717]
Post-lockdown period *2020	-20.107***	-8.716*	5.088**	20.585***
	(4.377)	(4.389)	(1.644)	(4.047)
	[-28.694,-11.520]	[-17.326,-0.106]	[1.863,8.314]	[12.646,28.525]
OxCGRT (Origins)	0.386***	0.253***	-0.053*	-0.432***
	(0.064)	(0.066)	(0.025)	(0.064)
	[0.259,0.512]	[0.124,0.382]	[-0.102,-0.003]	[-0.557,-0.307]
Confirmed cases (Origins)	0.002	0.002	-0.002***	0.006**
	(0.001)	(0.001)	(0.000)	(0.002)
	[-0.001,0.004]	[-0.001,0.004]	[-0.003,-0.001]	[0.002,0.010]
F-test of 5 vars	0.0000	0.0000	0.0000	0.0000
R-squared	0.081	0.056	0.34	0.339
Obs	1470	1470	1470	1470

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people, as well as country, month, day of week and day fixed effects.

Table 7. Phase effects (Queries with Japan)

	Job-related queries				Remittance-related
	Job Japan	Recruitment Japan	Income Japan	Business Japan	Remittance Japan
	(1)	(2)	(3)	(4)	(5)
WHO declaration period	-1.457	7.174	1.179	2.493	0.701
*2020	(4.619)	(7.903)	(4.824)	(2.538)	(4.456)
	[-10.519,7.605]	[-8.342,22.690]	[-8.287,10.644]	[-2.486,7.472]	[-8.048,9.450]
Lockdown period	13.703+	16.364	-1.14	3.589	-5.635
*2020	(7.953)	(14.580)	(7.892)	(4.474)	(8.529)
	[-1.900,29.305]	[-12.260,44.988]	[-16.624,14.343]	[-5.188,12.366]	[-22.381,11.111]
Post-lockdown period	10.802	11.902	-2.148	5.724	-7.366
*2020	(6.607)	(11.791)	(6.614)	(4.274)	(7.690)
	[-2.160,23.764]	[-11.246,35.050]	[-15.124,10.828]	[-2.662,14.109]	[-22.463,7.732]
OxCGRT	-0.356***	-0.097	-0.088	0.008	0.137
(Origins)	(0.092)	(0.149)	(0.088)	(0.062)	(0.094)
	[-0.535,-0.176]	[-0.390,0.195]	[-0.261,0.085]	[-0.114,0.130]	[-0.048,0.322]
Confirmed Cases	-0.002	-0.001	0.001	0.002	-0.002+
(Origins)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
	[-0.004,0.001]	[-0.005,0.002]	[-0.002,0.004]	[-0.002,0.006]	[-0.005,0.000]
OxCGRT(Japan)	0.343*	-0.259	0.2	0.021	0.063
	(0.155)	(0.247)	(0.164)	(0.109)	(0.177)
	[0.038,0.647]	[-0.744,0.227]	[-0.122,0.522]	[-0.192,0.233]	[-0.286,0.411]
Confirmed Cases(JP)	0	0.007	0.004	-0.007*	0.004
	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)
	[-0.008,0.009]	[-0.004,0.019]	[-0.005,0.014]	[-0.015,-0.000]	[-0.005,0.013]
F-test of 7 vars	0.0001	0.623	0.5597	0.0507	0.0621
R-squared	0.107	0.006	0.001	0.017	0.019
Obs	1470	980	1470	1470	980

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people in both home and host countries, as well as country, month, day of week and day fixed effects. For Columns (2) & (5), we obtain the GTI data only from the Philippines and Viet Nam.

Table 8. Phase effects (Queries with Taiwan)

	Job-related queries			Remittance-related
	Job Taiwan	Recruitment Taiwan	Business Taiwan	Remittance Taiwan
	(1)	(2)	(3)	(4)
WHO declaration period	4.446	4.038	-8.249	3.273
*2020	(5.227)	(21.691)	(5.314)	(18.302)
	[-5.809,14.702]	[-38.702,46.778]	[-18.675,2.178]	[-32.788,39.334]
Lockdown period	9.521	-2.798	-4.744	-4.22
*2020	(7.271)	(34.278)	(7.346)	(29.906)
	[-4.744,23.786]	[-70.338,64.741]	[-19.157,9.669]	[-63.146,54.707]
Post-lockdown period	7.209	0.901	-5.582	-9.802
*2020	(6.900)	(28.679)	(6.656)	(24.920)
	[-6.329,20.747]	[-55.607,57.409]	[-18.642,7.477]	[-58.904,39.299]
OxCGRT	-0.121+	0.185	-0.053	0.214
(Origins)	(0.069)	(0.461)	(0.070)	(0.378)
	[-0.257,0.015]	[-0.724,1.093]	[-0.190,0.083]	[-0.532,0.960]
Confirmed Cases	-0.001	0.198	0.001	-0.168
(Origins)	(0.001)	(0.450)	(0.001)	(0.245)
	[-0.003,0.001]	[-0.688,1.084]	[-0.001,0.003]	[-0.650,0.314]
OxCGRT(Taiwan)	-0.034	-0.205	0.302+	-0.11
	(0.176)	(0.605)	(0.165)	(0.640)
	[-0.379,0.312]	[-1.397,0.986]	[-0.021,0.625]	[-1.371,1.150]
Confirmed Cases(TW)	-0.158	-0.58	0.052	-0.137
	(0.215)	(0.362)	(0.161)	(0.462)
	[-0.580,0.263]	[-1.295,0.134]	[-0.264,0.369]	[-1.048,0.774]
F-test of 7 vars	0.2321	0.7657	0.5007	0.3362
R-Squared	0.03	0.01	0.002	0.03
Obs	1470	490	1470	490

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard error, clustered at the country-specific day level, in parenthesis. 95% CI in bracket. The models include log-annual GDP per capita and log-annual estimated unemployed people in both home and host countries, as well as country, month, day of week and day fixed effects. For Columns (2) & (4), we obtain the GTI data only from Viet Nam.

Appendix

A. Robustness check for prediction model

In this section, we analyze the workhorse models of international migration to verify whether our selected GTIs would predict the international migration flow. Our procedure is following Böhme et al. (2020). We compare the gravity model depending on the traditional macroeconomic factors and the other model containing the four GTIs we assigned in this research, and evaluate how accurately these models capture the international migration flow. The assumption of this research is the inflows to Japan and Taiwan from three Southeast Asian countries; however, as the data about the number of entries by nationalities is not in public by the Taiwan government, we consider the case of Japan here. We obtain the monthly data about entries into Japan sorted by the nationalities and the type of visas n from the Immigration Services Agency of Japan. The survey period is from January 2009 to December 2019. We exclude the number of entries by the short-term visa and construct the monthly entry data from three countries for 120 months. Thus, we have 360 monthly data. About the GTI data, we obtain the monthly GTI data of four single keywords, four bilateral keywords, and two country's names during the period from January 2008 to December 2018 in each origin because the preparation for migration takes time, and we omit the reverse causality[19]. We acquire the annual GDP and population records of both origins and Japan from the World Bank database within the same period as those of the GTI data.[20] After constructing the year-month-based panel data, we run the fixed-effect model. The model is as follows:

$$Y_{c,m,y+1} = \beta_1 GTIbil_{c,m,y} + \beta_2 GTIuni_{c,m,y} * GTIdest_{c,m,y} + \beta_3 O_{c,y} + \beta_4 D_y + \gamma_{m,y} + \delta_c + \varepsilon \quad \text{(A1)}$$

[19] When we set the time range more than five years, we obtain the monthly-GTIs of each keyword.

[20] We will provide the summary statistics of the data used for this robustness check upon request.

The above model adopts almost the same specification as eq. (2) in Böhme et al. (2020). $Y_{c,m,y+1}$ is the log of the number of monthly new entry of long-term visa holders to Japan from each origin country c on month m in year $y+1$. $GTIbil_{c,m,y}$ is the GTI of bilateral words (e.g. "job Japan") on month m year y in country c. $GTIuni_{c,m,y}$ is the GT index of unitary keywords (e.g., "job") at month m in year y in country c. $GTIdest_{c,m,y}$ is the GTI of keyword "Japan" at month m in year y and country c, and which is interacted with $GTIuni_{c,m,y}$ in this model[21]. $O_{c,y}$ is the macroeconomic factors of the country c in year y, and D_y is the macroeconomic factors in year y in Japan. We use the year-month based time-specific fixed effects ($\gamma_{m,y}$) and origin-specific fixed effects (δ_c) and employ the robust standard error.

Table A1 reports the results of the prediction models. Column (1) shows the results for the benchmark regression specification, which uses the only static and traditional macroeconomic indicators in the model. On the contrary, Column (2) augments the four GTI we assigned in this research. According to Böhme et al. (2020), we judge the prediction performance of each model based on the within R^2, which implies the predictive power of time-varying explanatory variables controlling fixed effects. The essential predictors in Column (1) hold a within R^2 of 67.9%. On the contrary, the augmented model including the GTI indicators in Column (2) rise to 75.2%. We calculate the adjusted R^2 in each model as a robustness check; 67.6 % in (1) and 74.4% in (2). The model including the GTIs will outperform the traditional gravity model for predicting international migration flows, as Böhme et al. (2020) explained. These results suggest that our selected GTIs offer additional predictive power for international migration flows in Asian countries.

[21] Böhme et al. (2020) include the interaction term of the unilateral keyword and the destination name in the bilateral flow model because the GTI of bilateral keywords often cannot be obtained due to the minimum threshold of the Google Trend database. Furthermore, this interaction variable would provide complementary predictive power. Although we can acquire data about the GTIs of bilateral keywords in our setting, we include these interaction terms to replicate Böhme et al. (2020).

Table A1. Results of prediction model

VARIABLES	Benchmark	With 4 GTIs
	(1)	(2)
Log GDP (Origin)	1.315	0.680
	(0.497)	(0.711)
Log Population (Origin)	-19.01**	-4.401
	(3.689)	(5.639)
Log GDP (Japan)	-0.317	-0.212
	(0.454)	(0.390)
Log Population (Japan)	-231.4***	-79.67
	(23.09)	(35.13)
Constant	4,657**	1,566
	(491.1)	(749.9)
Observations	360	360
Four GTI	NO	YES
R-squared (Within)	0.679	0.752
R-squared (Adjusted)	0.676	0.744

Note) + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Robust standard error in parenthesis. The models include log-annual GDP and log-annual populations in both origins and Japan, as well as origin-country, month-year fixed effects. For Column (2) we include the four GTIs as forms represented by eq.A1.

B. Figures

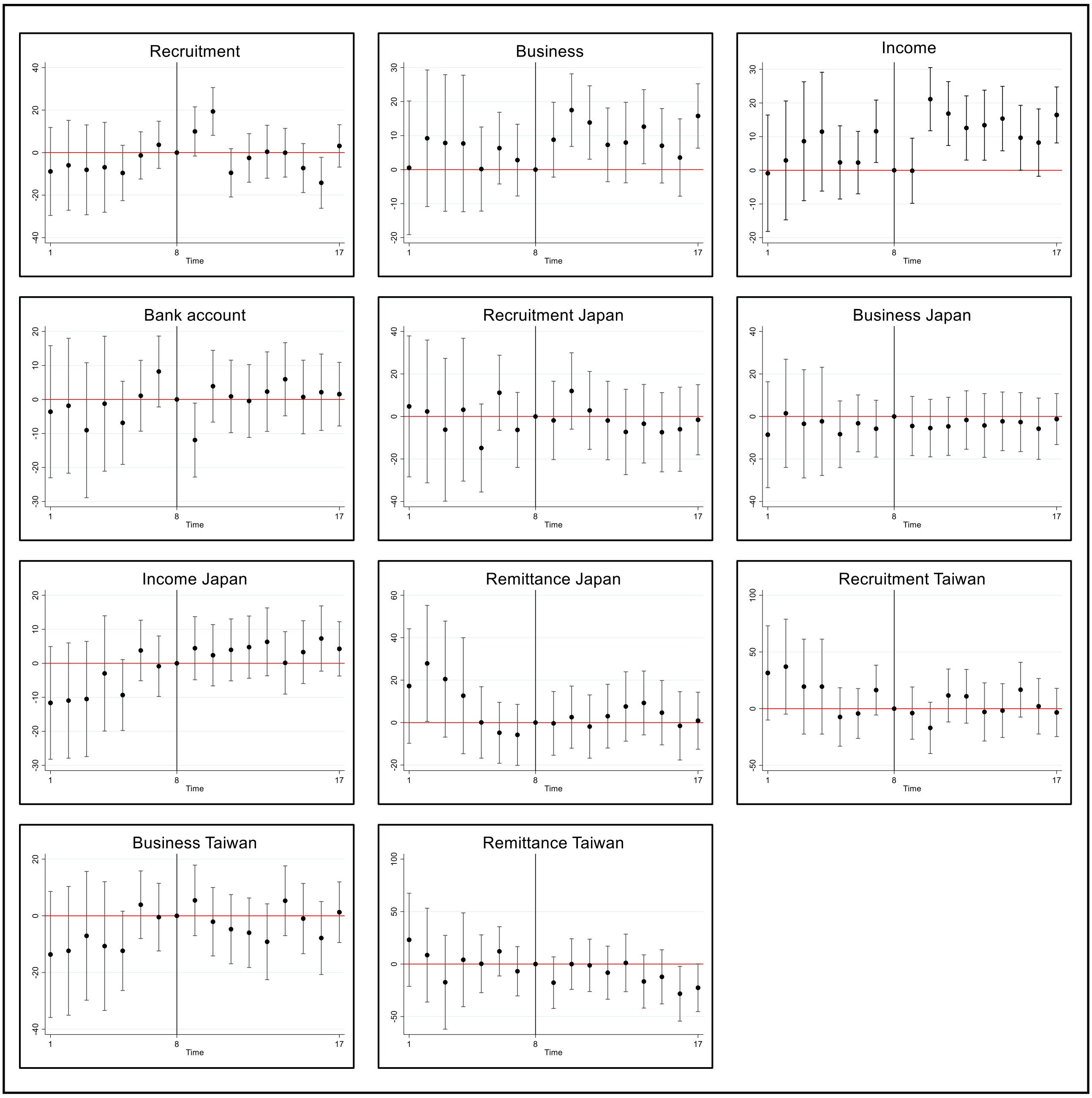

Figure A-1. Event study plots (Queries other than Figure 6)
Note: The black dots are the coefficients of the event study; the gray lines refer to the bounds of the 95% confidence interval of the coefficients.