Analysis of international migration using a network approach: How is it different from international tourism?

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Abstract

In this paper, I discuss the characteristics of international migration and tourism using a network approach. I identify the characteristics of international migration by comparing them with international tourism. International migration networks have shown quite stable structural properties as time passes. The migration networks are regressed on several explanatory factors to identify the relationship between the formation of international migration networks and many factors driving migration. The explanatory variables in my models are classified into two categories: non-network structural and network structural variables. Social, economic, distance, language, safety, and climate change factors are non-network structural variables. I consider the community structure, in-degree, betweenness, and closeness centralities. Migration to wealthy, economically equal, and safe countries for investment is significantly observed. Migration to escape climate change is not significant for now, but the result shows the future negative impact of climate change on international migration. The international tourism networks show quite different characteristics from the migration networks. International tourism networks have been denser as time passes, contrary to international migration networks. Tourism for consumption, not investment, is significantly observed. The betweenness centrality of a destination country and the community structure are strongly tied to forming international migration and tourism networks. Migration and tourism to linguistically similar and shorter in distance countries have been observed.

Keywords: international migration networks, international tourism networks, global migration, network centrality, community structure.

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1 Introduction

The world is closely connected economically and politically, allowing people to migrate to other countries more easily. According to the United Nations (UN) report, the number of international migrants was 272 million in 2019 (see UN (2018)).

There are many reasons to migrate to other countries. These reasons can be related to individual preferences and differences in a nation's political system for individuals to live better lives as investments. It indicates that migration is different from tourism to enjoy leisure. Identifying the structural disparities between the origin and destination that generate the conditions in which migration increases is useful in understanding the reasons for migration. Czaika and Reinprecht (2020) introduce "migration drivers" as the structural disparities between the origin and destination country that lead to the decision to migrate and categorize drivers of migration: demographic drivers, economic drivers, environmental drivers, human development drivers, individual drivers, politico-institutional drivers, security-related drivers, socio-cultural drivers, and supranational drivers. I briefly explain the drivers introduced in Czaika and Reinprecht (2020) to understand the motivation to migrate to other countries[1].

Demographic drivers are related to population dynamics, and family size and structure. For example, young people are more likely to migrate to achieve potential gain, such as a higher chance to accumulate economic wealth, from migrating at a young age. Also, the smaller is the family size, the easier is to reach the consent of all family members for migration.

Economic drivers are associated with economic and business conditions, labor market and employment, urban/rural development and living standards, and poverty and inequality. For example, individuals are more likely to migrate to a country that provides more chances to

[1] Czaika and Reinprecht (2020) introduce the literature that shows the empirical evidence of drivers of migration. Thus, I do not introduce the literature on the empirical evidence of drivers of migration in this paper. If you want to know the literature on empirical evidence of drivers of migration, please read the paper of Czaika and Reinprecht (2020).

reduce poverty and increase their wealth than in their home countries. Economic drivers can be the most important factors in migration decisions because many other drivers are closely related to economic drivers. If economic conditions are not improved by migrating, it cannot be easy to migrate to other countries, even if other drivers are satisfied.

Environmental drivers include climate change, natural disasters, and environmental shocks. Climate change is one of the most important global issues. Some countries may be very vulnerable to climate change. Thus, people in these countries are more likely to migrate to less vulnerable countries.

Human development drivers are education, training opportunities, and health services. The right to receive high-quality education and training services to achieve one's dreams and goals is one of the fundamental human rights. If unsatisfied with their home country's education system, migrants are more likely to migrate to a country that provides better education. Also, the right to get high-quality healthcare services is one of the essential human rights. Thus, Access to a high-quality healthcare system can contribute to a greater desire to migrate.

Personal resources, migration experience, and migrant aspirations and attitudes can drive migration decisions. Individuals with migration experience are more likely to migrate in the future. Also, certain people have an openness to migrating. Then, they are more likely to migrate than others not open to migrating.

Politico-institutional drivers include public infrastructure, immigration policy, and civil and political rights. Individuals who want to migrate are more likely to migrate to countries with a public infrastructure and policies that are favorable to migrants. Also, individuals want to live in countries with more civil and political rights than their home countries. In a democratic society, a democratic system that allows political rights is closely connected to economic freedom. Thus, politico-institutional factors can be critical factors considered in migration decisions.

Security-related drivers are conflict, war, violence, political situations, repression, and transitions. To want to live in a safe place is one of the fundamental desires. Thus, if individuals live in a dangerous country due to conflict, war, violence, or negative political situation, they want to migrate to countries more socially or politically secure than their countries.

Social-cultural drivers are correlated with migrant communities and networks, cultural norms and ties, and gender relations. When individuals choose the country to migrate to, it is important whether the community or networks are formed by their friends or people of the same race as they are in the country. Also, the similarity of cultural norms is important for migration decisions. Individuals are more likely to migrate to countries with similar cultural norms as their home country. It is called "cultural homophily." For women, gender relations between men and women in the country they want to migrate to can be critical.

Supranational drivers are globalization and post-colonialism, transnational ties, international relations, and geopolitical transformations. If individuals have two options, they migrate to a country with positive international relations with their country of origin. These drivers show that international relations in the globalized world can critically affect migration decisions.

The additional drivers are geographical drivers. For example, people are more likely to migrate to a country not far away from their home country. In addition, if two countries are close to each other, their cultures would be similar (cultural homophily), and migration between these countries is effortless. The gravity model in economics has explained the geographical factors in migration (see Anderson (2011); Beine, Bertoli and Fernández-Huertas Moraga (2016)). By the gravity model, the migration flow from the origin to the destination is inversely proportional to the distance between the origin and the destination.

In this paper, I discuss the five drivers or factors that categorize all migration drivers that I explained since all drivers are weakly or strongly tied to each other: (1) social and economic factors; (2) distance factor; (3) language factor; (4) safety factor; (5) climate change factor. Demographic, economic, human development and politico-institutional drivers are strongly tied to social and economic factors. The distance between two countries is still an important migration driver. Social-cultural and supranational drivers are strongly tied to language factors, such as the similarity of official languages in an origin and a destination country. Also, it is more likely that individuals have more desire to migrate when living in countries with similar official languages. The drivers related to security-related drivers are strongly linked to the safety factor. Finally, climate change factor is strongly tied to environmental drivers.

In addition, I discuss tourism drivers to understand migration decisions by comparing migration with tourism. The drivers of tourism can also be classified into five factors: (1) social and economic factors; (2) distance factor; (3) language factor; (4) safety factor; (5) climate change factor.

International tourism is a temporary visit to other countries contrary to permanent living in other countries of international migration. Tourism is different from migration. Tourism is a kind of consumption good if we assume migration is an investment. Thus, the economic factors in reducing travel costs, such as income, price-level differences, and the foreign exchange rate between an origin and a destination country, are the most important in travel decisions. For example, higher-income persons are more likely to travel than lower-income persons. Also, people in wealthier countries are more likely to travel to poorer countries due to the higher value of wealthier countries' currencies (see Cheng (2012); Vita, Kyaw et al. (2013); Dogru, Sirakaya-Turk and Crouch (2017); Chung et al. (2020)).

The physical distance between an origin and a destination country is one of the most important factors in travel decisions. Tourists can reduce time and transportation costs by traveling to nearer countries (see Eilat and Einav (2004); Khadaroo and Seetanah (2008); Chung et al. (2020)). Thus, tourists are more likely to select nearer countries if other factors are very similar.

Tourists also consider a language factor, such as the linguistic similarity between an origin and a destination country, to select the destination country in their travel decisions.

Suppose the official language of a destination country is the same as the origin country. In that case, tourists have no costs by the different languages and are more likely to travel between these two countries (see Eilat and Einav (2004); Khadaroo and Seetanah (2008); Chung et al. (2020)).

Tourists can also be sensitive to safety factors, such as the terrorism risks or political instability of the destination country. If the destination country is unsafe, it might be challenging to travel. However, by some research, the negative effect of terrorism risks or political instability of the destination country on travel decisions are not observed, and the debate related to the negative effect is still ongoing (see Van der Zee and Vanneste (2015); Liu and Pratt (2017); Chung et al. (2020)).

Finally, the climate change factor can change the structure of the tourism industry and change travel decisions. For example, an increase in temperature in the winter can reduce the demand for tourism related to the ski industry, and a rise in sea level can reduce the demand for tourism in the summer (see Scott, Gössling and Hall (2012)).

The international migration pattern has become more complex due to various drivers and reasons that lead to migration decisions. An international migration network is created by flows of migrants from the origin to the destination country. If the flow is massive, the interconnection between countries is meaningful. In addition, most countries are connected in the world. It implies that we need to understand not only the bilateral flows of migrants between two countries but also the interaction structures among more than three countries in the network. Thus, it is necessary to understand the relationship between international migration network structures and migration drivers to understand migration patterns.

Also, the international tourism pattern and networks, created by flows of travelers from the origin to the destination country, could become more complex due to various drivers of tourism but are quite different from the international migration and networks. By identifying the difference between migration and tourism, we can better understand the characteristics of the international migration pattern than analyzing only the international migration pattern.

Network theory is useful for analyzing the interaction structure of the system and has been applied to many areas to identify the interaction structure in the economic system (see Goyal (2009); Jackson (2014); Carvalho and Tahbaz-Salehi (2019)). A network consists of nodes and links. Nodes represent agents in the system, and links represent the relationship between nodes. For example, in the international migration network, nodes are countries. The node between two countries is formed if two countries are the sending and destination countries in the migration. Countries worldwide are heterogeneous, and interactions formed by migration flows are nonlinear in international migration networks and include characteristics beyond pairwise interactions.

In this paper, I apply the novel methodology in network theory to identify migration drivers and the effect of interaction structure among countries on migration decisions. I use the migration stock data provided by the UN to construct international migration networks. Nodes in the international migration networks represent the countries, and two nodes are linked if the share of emigrants from a sending country to a destination country at the overall population in the sending country falls into the 75^{th} percentile of the distribution. Then, I consider the network centralities, which measure the influence of countries in international migration networks, and the structure of communities in which countries are clustered in international networks based on modularity maximization: (1) in-degree centrality; (2) betweenness centrality; (3) closeness centrality; (4) community index. International migration networks have shown stable structural properties using the centralities as time passes.

Links formed in the networks are regressed on non-networks structure variables, such as social and economic, distance, language, safety, climate change, and network structures. The links are more likely formed from a poor country to a wealthy country as well as from a less safe country to a safer country. Also, the links are more likely to be formed from an economically more unequal country to an equal country. As countries are physically closer or the linguistic distance is shorter, they are more likely to be connected in the networks. The migration flows to escalate climate change risk are not significantly observed. However, the migration flows to countries vulnerable to climate change are significantly observed. It implies that most countries preferred by migrants are in danger of climate change. This result also warns of the future negative impact of climate change on international migration. The network structures, measured by the betweenness centrality of a destination country and the community structure, are strongly tied with the formation of links in the networks.

Additionally, I analyze the international tourism networks constructed using the outbound tourism data provided by the World Tourism Organization (UNWTO) to understand migration decisions by comparing the characteristics of migration with tourism. The results show that the characteristics of the international tourism networks are quite different from the international migration networks. International tourism networks have been denser as time passes, contrary to international migration networks. Visiting wealthy, economically equal, and safer countries is not a strong factor in travel decisions. Tourism for consumption, not investment, is significantly observed. The links are more likely formed from a wealthy country to a poor country as well as from a safe country to a less safe country. The links are more likely to be formed from an economically more equal country to an unequal country. As countries are physically closer or the linguistic distance is shorter, they are more likely to be connected in the networks. The tourism flows to countries vulnerable to climate change are significantly observed. It implies that most countries preferred by tourists are in danger of climate change. This shows the negative impact of climate change on the tourism industry in the future. The betweenness centrality and community structure are strongly tied to the international tourism networks.

The paper is organized as follows. Section 2 represents the literature related to international migration and tourism research. I introduce the data sets used in this research in Section 3. Section 4 represents the methodology used in this paper. Section 5 introduces the hypotheses I want to test in this research. Section 6 represents the results. Section 7 concludes.

2 Literature Review

There are two branches of previous research related to the relationship between migration networks and migration decisions. The first branch is the research at the micro-level. The micro-level study has the advantage of identifying the motivation for individual migration decisions. Also, we can test the theory based on individual decisions using micro-level data.

Deléchat (2001) shows that previous migration experience and individuals' social networks are the strongest predictors of current migration decisions using Mexico-US migration data. She suggests the sequential model that explains the migration pattern from Mexico to the U.S. She finds that previous migration experience and community or family networks of Mexican migrants reduce migration costs. Reduced migration costs may result in less effort to migrate.

Munshi (2003) analyzes the effect of community networks among Mexican migrants on the U.S. labor market. He shows that community networks among Mexican migrants have a positive role in the employment and occupation of Mexican migrants in the U.S. labor market. In particular, Mexican migrants can acquire information about a non-agricultural job using the community formed in the U.S. It shows that social networks are an information channel for migrants to get information related to settling down in the destination country.

Liu (2013) shows that this strength of weak ties (acquaintances) is observed in the migration between Africa (Senegal) and Europe (France, Italy, and Spain). In particular, the research reports that networks with many acquaintances are more beneficial to migrating than networks with a small number of friends. Granovetter (1973) suggests that gathering information through many weak ties (acquaintances) is more beneficial than through a few strong ties (friends). Thus, Liu (2013) 's study shows that Granovetter's hypothesis works in international migration.

Windzio (2015) measures the effect of parents' networks on children's networks using birthday party data of 1226 immigrant children in school classes in Bremen, Germany. As a result, the effect of parents' networks on children's networks is positive with high statistical significance. It implies that network effects are intergenerationally transmitted in an immigrant family.

However, the study based on micro-level data has some limitations. First, most micro-level data is only based on bilateral migration flows between two countries. All countries are connected globally. Thus, multiple countries or the structure of international migration networks can affect individual migration decisions. However, we cannot measure the effect of the structure of international migration networks on individual migration decisions using micro-level data. Second, most micro-level data is based on a survey, and it is retrospective. Thus, the data might be incorrect. Third, it is not easy to get data. To create networks of migrants, we need information about the relationships among migrants, but the information about the relationship is censored and not publicly available. Finally, the micro-level data is focused on migration among particular countries. For example, most studies based on micro-level data have focused on the Mexico-U.S. migration and the Africa-Europe migration because it is difficult to find other micro-level data. However, international migration is global. Thus, to understand international migration, we need to analyze international migration among most countries in the world.

The second branch is the research at the macro level. The macro-level studies have focused on analyzing the structure of international migration networks. Most micro-level studies have focused on bilateral migration flows between two countries, and we cannot measure the effect of the structure of networks using the micro-level data. However, the macro-level data includes most of all countries' migration flows. Also, it is publicly available, and we can freely download data.[2] Many studies about international migration networks using macro-level data have been conducted.

Fagiolo and Mastrorillo (2013) characterize the structure of international migration networks. They find that international migration networks show disassortativity, representing the connection between high-population and low-population countries and high clustering

[2] You can freely download international migration data at `https://www.un.org/en/development/desa/population/migration/data/index.asp`.

among geographically close countries. By the gravity model, the flow of migrants is proportional to the product of the population of the origin and the destination country. These characteristics are consistent with the gravity model.

Danchev and Porter (2018) characterize the dynamics of international networks. They find that the movement of international migration is deviating from geographical boundaries. They also categorize communities in international migration networks into three types: global, local, and glocal. If most migration flows are outside the communities, the communities are global. If most migration flows are inside the communities, the communities are local. If migration flows in the communities are between global and local, the communities are glocal. They find that local communities are observed in contiguous geographic regions for most periods, whereas global communities span non-contiguous countries. It implies that world migration is glocal and neither completely regionally (or locally) concentrated nor completely globally interconnected. It also implies that the world migration pattern is heterogeneous, with unequal migration chances worldwide.

Windzio (2018) analyzes international migration networks using the exponential random graph model (ERGM)[3]. In particular, he adds geographical, demographic, and cultural factors in ERGM. He finds that ERGM explains "cultural" clustering in international migration networks, which shows large migration flows between culturally similar countries, and "geographical" clustering in international migration networks, which shows large migration flows between geographically close countries. Thus, his results are also consistent with the gravity model results. In addition, he finds that hierarchical network structure is closely associated with international migration flows, and international migration networks depend on the structural properties of past networks.

The network methodology has been applied to identify the factors affecting travel decisions using macro-level data (see Van der Zee and Vanneste (2015); Lozano and Gutiérrez

[3]The probability of network formation has the exponential function form in ERGMs (see Lusher, Koskinen and Robins (2013)). The probability of network formation in ERGMs generally includes mutual link formation and the effect of network structures on link formation.

(2018); Chung et al. (2020); Seok, Barnett and Nam (2021)). They find stylized facts and common properties in international tourism networks. In this paper, I introduce the recent literature about analyzing international tourism networks using the tourism data provided by UNWTO.

Chung et al. (2020) characterize the dynamics of international tourism structure using international tourism networks constructed using the tourism data of UNWTO. They find that the international tourism network has become decentralized, and the network centralities measured, such as outdegree, indegree, betweenness, and eigenvector centrality, correlate. The strong positive effect of the economic conditions of sending countries on link formation is observed. However, the strong negative effect of terrorism risks and political instability in receiving countries is not observed. It implies that tourists are not vulnerable to terrorism risks and political instability in receiving countries. Also, the clustering among countries with shorter distances and more similar cultures and languages is observed in the networks.

Seok, Barnett and Nam (2021) also investigate the dynamic property of international tourism network structure using the tourism data provided by UNWTO. They also get similar results as Chung et al. (2020): the strong positive effect of sending countries' economic conditions on link formation, tourists' resilience to terrorism and political instability of the receiving countries, and the correlation among network centralities. In addition, a strong memory effect of network structure on international tourism networks is observed. It implies that international tourism networks depend on the structural properties of past networks.

This paper contributes to the international migration network studies and tourism studies based on macro-level data (see Fagiolo and Mastrorillo (2013); Danchev and Porter (2018); Windzio (2018); Chung et al. (2020); Seok, Barnett and Nam (2021)). I add social and economic inequality, safety, and climate change factors to the study of Windzio (2018). Thus, the relationship between most factors or drivers of migration decisions introduced in Czaika and Reinprecht (2020) and international migration network formation can be tested through my research. In particular, climate change is one of the most important global issues affecting international migration and tourism. Recently, many developed countries have tried to prepare for disasters due to climate change.[4] In addition, the characteristics of international migration networks different from international tourism networks have not been identified enough. Individual migration decisions are based on long-term investment to live better lives. However, individual traveling decisions are based on short-term consumption to enjoy leisure. Thus, the structure of international migration networks may differ from international tourism networks. Consequently, my study contributes to the comparative studies between international migration and tourism networks and the study of international tourism networks itself.

3 Data sets

3.1 International Migration and Tourism Data

UN provides international migration data. The data includes total international migrant stock, international migrant stock by age and sex, and destination and origin. Thus, we can construct an international migration network using international migrant stock by destination and origin in 232 countries. The data estimated by the UN are presented for 1990, 1995, 2000, 2005, 2010, 2015, and 2019.[5] Thus, I construct international migration networks for 1990, 1995, 2000, 2005, 2010, 2015, and 2019.

Also, I construct international tourism networks for 1990, 1995, 2000, 2005, 2010, 2015, and 2019 using the outbound tourism data provided by the World Tourism Organization (UNWTO).[6] The data provides the number of travelers by destination and origin in outbound tourism of 38 countries in the Organization for Economic Cooperation and Development (OECD), 38 countries in the Economic Commission for Latin America and the Caribbean

[4] According to the World Risk Report, most developed countries are vulnerable to disasters due to climate change (see `https://weltrisikobericht.de/weltrisikobericht-2022-e/#worldmap`). Thus, most developed countries have tried to enact laws related to climate change (see `https://climate-laws.org`).

[5] `https://www.un.org/development/desa/pd/content/international-migrant-stock`

[6] `https://www.unwto.org/tourism-statistics/tourism-statistics-database`

(ECLAC), and 53 countries in the United Nations Economics and Social Commission for Asia and the Pacific (UNESCAP).

In international migration and tourism networks, nodes in the networks are countries. Links in international migration networks are the connections between countries through the flow of migrants between countries. Links in international tourism networks are the ties between countries through the flow of tourists between two countries.

3.2 Social and Economic Data

The World Bank provides social and economic data by countries, such as the Gross Domestic Product (GDP) per capita, Gini index, and life expectancy at birth. These data are used to measure the effect of social and economic factors on international migration and tourism network formation.[7] The GDP per capita is measured by the market value of all final products and services produced and sold divided by the population in a country. The GDP per capita is widely used to measure the prosperity of a nation based on economic growth per person. The Gini index measures the income or consumption inequality among individuals or households in a country, ranging from 0, indicating perfect equality, to 1, indicating perfect inequality. The Gini index is calculated by the difference between the Lorenz curve, the cumulative income or consumption distribution, and a perfectly equal income or consumption distribution. The Gini index is widely used to measure the economic inequality of society. A society with a higher Gini index implies a more unequal society. Life expectancy at birth measures the number of years a newborn infant would live if we assumed that mortality patterns at the time of its birth remain unchanging in the future. As the society in a country is safer and more resilient, life expectancy at birth is higher. However, as the society in a country is more dangerous and less resilient, life expectancy at

[7] 1) GDP per capita, PPP (constant 2017 international $), https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.PCAP.PP.KD; 2) Gini index, https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SI.POV.GINI; 3) total life expectancy, https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SP.DYN.LE00.IN.

Descriptive statistics of nodes attributes				
Panel A: International migration networks				
	Mean	SD	Min	Max
GDP per capita	23,725.153	20,308.987	671.541	114,542.496
Gini index (%)	37.462	8.668	23.000	64.800
Life expectancy at birth (year)	73.318	7.288	46.024	83.832
Distance between countries (km)	6,899.220	4,477.459	106.807	19,740.366
Language distance between countries	0.846	0.307	0.000	1.000
Political Stability	0.124	0.909	-2.677	1.759
Climate-related Disasters Frequency	2.687	4.297	0.000	31.000
Panel B: International tourism networks				
	Mean	SD	Min	Max
GDP per capita	24,580.166	20,293.933	671.541	114,542.496
Gini index (%)	37.257	8.724	23.000	64.800
Life expectancy at birth (year)	73.922	6.746	46.024	83.832
Distance between countries (km)	6,885.224	4,559.831	106.807	19,740.366
Language distance between countries	0.852	0.301	0.000	1.000
Political Stability	0.154	0.905	-2.677	1.759
Climate-related Disasters Frequency	2.738	4.359	0.000	31.000

Table 1: Descriptive statistics of nodes attributes in international migration (Panel A) and tourism networks (Panel B).

birth is lower.

Table 1 shows the descriptive statistics of the GDPs per capita, Gini indices, and life expectancy at birth of the countries used in international migration (Panel A) and tourism networks (Panel B).

3.3 Distance and Language Data

I use the geodesic distance between two countries based on the World Geodetic System 84 (WGS 84) in GeoPy[8] to measure the effect of a distance factor on international migration and tourism network formation. I use the data in the World Atlas of language structure online to construct the language distance between countries to measure the effect of a language

[8] `https://geopy.readthedocs.io/en/stable/#`

factor on international migration and tourism network formation (see Dryer and Haspelmath (2013)). The world atlas data includes the characteristics of structural (phonological, grammatical, lexical) properties of 2,662 languages used in the world. The language distance between the two countries is measured as follows:

$$LangDist(i, j) = 1 - \frac{|i \cap j|}{|i \cup j|}, \tag{1}$$

where $LangDist(i, j)$ denotes the language distance between languages i and j. $|i \cup j|$ denotes the total number of structural factors, explaining the characteristics of phonological, grammatical, lexical properties of languages, listed in the data of languages i and j. $|i \cap j|$ denotes the number of the structural factors listed in the data that languages i and j have the same characteristics. $LangDist(i, j)$ is between 0 and 1. As languages i and j have similar linguistic structures (dissimilar), $LangDist(i, j)$ is shorter (longer).

Babel in python[9], based on the Unicode Common Local Data Repository (CLDR)[10], provides the data of official languages of countries. I estimate the language distance between the two countries using their official languages provided by Babel.

Table 1 shows the descriptive statistics of the distances and language distances between the countries in international migration (Panel A) and tourism networks (Panel B).

3.4 Safety Data

The World Bank provides Political Stability and Absence of Violence/Terrorism referred to Political Stability in 214 countries from 2000 and 2012 to 2021.[11] I use Political Stability of countries to measure the effect of a safety factor on international migration and tourism network formation. This measure provides the likelihood of Political Stability and/or absence of politically motivated violence, including terrorism, in a country ranging from approximately

[9] `https://babel.pocoo.org/en/latest/index.html#`

[10] `https://cldr.unicode.org/index`

[11] `https://databank.worldbank.org/metadataglossary/worldwide-governance-indicators/series/PV.EST`

-2.5 to 2.5. As a country is more politically stable and safer (more politically unstable and dangerous), this measure is bigger (smaller).

Table 1 shows the descriptive statistics of the Political Stability of the countries in international migration (Panel A) and tourism networks (Panel B).

3.5 Climate Change Data

I use the Climate-related Disasters Frequency to measure the effect of the risk of natural disasters due to climate change in countries on international migration and tourism network formation provided by the climate change dashboard of the IMF. [12] the Climate-related Disasters Frequency is the number of disasters[13] related to climates, such as drought, extreme temperature, flood, landslide, storm, and wildfire. Strong evidence of an increase in the likelihood of natural hazards due to climate change has been observed (see Van Aalst (2006); Banholzer, Kossin and Donner (2014); Hallegatte et al. (2016); Abbass et al. (2022)). Thus, the Climate-related Disasters Frequency is a good measure to estimate a country's climate change risk. The higher the Climate-related Disasters Frequency of the country is, the higher the disaster risk due to climate change in countries.

Table 1 shows the descriptive statistics of the Climate-related Disasters Frequency of the countries in international migration (Panel A) and tourism networks (Panel B).

4 Methodology

4.1 The construction of networks

I construct networks using the migration stocks of countries and the outbound tourism data using the way to construct networks in Windzio (2018). The international migration

[12] `https://climatedata.imf.org/datasets/b13b69ee0dde43a99c811f592af4e821_0/about`

[13] Disasters meet the following criteria: (i) resulted in the death of ten (10) or more individuals; (ii) affected a hundred (100) or more people; (iii) resulted in the declaration of a state of emergency; (iv) prompted a request for international assistance.

network or tourism network at year t N_t consists of nodes representing countries and links representing ties between two countries. If there exists migration or traveling flows between two countries, they are linked.

The link formation between a sending country i and a destination country j in the international migration network or tourism network at a year $t \in \{1990, 1995, 2000, 2005, 2010, 2015, 2019\}$ is as follows:

$$\begin{aligned} Y_{ijt} &= 1, \text{if } SHR_{ijt} \geq Q_{3t} \\ &= 0, \text{otherwise.} \end{aligned} \tag{2}$$

where SHR_{ijt} is the "population sent-to-alter/population at home" ratio, which is the share of migrants or travelers from a sending country i to a destination country j at the overall population in the sending country i at the year t. Q_{3t} denotes the third quartile or 75^{th} percentile of the distribution of SHR_{ijt} for all pairs ij in all countries. If $SHR_{ijt} \geq Q_{3t}$, $Y_{ijt} = 1$. Otherwise, $Y_{ijt} = 0$. Y_{ijt} is the binary variable that shows the connection between the sending country i and the destination country j in the international migration network or tourism network at the year t. If $Y_{ijt} = 1$, countries i and j are connected in the network. If $Y_{ijt} = 0$, countries i and j are not connected.

The method using the highest quartile in the distribution of connections provides meaningful migration patterns or traveling patterns among countries by large flows of migrants or travelers from origin countries, and it is useful to understand the important connections among all connections. For this reason, the method of constructing networks using the highest quartile in the distribution of connection or the threshold of intensity of a tie has been used in the previous research based on macro-level data (see Fagiolo and Mastrorillo (2013); Vögtle and Windzio (2016); Windzio (2018)).

Figures 1 and 2 show the international migration and tourism networks in 2019, respectively. Canada, United Kingdom, United States, Australia, and France (United States,

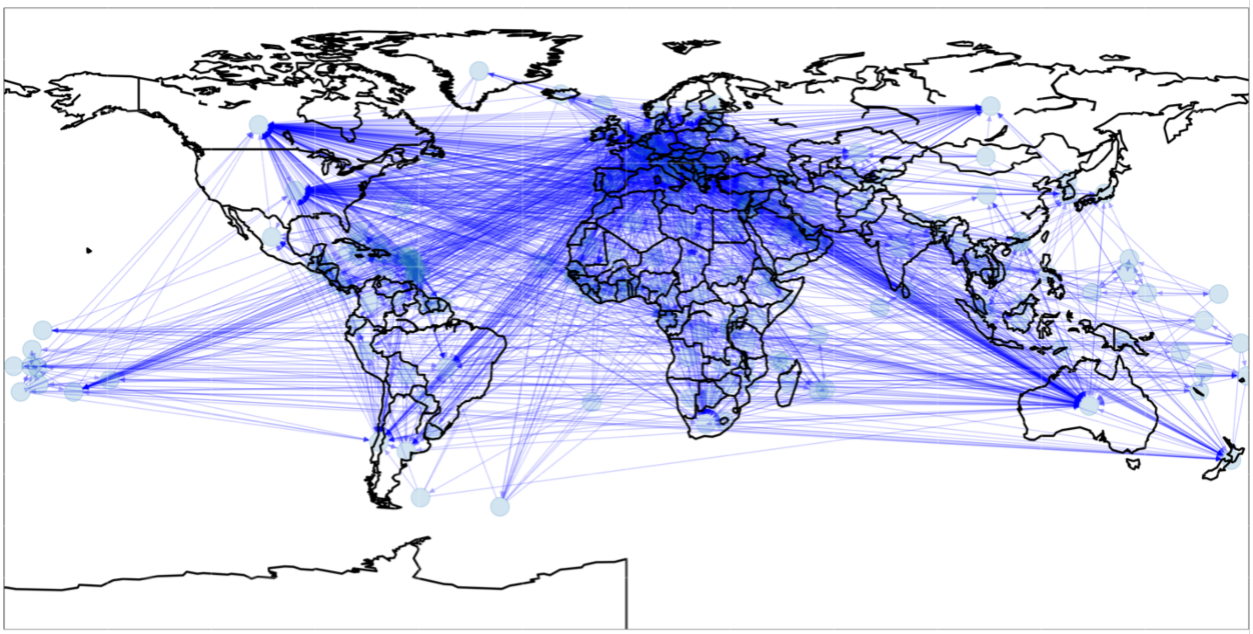

Figure 1: The international migration network in 2019.

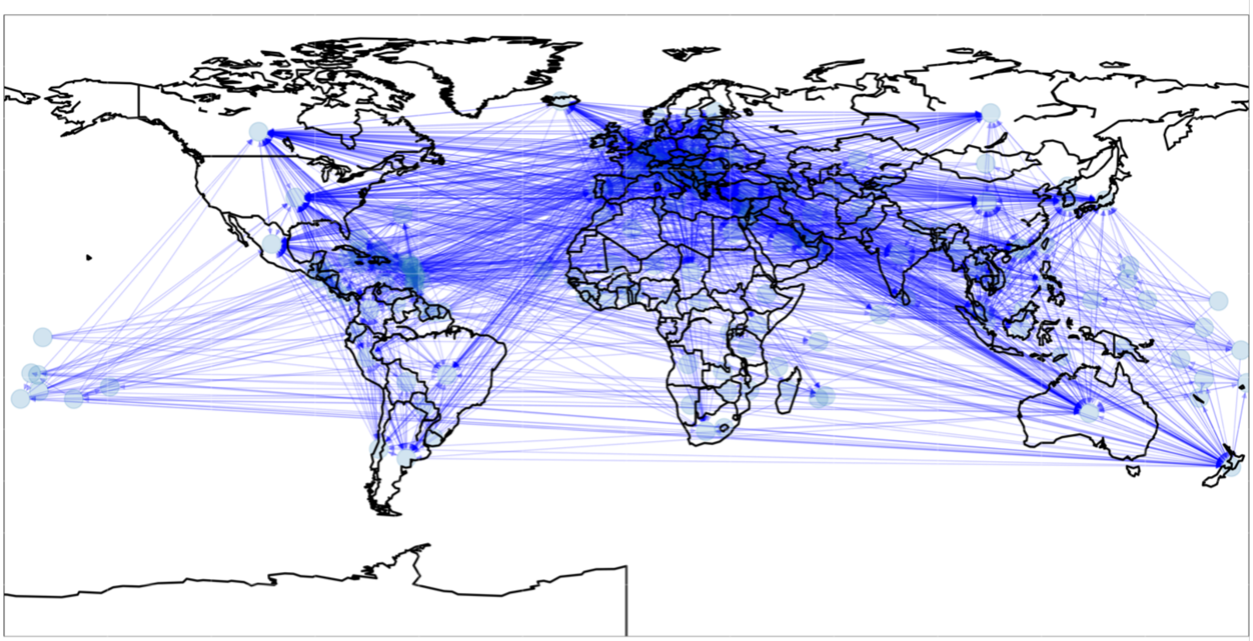

Figure 2: The international tourism network in 2019.

China, Türkiye, Mexico, and Canada) are ranked in the five highest countries according to the number of connections from other countries in the international migration network (tourism network) in 2019. Eritrea, Dominica, Syria, Moldova, and Armenia (Switzerland, Netherlands, United Kingdom, Denmark, and France) are ranked in the five highest countries according to the number of connections to other countries in the international migration network (tourism network) in 2019.

4.2 The regression

The link formation vector Y_{ijt} is regressed on the non-network structural explanatory variables $\vec{X}_{ijt}$ of a sending country i and a destination country j and network structural variable of the international migration or tourism network (N_t) $\vec{g}(N_{t'})$ at the previous year $t^{'}(t^{'} < t)$[14] using the logistic regression as follows:

$$P(Y_{ijt} = 1|\vec{X}_{ijt}, \vec{g}(N_{t'})) = \frac{1}{1 + \exp\left(-\vec{\theta}'\vec{h}(\vec{X}_{ijt}, \vec{g}(N_{t'}))\right)}, \tag{3}$$

where $P(Y_{ijt} = 1|\vec{X}_{ijt}, \vec{g}(N_{t'}))$ is the probability that countries i and j are connected in the network N_t given non-network structural explanatory variables $(\vec{X}_{ijt})$ and network structural variables at the previous year $t^{'}$ $(\vec{g}(N_{t'}))$. $N_{t'}$ is the network at year $t^{'}$. $\vec{\theta}$ denotes the vector of parameters. $\vec{h}(\vec{X}_{ijt}, \vec{g}(N_{t'}))$ is the statistic that affects the network formation.

The logistic regression of link formation has been applied to analyze the relationship between explanatory variables and network formation in social and economic systems (see the review paper of De Paula (2020)). If the explanatory variables include network structural variables, the logistic regression of link formation is one of ERGMs (see Lusher, Koskinen and Robins (2013)). In particular, if the network structural variables include the past network formation, the logistic regression is one of the temporal ERGMs (TERGMs) (see Hanneke, Fu and Xing (2010)). Thus, my logistic regression model is one of TERGMs.

[14](1) $t^{'} = t - 5$ if $1995 \le t \le 2015$; (2) $t^{'} = 2015$ if $t = 2019$

The explanatory variables are classified into two categories: non-network structural variables ($\vec{X}_{ijt}$) and network structural variables ($\vec{g}(N_{t'})$). Non-network structural variables are not directly measured from networks. Non-network structural variables include social and economic, distance, language, and climate change factors of sending and destination countries. The differences in the GDP per capita, Gini index, life expectancy at birth, and Political Stability between the sending and the destination countries are used as social and economic factors. The distance between the sending and the destination countries is used as a distance factor. The language distance between the sending and the destination countries is used as a language factor. The difference in the Climate-related Disasters frequencies between the sending and the destination countries is used as a climate change factor.

Network structural variables are directly measured from networks and related to the characteristics of pairwise links among nodes and beyond the pairwise links' characteristics in a network. Battiston et al. (2020) introduce the network structural variables widely used in network analysis. In this analysis, I consider the community structure in a network and node centralities that measure the influence of a node in a network. The community index, whether a sending country and a destination country are in the same community, and the in-degree centrality, betweenness centrality, and closeness centrality of a destination country in the network $N_{t'}$ are used as network structural variables ($\vec{g}(N_{t'})$).

Community detection in a network based on maximizing modularity has been widely used in network analysis (see Porter et al. (2009); Fortunato and Hric (2016)). Danchev and Porter (2018) show that countries in the same community detected by modularity maximization are tied to each other on international migration networks. The modularity of the network $N_{t'}$ ($Q(N_{t'})$) is defined as follows:

$$Q(N_{t'}) = \frac{1}{2Y_{t'}} \sum_{ij} [Y_{ijt'} - P_{ijt'}]\delta(c_{it'}, c_{jt'}), \tag{4}$$

where $Y_{t'} = \frac{1}{2}\sum_{ij} Y_{ijt'}$. $P_{ijt'}$ is the expected weight of a link between nodes i and j at year t':

$P_{ijt'} = \frac{k_{it'}k_{jt'}}{2Y_{t'}}$, where $k_{it'} = \sum_w Y_{iwt'}, k_{jt'} = \sum_w Y_{wjt'}$. $\delta(c_{it'}, c_{jt'}) = 1$ if nodes i and j are in the same community (i.e., $c_{it'} = c_{jt'}$). $\delta(c_{it'}, c_{jt'}) = 0$ otherwise (i.e., $c_{it'} \neq c_{jt'}$). $Q(N_{t'})$ is from -1(all links are between communities) to 1 (all links are within communities). Communities in $N_{t'}$ are detected by maximizing $Q(N_{t'})$. Communities in international migration networks are the clusters of countries connected through international migration.

$ComIndex_{t'}(i, j)$ denotes the community index of a sending country i and a destination country j in the network $N_{t'}$. The community index shows whether a sending and a destination country are in the same community in a network. The definition of $ComIndex_{t'}(i, j)$ is as follows: (1) $ComIndex_{t'}(i, j) = 1$ if i and j are in the same community in the network $N_{t'}$; (2) $ComIndex_{t'}(i, j) = 0$ otherwise.

The *in-degree centrality* of a node shows the importance of a node in the network using the number of other nodes connected to a node[15]. The definition of the in-degree centrality of a node i in the network $N_{t'}$, $InDeg(i, N_{t'})$, is as follows:

$$InDeg(i, N_{t'}) = \frac{1}{(N(t') - 1)} \sum_j Y_{jit'}, \tag{5}$$

where $N(t')$ is the number of nodes in the network $N_{t'}$. $\sum_j Y_{jit'}$ is between 0 and $N(t') - 1$ inclusive. Thus, $0 \leq InDeg(i, N_{t'}) \leq 1$. The in-degree centrality of a country in the international migration network shows the influence of a country in the international migration network. The country with the higher in-degree centrality is the country with more various migrants' original countries.

The *betweenness centrality* of a node shows the importance of a node to bridge between two nodes. The definition of the betweenness centrality of a node i in the network $N_{t'}$, $Between(i, N_{t'})$, is as follows:

$$Between(i, N_{t'}) = \sum_{j \neq k \neq i} \frac{NSP_{jk}(i, N_{t'})}{NSP_{jk}(N_{t'})} / C(N_{t'}), \tag{6}$$

[15]We can also define the *out-degree centrality* of a node using the number of other nodes connected from a node.

where $NSP_{jk}(i, N_{t'})$ denotes the number of shortest paths between nodes j and k through node i in the network $N_{t'}$. A path in $N_{t'}$ between nodes j and k is a series of distinct nodes $j = j^0, j^1, \ldots, j^L = k$ such that $Y_{j^l j^{l+1} t'} \neq 0$ for all $l = 0, .., L-1$. L is the path length between nodes j and k in the network $N_{t'}$. The shortest path between nodes j and k is a path such that no other path between them has a shorter path length. $C(N_{t'})$ is the normalization constant $(C(N_t') = (N(t') - 1)(N(t') - 2)/2)$. $N(t')$ is the number of nodes in the network $N_{t'}$. Thus, $0 \leq Between(i, N_{t'}) \leq 1$. The betweenness centrality of a country shows the importance of a country in bridging two countries in the international migration network. The country with the higher betweenness centrality is the country with the higher accessibility to the countries with the more various migrants' original countries.

The *closeness centrality* of a node shows how close a node is to other nodes in the network. The shortest path length between two nodes shows the distance between two nodes. Thus, we can define the closeness centrality of a node using the reciprocal of the average distance with other nodes. The definition of the closeness centrality of a node i in the network $N_{t'}$, $Close(i, N_{t'})$, is as follows:

$$Close(i, N_{t'}) = \frac{N(t') - 1}{\sum_{j \neq i} LSP_{ji}(N_{t'})}, \tag{7}$$

where $LSP_{ji}(N_{t'})$ denotes the shortest path length between nodes j and i in the network $N_{t'}$. The closeness centrality of a country shows how close a country is to other countries in the international migration network based on node distance, measured by the shortest path length between two nodes. The country with the higher closeness centrality has a higher accessibility to migrate to other countries.

Figures 3 and 4 show the communities detected in the international migration and tourism networks. The countries indicated by the same color are in the same community. The regions indicated by white are not in the network. The large clusters in the international migration network are observed: (1) U.S. and East Asian countries exclude North Korea, Northeastern African, and Oceanian countries; (2) Western European, Northwestern African, and Latin

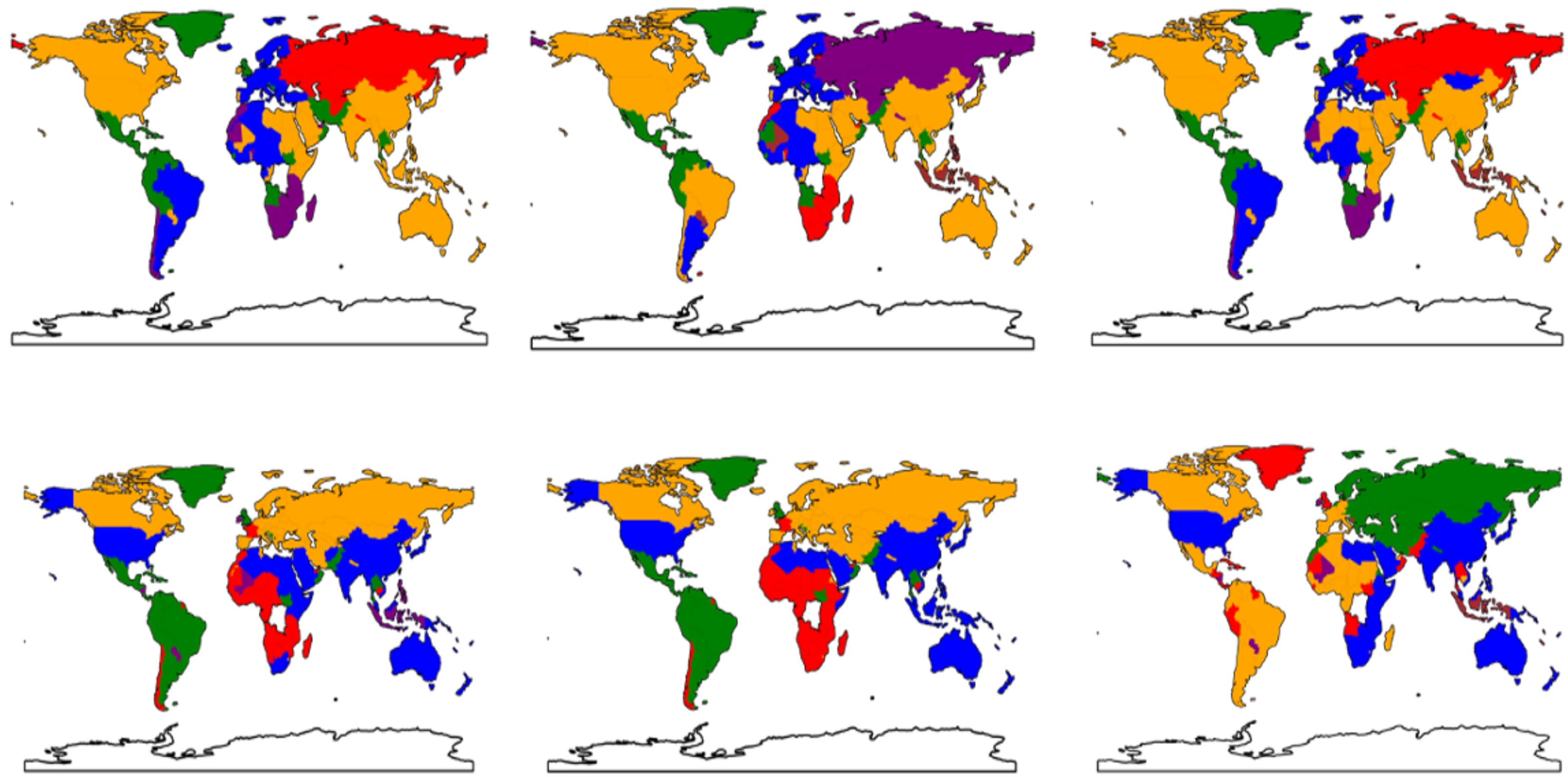

Figure 3: Communities in international migration networks for 1995, 2000, 2005, 2010, 2015, and 2019 (left-to-right then top-to-bottom). The countries indicated by the same color are in the same community. The regions indicated by white are not included in the network.

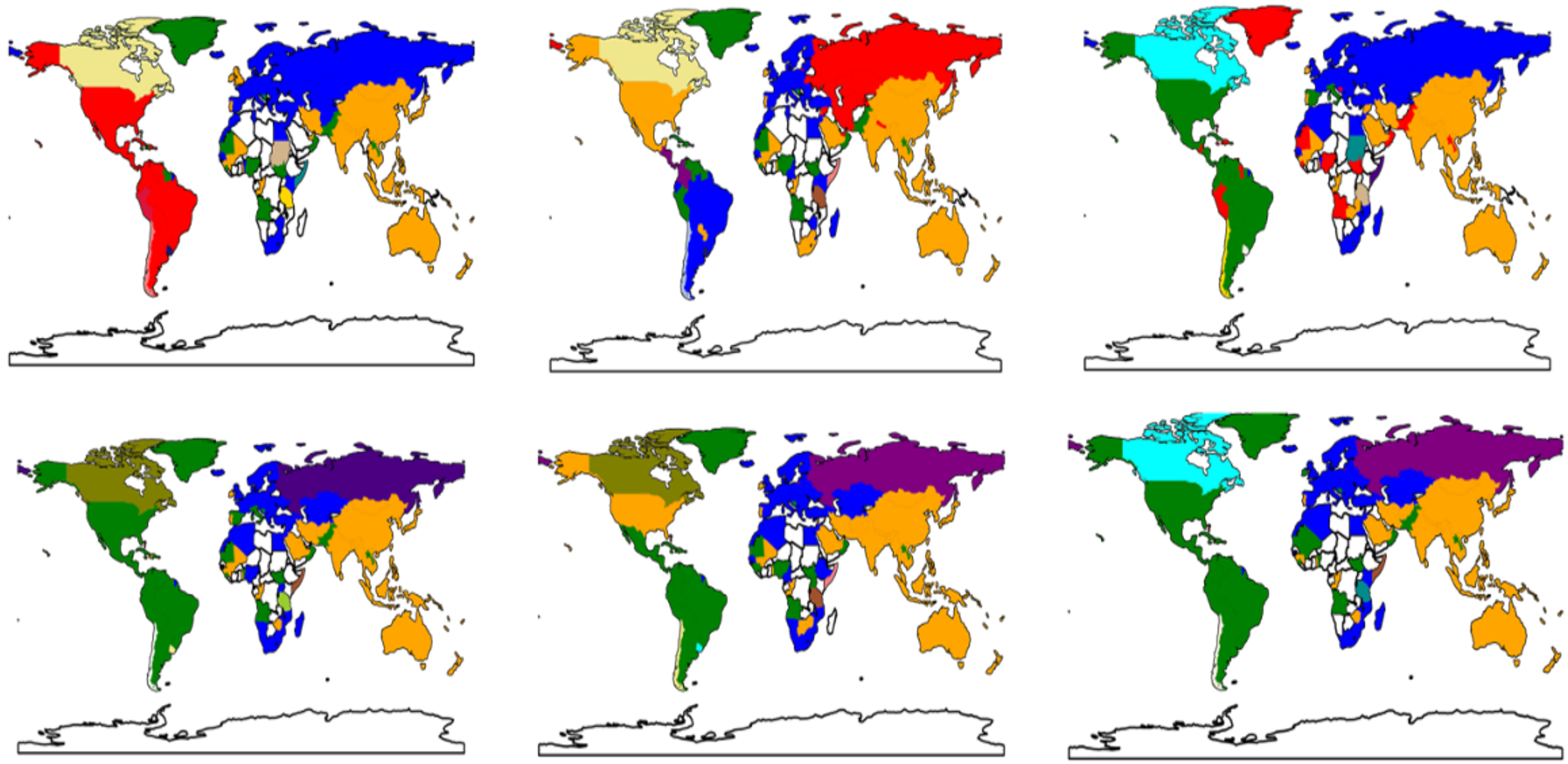

Figure 4: Communities in international tourism networks for 1995, 2000, 2005, 2010, 2015, and 2019 (left-to-right then top-to-bottom). The countries indicated by the same color are in the same community. The regions indicated by white are not included in the network.

Descriptive statistics of networks					
Panel A: International migration networks					
Year	# Nodes	# Links	Avg. in-degree centrality	Avg. betweenness centrality	Avg. closeness centrality
1995	225	2,858	0.057	0.009	0.312
2000	225	2,824	0.056	0.009	0.306
2005	225	2,852	0.057	0.009	0.299
2010	225	2,983	0.059	0.009	0.314
2015	225	3,015	0.059	0.009	0.309
2015	225	3,018	0.059	0.009	0.309
Panel B: International tourism networks					
Year	# Nodes	# Links	Avg. in-degree centrality	Avg. betweenness centrality	Avg. closeness centrality
1995	171	1,188	0.041	0.004	0.153
2000	178	1,674	0.053	0.003	0.191
2005	182	1,827	0.055	0.004	0.191
2010	186	2,194	0.063	0.004	0.208
2015	191	2,607	0.071	0.003	0.223
2019	190	2,759	0.076	0.003	0.226

Table 2: Descriptive statistics of the international migration (Panel A) and tourism networks (Panel B).

American countries; (3) Russia, Eastern European, and Central Asian countries. Canada is in the same community as the U.S. in 1995, 2000, and 2005. However, Canada has been in the same community as Western European countries since 2010. The communities in the international migration networks have changed, but the three large clusters have been observed all years. In the international tourism networks, the countries that are closer in distance are clustered in the same community: (1) U.S. and Latin American countries; (2) European and Northwestern African countries; (3) Asian and Oceanian countries.

The countries closer in the distance are more likely to be in the same community in the international migration networks. However, East Asian countries are in the same community as the U.S. even if East Asia is quite far away from the U.S. It implies that migration differs from traveling. Traveling does not have the purpose of living permanently in another country. Thus, the most important factor in traveling decisions is the cost of traveling, and it is challenging to travel the countries far away from the sending country. However, the

Year	The five highest in-degree centrality countries	The five highest out-degree centrality countries	The five highest betweenness centrality countries	The five highest closeness centrality countries
1995	USA, CAN, GBR, FRA, AUS	LBN, DMA, SYR, SOM, CHE	FRA, GBR, NZL, CHE, LBY	USA, CAN, GBR, AUS, FRA
2000	USA, GBR, CAN, AUS, FRA	LBN, DMA, LKA, AUT, GBR	FRA, GBR, NZL, ISR, CAN	USA, GBR, CAN, AUS, FRA
2005	GBR, CAN, USA, AUS, FRA	DMA, LBN, LKA, MDA, AUT	FRA, GBR, ISR, USA, NZL	CAN, GBR, USA, AUS, FRA
2010	CAN, GBR, USA, AUS, FRA	DMA, LBN, LKA, ARM, MKD	FRA, GBR, MLI, USA, PRI	CAN, GBR, USA, AUS, FRA
2015	CAN, GBR, USA, AUS, FRA	ERI, DMA, LBN, SYR, LKA	FRA, GBR, MLI, NZL, USA	CAN, GBR, USA, AUS, FRA
2019	CAN, GBR, USA, AUS, FRA	ERI, DMA, SYR, MDA, ARM	FRA, GBR, MLI, USA, AUS	CAN, GBR, USA, AUS, FRA

Table 3: The five highest centrality countries of international migration networks.
USA: United States of America, CAN: Canada, GBR: United Kingdom of Great Britain and Northern Ireland, FRA: France, AUS: Australia, LBN: Lebanon, DMA: Dominica, SYR: Syria, SOM: Somalia, CHE: Switzerland, LKA: Sri Lanka, AUT: Austria, ARM: Armenia, MKD: North Makedonia, ERI: Eritrea, NZL: New Zealand, MDA: Moldova, Republic of, LBY: Libya, MLI: Mali, ISR: Israel

Year	The five lowest in-degree centrality countries	The five lowest out-degree centrality countries	The five lowest betweenness centrality countries	The five lowest closeness centrality countries
1995	LSO, PRK, GIB, LAO, MCO	MYT, PRK, MEX, PNG, MDG	MDG, DJI, LSO, PRK, GIB	LSO, PRK, GIB, LAO, MCO
2000	SOM, LSO, PRK, GIB, LAO	PNG, MEX, MYT, LSO, PRK	MDG, SOM, LSO, PRK, GIB	SOM, LSO, PRK, GIB, LAO
2005	SOM, ERI, LSO, PRK, GIB	PNG, MDG, JPN, MYT, LSO	MDG, SOM, ERI, LSO, MDV	SOM, ERI, LSO, PRK, GIB
2010	LSO, PRK, GIB, LAO, MCO	PNG, MDG, MYT, LSO, PRK	MDG, LSO, MDV, PRK, GIB	LSO, PRK, GIB, LAO, MCO
2015	ERI, LSO, PRK, GIB, LAO	PNG, MDG, MYT, LSO, PRK	MDG, MRI, LSO, MDV, PRK	ERI, LSO, PRK, GIB, LAO
2019	ERI, LSO, PRK, GIB, LAO	PNG, VAT, MDG, MYT, LSO	MDG, ERI, LSO, MDV, PRK	ERI, LSO, PRK, GIB, LAO

Table 4: The five lowest centrality countries of international migration networks.
LSO: Lesotho, PRK: North Korea, GIB: Gibraltar, LAO: Lao People's Democratic Republic, MCO: Monaco, SOM: Somalia, ERI: Eritrea, MYT: Mayotte, MEX: Mexico, PNG: Papua New Guinea, MDG: Madagascar, JPN: Japan, VAT: Holy See, DJI: Djibouti, MDV: Maldives

Year	The five highest in-degree centrality countries	The five highest out-degree centrality countries	The five highest betweenness centrality countries	The five highest closeness centrality countries
1995	USA, CHN, RUS, HKG, GBR	CHE, NLD, DNK, DEU, GBR	USA, NZL, GBR, CAN, DEU	USA, CHN, HKG, GBR, CAN
2000	USA, CAN, ITA, AUS, CHN	CHE, NLD, GBR, DNK, SWE	USA, CAN, AUS, GBR, NZL	USA, CHN, CAN, ITA, AUS
2005	USA, CHN, CAN, RUS, ITA	CHE, DNK, GBR, DEU, NLD	USA, AUS, CAN, NZL, GBR	USA, CHN, ITA, CAN, HKG
2010	USA, CHN, CAN, RUS, ITA	CHE, DNK, GBR, NLD, SWE	USA, AUS, CAN, NZL, ITA	USA, CHN, ITA, HKG, RUS
2015	USA, CHN, MEX, TUR, ITA	CHE, GBR, SWE, NLD, DNK	USA, NZL, AUS, CAN, TUR	USA, CHN, TUR, ITA, ARE
2019	USA, CHN, TUR, MEX, CAN	CHE, NLD, GBR, DNK, FRA	USA, AUS, CAN, TUR, NZL	USA, CHN, TUR, ARE, MEX

Table 5: The five highest centrality countries of international tourism networks.
USA: United States of America, CHN: China, RUS: Russia, HKG: Hong Kong, GBR: United Kingdom of Great Britain and Northern Ireland, CAN: Canada, ITA: Italy, AUS: Australia , MEX: Mexico, TUR: Türkiye, CHE: Switzerland, NLD: Netherlands, DNK: Denmark, DEU: Germany, SWE: Sweden , NZL: New Zealand, DEU: Germany, ARE: United Arab Emirates

Year	The five lowest in-degree centrality countries	The five lowest out-degree centrality countries	The five lowest betweenness centrality countries	The five lowest closeness centrality countries
1995	FSM, DZA, AGO, ARM, BLR	ZAF, CUB, EGY, KWT, MAC	FSM, ASM, ZAF, CUB, EGY	FSM, DZA, AGO, ARM, BLR
2000	FSM, MNG, DZA, ARM, BLR	SAU, ZAF, IND, KWT, LBN	FSM, SAU, ZAF, IND, KWT	FSM, MNG, DZA, ARM, BLR
2005	FSM, MNG, ARM, BLR, BLZ	MUS, ZAF, EGY, IND, KWT	FSM, MUS, MNP, ZAF, EGY	FSM, MNG, ARM, BLR, BLZ
2010	FSM, MNG, SYC, AIA, BLR	MAC, ZAF, AGO, EGY, IND	FSM, MAC, MNP, ZAF, AGO	FSM, MNG, SYC, AIA, BLR
2015	FSM, MNG, MDG, RWA, AIA	MAC, MUS, UGA, ARE, AGO	FSM, MAC, MUS, MNG, MNP	FSM, MNG, MDG, RWA, AIA
2019	FSM, BHR, BTN, RWA, AIA	BGR, MAC, MUS, ZAF, ARE	FSM, BGR, MAC, MUS, MNP	FSM, BHR, BTN, RWA, AIA

Table 6: The five lowest centrality countries of international tourism networks.
FSM: Micronesia (Federated States of), DZA: Algeria, AGO: Angola, ARM: Armenia, BLR: Belarus, MNG: Mongolia, BLZ: Belize, SYC: Seychelles, AIA: Anguilla, RWA: Rwanda, BHR: Bahrain, BTN: Bhutan, ZAF: South Africa, CUB: Cuba, EGY: Egypt, KWT: Kuwait, MAC: Macao, SAU: Saudi Arabia, IND: India, LBN: Lebanon, MUS: Mauritius, BGR: Bulgaria, ARE: United Arab Emirates, MNP: Northern Mariana Islands, MDG: Madagascar, UGA: Uganda

Descriptive statistics of nodes attributes for the five highest in-degree centrality				
Panel A: International migration networks				
	Mean	SD	Min	Max
GDP per capita	44,633.163	6,755.254	33,044.844	62,470.929
Gini index (%)	35.124	3.505	29.800	41.500
Life expectancy at birth (year)	79.782	1.998	75.622	82.900
Political Stability	0.876	0.342	0.107	1.334
Climate-related Disasters Frequency	7.367	7.714	1.000	30.000
Panel B: International tourism networks				
	Mean	SD	Min	Max
GDP per capita	32,807.327	16,050.259	2,391.477	62,470.930
Gini index (%)	38.265	4.755	31.5	52.6
Life expectancy at birth (year)	76.811	4.802	64.691	85.180
Political Stability	0.127	0.876	-1.494	1.275
Climate-related Disasters Frequency	7.630	8.514	0.000	31.000

Table 7: Descriptive statistics of nodes attributes in the five highest in-degree centrality countries in international migration (Panel A) and tourism networks (Panel B).

purpose of migration is to live permanently in another country. Thus, there may be many factors to consider in migration decisions that I have explained in Section 1 (see "migration drivers" in Czaika and Reinprecht (2020)).

4.3 How is international migration different from international tourism?: descriptive statistics analysis.

Table 2 shows the descriptive statistics of the international migration (Panel A) and tourism networks (Panel B): (1) the number of nodes; (2) the number of links; (3) the average in-degree centrality; (4) the average betweenness centrality; (5) the average closeness centrality. An increase in the number of links and almost constant values of the average in-degree centrality and the average closeness centrality in the international migration networks as time passes are observed (see Panel A in Table 2). It implies that the structural properties of international migration networks have been stable even if the number of links in the networks has increased. However, increases in the number of links, the average in-degree, and the average closeness centrality in the international tourism networks as time passes are observed (see Panel B in Table 2). It implies that international tourism networks have become denser, and countries are more closely connected by easier traveling among countries as time passes.

Tables 3 - 6 show the five highest and lowest centrality countries in the international migration and tourism networks. Unlike other centralities, the five highest in-degree centrality countries have been quite unchanged in the international migration networks for all years: the United States, Canada, United Kingdom, France, and Australia.

The difference between the structural characteristics of international migration and tourism networks comes from the difference in economic decisions between migration and tourism. Migration decisions are based on long-term investment. Migrants carefully choose countries that they want to migrate to. They consider many factors in their migration decisions: social, economic, political stability, language similarity, and distance accessibility. Thus, migration inflows are concentrated in some developed countries that have policies favorable to migrants. Connections to these countries are sustained in international migration networks, and average centralities in international migration networks are almost constant (see Panel A in Table 2).

On the other hand, tourism is based on short-term consumption. Tourists choose countries with easy access and low travel costs to enjoy leisure with low costs. In addition, with the development of transportation systems, travel costs have decreased. This results in an increased number of countries we can travel to. The number of connections or average centralities in international tourism networks increases as time passes (see Panel B in Table 2).

To identify the difference between drivers of migration and tourism, I compare the countries with the five highest in-degree centrality in international migration networks with the countries with the five highest in-degree centrality in international tourism networks. Table 7 shows the descriptive statistics of countries' attributes for the five highest in-degree centrality in international migration and tourism networks (see the five highest in-degree centrality countries in Tables 3 and 5). The countries with the five highest in-degree centrality in international migration networks have higher GDP per capita, lower Gini index, longer Life expectancy at birth, higher Political Stability and Absence of Violence/Terrorism than those with the five highest in-degree centrality in international tourism networks with a 1% statistical significance ($p < 0.01$). This implies that social and economic factors and political stability are more important in migration decisions when we compare them with tourism decisions. The mean of Climate-related Disasters Frequencies of the countries with the five highest in-degree centrality in international migration networks is almost the same as that of the countries with the five highest in-degree centrality in international tourism networks (the difference between them is not statistically significant). However, the values (7.367, 7.630) are greater than the world average (2.687, 2.738) (see the means of the Climate-related Disasters Frequencies of countries in international migration (Panel A) and tourism networks (Panel B) in Table 1). This shows that countries preferable by migrants and tourists are vulnerable to Climate-related Disasters. This implies the future negative impact of climate change on international migration and the tourism industry.

5 Testable Hypotheses

I test the relationship between the explanatory variables and the international migration network formation through this research. Also, even if this research is based on macro-level data, we can determine the factors that affect individuals' migration decisions if the relationship between the factors and the international migration network formation is statistically significant.

The first hypothesis (**H1**) that I want to test is the relationship between social and economic factors and international migration network formation or tourism network formation.

H1-A. *Links in international migration networks are more likely to be formed from countries with lower GDP per capita, greater economic inequality, and lower life expectancy at birth to countries with higher GDP per capita, smaller economic inequality, and higher life expectancy at birth.*

H1-B. *Links in international tourism networks are more likely to be formed from countries with higher GDP per capita, smaller economic inequality, and higher life expectancy at birth to countries with lower GDP per capita, greater economic inequality, and lower life expectancy at birth.*

Previous research has widely observed migration from poor to rich countries (see Collier (2013); De Haas, Castles and Miller (2019); Windzio (2018)). It implies that poor people are more likely to live in rich countries for economic reasons. It also shows the characteristics of migration as a kind of long-term investment. Thus, links from poor to rich countries are observed in international migration networks. However, tourism is different from migration. Tourism can be considered as a kind of consumption good to enjoy leisure. The cost of traveling is the most important factor in travel decisions. In addition, people in rich countries have more opportunities to travel than those in poor countries due to foreign exchange since the value of currencies in rich countries is higher than in poor countries. It implies that rich people are more likely to travel than poor people. The flows of travelers from rich to poor countries have been observed (see Cheng (2012); Vita, Kyaw et al. (2013); Dogru, Sirakaya-Turk and Crouch (2017); Chung et al. (2020)). The better social and economic factors of the countries with the five highest in-degree centrality in international migration networks than tourism networks also support **H1-A** and **B**.(see Table 7). Thus, links from rich to poor countries are observed in international tourism networks.

The second hypothesis (**H2**) that I want to test is the relationship between safety factors and international migration network formation or tourism network formation.

H2-A. *Links in international migration networks are more likely to be formed from countries with lower Political Stability to countries with higher Political Stability.*

H2-B. *Links in international tourism networks are more likely to be formed from countries with higher Political Stability to countries with lower Political Stability.*

Previous studies about refugees have identified migration flows from unsafe countries to safe countries (see Fiddian-Qasmiyeh et al. (2014); FitzGerald and Arar (2018); Richmond (1993)). According to these studies, the safety issue is an important factor to drive the migration decisions of people living in dangerous countries. However, people in rich countries are more likely to travel to poor countries, and poor countries are more likely to be less politically stable and less safe than rich countries. In addition, tourists' resilience to the terrorism risk or political instability of destination countries has been observed (see Van der Zee and Vanneste (2015); Liu and Pratt (2017); Chung et al. (2020)). The higher average Political Stability with the five highest in-degree centrality in international migration networks than the countries with the five highest in-degree centrality in international tourism networks also supports **H2-A** and **B** (see Table 7). Thus, links from less safe to safer countries are observed in international tourism networks.

The third hypothesis (**H3**) that I want to test is the relationship between a distance factor and international migration or tourism network formation.

H3. *Links in international migration or tourism networks are more likely to be formed between countries within a shorter distance.*

The relationship between the distance between two countries and the flow of migrants between two countries has been identified by using the gravity model (see Anderson (2011); Beine, Bertoli and Fernández-Huertas Moraga (2016)). The migration pattern of countries due to geopolitical factors has been observed (see Grosfoguel (1997); Özden et al. (2011)). Windzio (2018) shows that the effects of distance and geopolitical factors on international migration networks are significant so that migrants reduce the cost of moving. Also, people are more likely to travel the countries closer to their home countries to reduce the cost of traveling. More traveling with a shorter distance has been observed in previous research (see Eilat and Einav (2004); Khadaroo and Seetanah (2008); Chung et al. (2020)). Thus, ties between shorter-distance countries are more likely to be formed in international tourism networks.

The fourth hypothesis (**H4**) that I want to test is the relationship between a language factor and international migration or tourism network formation.

H4. *Links in international migration or tourism networks are more likely to be formed between countries with a shorter language distance.*

The "cultural homophily" and the flows of migration between two countries that have the same or similar cultures, such as language and religion, have been identified by many researchers (see Adsera and Pytlikova (2015); Levitt (2003); Windzio and Wingens (2014); Windzio (2018)). Traveling is also more convenient if the official language in the arrival country is similar to the traveler's home country. More traveling among countries with the same official language has been observed (see Eilat and Einav (2004); Khadaroo and Seetanah (2008); Chung et al. (2020)). Thus, ties between countries with a shorter language distance are more likely to be formed in international tourism networks.

The fifth hypothesis (**H5**) that I want to test is the relationship between climate change and natural disaster factors and international migration or tourism network formation.

H5. *Links in international migration or tourism networks are more likely to be formed from countries with lower Climate-related Disasters Frequency to countries with higher Climate-related Disasters Frequency.*

Climate change is one of the most important global issues, and some countries are vulnerable to climate change, such as sea levels and floods. In this case, mass migration from countries vulnerable to climate change to countries not vulnerable to climate change might be possible. The relationship between climate change and international migration has been identified, and many studies have shown that climate change can be one of the most important factors in affecting the migration decisions of people living in countries that are vulnerable to climate change (see Kaczan and Orgill-Meyer (2020); Kniveton et al. (2008); L Perch-Nielsen, B Bättig and Imboden (2008); White (2011)).

Climate change can also affect international tourism. One of the reasons why people travel is to visit famous historical spots and beautiful scenery, which is not allowed in their home countries. For example, many tourists enjoy swimming in beautiful beaches in summer or skiing in winter. Beaches and snow in winter are vulnerable to coastal flooding, sea-level rise, cyclones, tsunamis, and temperature rise due to climate change. According to a recent study, climate change can negatively affect the tourism industry based on natural resources (see Scott, Gössling and Hall (2012)).

Most developed countries are in regions vulnerable to climate change because these countries are located near the beach, which is vulnerable to extreme events, such as coastal flooding, sea-level rise, cyclones, and tsunamis, due to climate change (see Footnote 4). Furthermore, social, economic, and safety factors might be more important than climate change in migration decisions for now. The similar average of the Climate-related Disasters Frequency of the countries with the five highest in-degree centrality in international migration networks as the countries with the five highest in-degree centrality in international tourism networks while they are greater than the world average value, despite the better social, economic, and safety factors of the countries with the five highest in-degree centrality in international migration networks than the countries with the five highest in-degree in international tourism networks, also supports **H5** (see Table 7). Thus, it is more likely that **H5** is accepted in my model.

The sixth hypothesis (**H6**) that I want to test is the relationship between network structural factors and international migration or tourism network formation.

H6. *Links in international migration or tourism networks are more likely to be formed between countries in the same community and with countries having higher centrality in previous networks.*

The structural properties of international migration networks have been identified, and some stable structures have been observed in international networks (see Danchev and Porter (2018); Fagiolo and Mastrorillo (2013); Windzio (2018)). The stable structure properties show that rich countries have high connectivity in the international migration network. It implies that link formation in international migration networks can be affected by the structural properties of the previous network. Stable structural properties in international migration networks can support **H6** (see Panel A in Table 2 and Figure 3).

Quite stable communities are also detected in the international tourism networks (see Figure 4). It implies that some countries have high centrality and have been in the center of clusters in the international tourism networks for a long time, and the link formation can be affected by the structural properties in the previous network. Recent studies have observed the memory effect of network structures in international tourism networks (see Chung et al. (2020); Seok, Barnett and Nam (2021)). Thus, ties among countries in the same community and link formation to countries with higher centrality are observed in the international tourism networks.

6 Results

The link formation from a sending country i to a destination country j in the international migration network or tourism network N_t at a year t (Y_{ijt}) is regressed on social and economic factors or safety factor of countries i and j ($\Delta SES_t(i,j)$), the distance between countries i and j divided by 1,000 km ($Dist_t(i,j)$), the language distance between countries i and

Correlation matrices of differences in social and economic factors				
Panel A: International migration networks				
	GDP per capita	Life expectancy	Gini index	Political Stability
GDP per capita	–	0.710***	-0.443***	0.665***
Life expectancy	–	–	-0.391***	0.572***
Gini index	–	–	–	-0.354***
Political Stability	–	–	–	–
Panel B: International tourism networks				
	GDP per capita	Life expectancy	Gini index	Political Stability
GDP per capita	–	0.707***	-0.433***	0.659***
Life expectancy	–	–	-0.372***	0.560***
Gini index	–	–	–	-0.337***
Political Stability	–	–	–	–

Table 8: The correlation matrices of differences in the social and economic factors in international migration (Panel A) and tourism networks (Panel B). The differences in social and economic factors are calculated by the social and economic factors of a sending country minus those of a destination country. *** $p < 0.01$

j ($LangDist_t(i,j)$), the network structure variable related to i and j in the network $N_{t'}$ at the previous year t' ($Net_{t'}(i,j), t' < t$) (see the definition of t' in Footnote 14), and the difference from the Climate-related Disasters Frequency of a sending country i to a destination country j at year t ($\Delta Disasters_t(i,j) = Disasters_t(i) - Disasters_t(j)$) using the logistic regression (see the logistic regression equation in Eq. 3). To prevent possible multicollinearity, $\Delta SES_t(i,j), Net_t(i,j)$, and $\Delta Disasters_t(i,j)$ are standardized.

The GDP per capita, life expectancy, Gini index, and Political Stability of countries are used in $\Delta SES_t(i,j)$. The definition of $\Delta SES_t(i,j)$ is as follows: $\Delta SES_t(i,j) = SES_t(i) - SES_t(j)$, where $SES_t(i)$ and $SES_t(j)$ denote social and economics factors or safety factor of a sending country i and a destination country j at year t, respectively. The differences of GDP per capita ($\Delta GDP_t(i,j)$), life expectancy at birth ($\Delta LifeExpect_t(i,j)$), Gini index ($\Delta Gini_t(i,j)$), and Political Stability ($\Delta Stability_t(i,j)$) are used as $\Delta SES_t(i,j)$s. $\Delta GDP_t(i,j)$, $\Delta LifeExpect_t(i,j)$, $\Delta Gini_t(i,j)$, and $\Delta Stability_t(i,j)$ are strongly correlated (see Table 8). Thus, each is separately used for $\Delta SES_t(i,j)$ in each regression to prevent strong multicollinearity.

Correlation matrices of centralities of destination countries			
Panel A: International migration networks			
	In-degree	Betweenness	Closeness
In-degee	–	0.766***	0.878***
Betweenness	–	–	0.656***
Closeness	–	–	–
Panel B: International tourism networks			
	In-degree	Betweenness	Closeness
In-degree	–	0.748***	0.791***
Betweenness	–	–	0.495***
Closeness	–	–	–

Table 9: The correlation matrices of centralities of destination countries in international migration (Panel A) and tourism networks (Panel B). *** $p < 0.01$

$ComIndex_{t'}(i,j)$ and $Cent_{t'}(j)$, which are constructed using the community detection and the centralities, are used for $Net_{t'}(i,j)$. The in-degree, betweenness, and closeness centralities are used in $Cent_{t'}(j)$: (1) the in-degree centrality of a destination country j in the international migration network or tourism network ($InDeg(j, N_{t'})$); (2) the betweenness centrality ($Between(j, N_{t'})$); (3) the closeness centrality ($Close(j, N_{t'})$)). $InDeg(j, N_{t'})$, $Between(j, N_{t'})$, and $Close(j, N_{t'})$ are strongly correlated (see Table 9). Thus, each is separately used for $Cent_{t'}(j)$ in each regression to prevent strong multicollinearity.

Tables 10 – 13 show the results of all logistic regressions. All regressions are done using the maximum likelihood method. All regressions are tested to measure the goodness of fits using the log-likelihood ratio test under the null model, whose all coefficients except an intercept are zero, and the results show a statistical significance at the 1 percent level (p-value < 0.01). After adding a network structural variable ($Net_{t'}(i,j)$) in the regression, the goodness of fits in regressions, measured by the $Pseudo - R^2$, is improved (see $Pseudo - R^2$ in Tables 10 - 13).[16] It shows that network structural variables increase the explanatory power of the regression.

[16] $Pseudo - R^2$ is measured by using McFadden's R^2 (see McFadden et al. (1973)). $Pseudo - R^2$ is calculated as follows: $Pseudo - R^2 = 1 - \ln(L_M)/\ln(L_0)$, where $\ln(L_0)$ is the log-likelihood of the null model whose all coefficients are zero except an intercept, and $\ln(L_M)$ is the log-likelihood of the fitted model or alternative model whose all coefficients are not zero.

Dependent variable: Link formation between two countries (Y_{ijt})					
Panel A: International migration networks					
	(1)	(2)	(3)	(4)	(5)
ΔGDP per capita	-0.604***	-0.024	-0.429***	0.160***	-0.634***
(ΔGDP_t)	(0.019)	(0.026)	(0.021)	(0.026)	(0.020)
Distance / 1,000 km	-0.253***	-0.388***	-0.299***	-0.335***	-0.211***
($Dist_t(i,j)$)	(0.006)	(0.009)	(0.007)	(0.008)	(0.007)
Language distance	-0.933***	-0.963***	-0.877***	-1.224***	-0.880***
($LangDist_t(i,j)$)	(0.051)	(0.064)	(0.057)	(0.066)	(0.053)
ΔClimate-related Disasters	-0.618***	-0.273***	-0.471***	-0.305***	-0.631***
Frequency ($\Delta Disasters_t(i,j)$)	(0.021)	(0.030)	(0.023)	(0.027)	(0.021)
Network structure	–	1.569***	0.947***	1.889***	0.680***
($Net_{t'}(i,j)$)		(0.028)	(0.025)	(0.032)	(0.045)
Intercept	0.342***	0.567***	0.390***	0.167***	-0.263***
	(0.049)	(0.063)	(0.056)	(0.064)	(0.065)
$Pseudo-R^2$	0.203	0.457	0.312	0.465	0.218
Panel B: International tourism networks					
	(1)	(2)	(3)	(4)	(5)
ΔGDP per capita	0.536***	1.177***	0.955***	1.164***	0.567***
(ΔGDP_t)	(0.019)	(0.027)	(0.024)	(0.027)	(0.020)
Distance / 1,000 km	-0.279***	-0.327***	-0.332***	-0.312***	-0.222***
($Dist_t(i,j)$)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Language distance	-0.690***	-1.007***	-0.587***	-1.028***	-0.614***
($LangDist_t(i,j)$)	(0.053)	(0.062)	(0.058)	(0.063)	(0.055)
ΔClimate-related Disasters	-0.481***	0.217***	-0.082***	0.025	-0.514***
Frequency ($\Delta Disasters_t(i,j)$)	(0.021)	(0.022)	(0.023)	(0.022)	(0.022)
Network structure	–	1.456***	0.902***	2.048***	0.740***
($Net_{t'}(i,j)$)		(0.027)	(0.023)	(0.046)	(0.049)
Intercept	0.532***	0.744***	0.579***	0.346***	-0.222**
	(0.051)	(0.061)	(0.056)	(0.062)	(0.073)
$Pseudo-R^2$	0.210	0.378	0.294	0.380	0.224

Table 10: The result of the logistic regression using ΔGDP per capital ($\Delta GDP_t(i,j)$) in the international migration (Panel A) and tourism networks (Panel B) (see the logistic regression equation in Eq. 3). Each value in the table is the regression coefficient of each independent variable. The independent variables are indicated in the first column. The numbers in parentheses show the standard errors. Each column in the table shows results for a different regression specification: (1) without a network structural variable; (2) In-degree: $Net_{t'}(i,j) = InDeg(j, N_{t'})$; (3) Betweenness: $Net_{t'}(i,j) = Between(j, N_{t'})$; (4) Closeness: $Net_{t'}(i,j) = Close(j, N_{t'})$; (5) Community index: $Net_{t'}(i,j) = ComIndex_{t'}(i,j)$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dependent variable: Link formation between two countries (Y_{ijt})					
Panel A: International migration networks					
	(1)	(2)	(3)	(4)	(5)
ΔLife expectancy at birth	-0.501***	0.142***	-0.300***	0.377***	-0.5398***
($\Delta LifeExpect_t(i,j)$)	(0.020)	(0.029)	(0.023)	(0.030)	(0.021)
Distance / 1,000 km	-0.253***	-0.389***	-0.296***	-0.336***	-0.210***
($Dist_t(i,j)$)	(0.005)	(0.009)	(0.007)	(0.008)	(0.006)
Language distance	-0.923***	-0.978***	-0.876***	-1.272***	-0.865***
($LangDist_t(i,j)$)	(0.050)	(0.064)	(0.056)	(0.067)	(0.053)
ΔClimate-related Disasters	-0.583***	-0.258***	-0.444***	-0.294***	-0.595***
Frequency ($\Delta Disasters_t(i,j)$)	(0.021)	(0.030)	(0.022)	(0.028)	(0.021)
Network structure	–	1.637***	0.989***	1.989***	0.693***
($Net_{t'}(i,j)$)		(0.029)	(0.026)	(0.033)	(0.045)
Intercept	0.358***	0.590***	0.408***	0.259***	-0.263***
	(0.048)	(0.063)	(0.055)	(0.065)	(0.065)
$Pseudo-R^2$	0.187	0.458	0.302	0.470	0.201
Panel B: International tourism networks					
	(1)	(2)	(3)	(4)	(5)
ΔLife expectancy at birth	0.367***	0.934***	0.649***	1.063***	0.400***
($\Delta LifeExpect_t(i,j)$)	(0.019)	(0.026)	(0.023)	(0.028)	(0.020)
Distance / 1,000 km	-0.273***	-0.330***	-0.311***	-0.308***	-0.218***
($Dist_t(i,j)$)	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)
Language distance	-0.672***	-0.898***	-0.552***	-0.907***	-0.597***
($LangDist_t(i,j)$)	(0.052)	(0.060)	(0.056)	(0.062)	(0.054)
ΔClimate-related Disasters	-0.495***	0.157***	-0.160***	-0.001	-0.530***
Frequency ($\Delta Disasters_t(i,j)$)	(0.020)	(0.022)	(0.023)	(0.021)	(0.021)
Network structure	–	1.321***	0.733***	1.923***	0.725***
($Net_{t'}(i,j)$)		(0.026)	(0.022)	(0.043)	(0.048)
Intercept	0.525***	0.697***	0.555***	0.312***	-0.215**
	(0.050)	(0.058)	(0.054)	(0.060)	(0.072)
$Pseudo-R^2$	0.190	0.338	0.251	0.352	0.203

Table 11: The result of the logistic regression using ΔLife expectancy at birth ($\Delta LifeExpect_t(i,j)$) in the international migration (Panel A) and tourism networks (Panel B) (see the logistic regression equation in Eq. 3). Each value in the table is the regression coefficient of each independent variable. The independent variables are indicated in the first column. The numbers in parentheses show the standard errors. Each column in the table shows results for a different regression specification: (1) without a network structural variable; (2) In-degree: $Net_{t'}(i,j) = InDeg(j, N_{t'})$; (3) Betweenness: $Net_{t'}(i,j) = Between(j, N_{t'})$; (4) Closeness: $Net_{t'}(i,j) = Close(j, N_{t'})$; (5) Community index: $Net_{t'}(i,j) = ComIndex_{t'}(i,j)$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dependent variable: Link formation between two countries (Y_{ijt})					
Panel A: International migration networks					
	(1)	(2)	(3)	(4)	(5)
ΔGini index	0.249***	-0.082**	0.156***	-0.079**	0.262***
($\Delta Gini_t(i,j)$)	(0.022)	(0.032)	(0.026)	(0.030)	(0.023)
Distance / 1,000 km	-0.243***	-0.386***	-0.293***	-0.334***	-0.202***
($Dist_t(i,j)$)	(0.005)	(0.009)	(0.007)	(0.008)	(0.006)
Language distance	-0.930***	-0.968***	-0.882***	-1.202***	-0.879***
($LangDist_t(i,j)$)	(0.050)	(0.064)	(0.056)	(0.066)	(0.052)
ΔClimate-related Disasters	-0.603***	-0.253***	-0.452***	-0.312***	-0.615***
Frequency ($\Delta Disasters_t(i,j)$)	(0.020)	(0.030)	(0.023)	(0.028)	(0.021)
Network structure	–	1.592***	1.054***	1.821***	0.644***
($Net_{t'}(i,j)$)		(0.026)	(0.026)	(0.029)	(0.044)
Intercept	0.376***	0.571***	0.429***	0.211**	-0.193**
	(0.047)	(0.063)	(0.055)	(0.064)	(0.064)
$Pseudo-R^2$	0.164	0.457	0.296	0.463	0.176
Panel B: International tourism networks					
	(1)	(2)	(3)	(4)	(5)
ΔGini index	-0.407***	-0.651***	-0.523***	-0.605***	-0.420***
($\Delta Gini_t(i,j)$)	(0.023)	(0.027)	(0.025)	(0.026)	(0.023)
Distance / 1,000 km	-0.279***	-0.314***	-0.305***	-0.292***	-0.224***
($Dist_t(i,j)$)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Language distance	-0.688***	-0.844***	-0.578***	-0.860***	-0.618***
($LangDist_t(i,j)$)	(0.052)	(0.058)	(0.055)	(0.058)	(0.054)
ΔClimate-related Disasters	-0.441***	0.143***	-0.137***	-0.017***	-0.468***
Frequency ($\Delta Disasters_t(i,j)$)	(0.020)	(0.022)	(0.023)	(0.022)	(0.021)
Network structure	–	1.046***	0.565***	1.423***	0.693***
($Net_{t'}(i,j)$)		(0.023)	(0.019)	(0.037)	(0.048)
Intercept	0.559***	0.678***	0.580***	0.393***	-0.144**
	(0.050)	(0.056)	(0.053)	(0.057)	(0.072)
$Pseudo-R^2$	0.188	0.299	0.231	0.297	0.200

Table 12: The result of the logistic regression using ΔGini index ($\Delta Gini_t(i,j)$) in the international migration (Panel A) and tourism networks (Panel B) (see the logistic regression equation in Eq. 3). Each value in the table is the regression coefficient of each independent variable. The independent variables are indicated in the first column. The numbers in parentheses show the standard errors. Each column in the table shows results for a different regression specification: (1) without a network structural variable; (2) In-degree: $Net_{t'}(i,j) = InDeg(j, N_{t'})$; (3) Betweenness: $Net_{t'}(i,j) = Between(j, N_{t'})$; (4) Closeness: $Net_{t'}(i,j) = Close(j, N_{t'})$; (5) Community index: $Net_{t'}(i,j) = ComIndex_{t'}(i,j)$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dependent variable: Link formation between two countries (Y_{ijt})					
Panel A: International migration networks					
	(1)	(2)	(3)	(4)	(5)
ΔPolitical Stability	-0.429***	0.066**	-0.332***	0.167***	-0.441***
($\Delta Stability_t(i,j)$)	(0.019)	(0.026)	(0.021)	(0.026)	(0.020)
Distance / 1,000 km	-0.246***	-0.388***	-0.297***	-0.335***	-0.204***
($Dist_t(i,j)$)	(0.005)	(0.009)	(0.007)	(0.008)	(0.006)
Language distance	-0.947***	-0.967***	-0.888***	-1.210***	-0.897***
($LangDist_t(i,j)$)	(0.050)	(0.064)	(0.056)	(0.066)	(0.052)
ΔClimate-related Disasters	-0.648***	-0.254***	-0.490***	-0.290***	-0.660***
Frequency ($\Delta Disasters_t(i,j)$)	(0.021)	(0.030)	(0.023)	(0.028)	(0.021)
Network structure	–	1.599***	1.029***	1.868***	0.660***
($Net_{t'}(i,j)$)		(0.027)	(0.026)	(0.030)	(0.044)
Intercept	0.371***	0.574***	0.424***	0.217**	-0.214***
	(0.048)	(0.063)	(0.055)	(0.064)	(0.064)
$Pseudo-R^2$	0.180	0.457	0.305	0.465	0.192
Panel B: International tourism networks					
	(1)	(2)	(3)	(4)	(5)
ΔPolitical Stability	0.447***	0.791***	0.677***	0.809***	0.468***
($\Delta Stability_t(i,j)$)	(0.019)	(0.024)	(0.022)	(0.024)	(0.020)
Distance / 1,000 km	-0.275***	-0.321***	-0.307***	-0.298***	-0.220***
($Dist_t(i,j)$)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
Language distance	-0.688***	-0.886***	-0.584***	-0.894***	-0.614***
($LangDist_t(i,j)$)	(0.052)	(0.059)	(0.056)	(0.060)	(0.054)
ΔClimate-related Disasters	-0.423***	0.199***	-0.061***	0.023	-0.450***
Frequency ($\Delta Disasters_t(i,j)$)	(0.020)	(0.022)	(0.023)	(0.021)	(0.021)
Network structure	–	1.162***	0.698***	1.565***	0.708***
($Net_{t'}(i,j)$)		(0.024)	(0.021)	(0.038)	(0.048)
Intercept	0.531***	0.691***	0.554***	0.389***	-0.189**
	(0.050)	(0.058)	(0.055)	(0.059)	(0.073)
$Pseudo-R^2$	0.198	0.328	0.258	0.331	0.211

Table 13: The result of the logistic regression using ΔPolitical Stability ($\Delta Stability_t(i,j)$) in the international migration (Panel A) and tourism networks (Panel B) (see the logistic regression equation in Eq. 3). Each value in the table is the regression coefficient of each independent variable. The independent variables are indicated in the first column. The numbers in parentheses show the standard errors. Each column in the table shows results for a different regression specification: (1) without a network structural variable; (2) In-degree: $Net_{t'}(i,j) = InDeg(j, N_{t'})$; (3) Betweenness: $Net_{t'}(i,j) = Between(j, N_{t'})$; (4) Closeness: $Net_{t'}(i,j) = Close(j, N_{t'})$; (5) Community index: $Net_{t'}(i,j) = ComIndex_{t'}(i,j)$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10 shows the results of the logistic regressions using $\Delta GDP_t(i,j)$ in the international migration and tourism networks. The coefficients of $\Delta GDP_t(i,j)$ in the international migration networks are negative with the in-degree, betweenness centralities of a destination country or the community as a network structural variable or without a network structural variable (see Panel A in Table 10). It implies that links from countries with lower GDP per capita to countries with higher GDP per capita are observed in the international migration networks if the in-degree, the betweenness centrality, or the community index is used as a network structural variable. The coefficients of $\Delta GDP(i,j)$ in the international tourism networks are positive (see Panel B in Table 10). It indicates that links from countries with higher GDP per capita to countries with lower GDP per capita are observed in international tourism networks.

Table 11 shows the results of the regressions using $\Delta LifeExpect_t(i,j)$ in the international migration and tourism networks. The coefficients of $\Delta LifeExpect_t(i,j)$ in international migration networks are negative when the betweenness centrality of a destination country or the community index is used as a network structural variable or a network structural variable is not used in the regression (see Panel A in Table 11). It implies that links from countries with lower life expectancy at birth to countries with higher life expectancy at birth with the betweenness centrality of a destination country or the community index as a network structural variable. The coefficients of $\Delta LifeExpect_t(i,j)$ in the international tourism networks are positive (see Panel B in Table 11). It indicates that links from countries with higher life expectancy at birth to countries with lower life expectancy at birth are observed in the international tourism networks.

Table 12 shows the results of the regressions using $\Delta Gini_t(i,j)$ in the international migration and tourism networks. The coefficients of $\Delta Gini_t(i,j)$ in international migration networks are positive when the betweenness centrality of a destination country or the community index is used as a network structural variable or a network structural variable is not used in the regression (see Panel A in Table 12). This result shows that links from countries with larger Gini indexes to countries with smaller Gini indexes are observed in the international migration networks with the betweenness centrality of a destination country or the community index as a network structural variable. It implies links from countries with greater economic inequality to countries with smaller economic inequality are observed in international migration networks if the betweenness centrality of a destination country or the community index is used as the network structural variable. The coefficients of $\Delta Gini_t(i,j)$ in the international tourism networks are negative (see Panel B in Table 12). This result means that links from countries with smaller Gini indexes to countries with larger Gini indexes. It indicates that links from countries with smaller economic inequality to countries with greater economic inequality are observed in the international tourism networks. Therefore, **H1-A** and **H1-B** are strongly supported when the betweenness centrality of a destination country or the community index is used as a network structural variable.

Table 13 shows the results of the regressions using $\Delta Stability_t(i,j)$ in the international migration and tourism networks. The coefficients of $\Delta Stability_t(i,j)$ in international migration networks are negative when the betweenness centrality of a destination country or the community index is used as a network structural variable or a network structural variable is not used in the regression (see Panel A in Table 12). It implies that links from countries with lower Political Stability to countries with higher Political Stability are observed in the international migration networks with the betweenness centrality of a destination country or the community index as a network structural variable. The coefficients of $\Delta Stability_t(i,j)$ in the international tourism networks are positive (see Panel B in Table 13). It indicates that links from countries with higher Political Stability to countries with lower Political Stability are observed in the international tourism networks. Therefore, **H2-A** and **H2-B** are strongly supported when the betweenness centrality of a destination country or the community index is used as a network structural variable.

The coefficients of $Dist_t(i,j)$ of the regressions are negative in the international migration and tourism networks (see Tables 10 – 13). It implies that links in international migration and tourism networks are more likely to be formed between two countries located within a shorter distance. Therefore, **H3** is strongly supported.

The coefficients of $LangDist_t(i, j)$ of the regressions are negative (see Tables 10 – 13). It implies that links in international migration and tourism networks are more likely to be formed between countries with a shorter language distance. Therefore, **H4** is strongly supported.

The coefficients of $\Delta Disasters_t(i, j)$ of the regressions in international migration and tourism networks are negative when the betweenness centrality of a destination country or the community index as a network structural variable or a network structural variable is not used in the regression (see Tables 10 – 13). It implies that links in international migration and tourism networks are more likely to be formed from countries with lower Climate-related Disasters Frequency to countries with higher Climate-related Disasters Frequency in the international migration and tourism networks with the betweenness centrality of a destination country or the community index as a network structural variable. Therefore, **H5** is strongly supported when the betweenness centrality of a destination country or the community index is used as a network structural variable.

The coefficients of all centralities and the community index are positive in the international migration and tourism networks (see Tables 10 – 13). It implies that links in international migration and tourism networks are more likely to be formed between countries in the same community and countries with a higher centrality in the previous networks. In particular, the regressions without centralities of a destination country or the community index show the same results as those with the betweenness centrality of a destination country or the community index. It implies that the regressions with the betweenness centrality of a destination country or the community index are robust. Therefore, **H6** is strongly supported.

To sum up, all hypotheses (**H1** – **H6**) are strongly supported when the betweenness centrality of a destination country or the community index is used as a network structural variable. Therefore, the effects of network structure as well as non-network structure factors, such as social, economic, distance, language, safety, and climate change factors, are observed in the international migration and tourism networks.

All results of this paper are consistent with the previous results of international migration and tourism network studies (see Fagiolo and Mastrorillo (2013); Windzio (2018); Chung et al. (2020); Seok, Barnett and Nam (2021)). Migration patterns show their characteristics as a long-term investment to live in countries with better social and economic conditions than their home countries. On the other hand, tourism patterns show their characteristics as a kind of consumption good to enjoy leisure. In addition, migration and tourism from countries with lower Climate-related Disasters Frequency to countries with higher Climate-related Disasters Frequency warn of the possible negative effects of climate change on migration and tourism in the future.

7 Conclusion and discussion

In this paper, I characterize international migration and tourism using a network approach focusing on the difference between migration and tourism. The migration stocks provided by the UN are used to construct international migration networks. The constructed migration networks are regressed on several explanatory factors to identify the relationship between the formation of international migration networks and many factors driving migration. The explanatory variables used in my models are classified into two categories: non-network structural variables and network structural variables. Social and economic, distance, language, safety, and climate change are non-network structural variables. Network structural variables are related to the characteristics beyond and including pairwise interactions. I consider the community structure based on modularity maximization, in-degree centrality, betweenness centrality, and closeness centrality of a destination country. International migration networks have shown quite stable network structures as time passes. The results show that social and economic factors strongly drive migration, such as a desire to live in wealthy, more economically equal, and safer countries. Migration patterns and the characteristics of international migration networks show their characteristic as a long-term investment to live in countries with better social and economic conditions than their home countries. Migration from countries less vulnerable to climate change to countries more vulnerable to climate change is significantly observed. It warns of the possible negative effect of climate change on migration in the future. The betweenness centrality of a destination country and the community structure in the previous network are strongly tied to forming networks.

Additionally, I analyze the international tourism networks constructed using the outbound tourism data provided by the World Tourism Organization (UNWTO) to compare the characteristics of migration with tourism. The results show that the characteristics of the international tourism networks are quite different from the international migration networks. International tourism networks have become denser as time passes. Visiting wealthy, economically equal, and safer countries is not a strong travel factor. Tourism patterns and the characteristics of international tourism networks show their characteristics as a kind of consumption good to enjoy leisure. Tourism from countries less vulnerable to climate change to countries more vulnerable to climate change is significantly observed. It warns of the possible negative effects of climate change on the tourism industry in the future. The betweenness centrality of a destination country and community structure in the previous network are strongly tied to the international tourism networks.

This study contributes to the previous international migration network studies and tourism network studies based on macro-level data (see Fagiolo and Mastrorillo (2013); Danchev and Porter (2018); Windzio (2018); Cheng (2012); Seok, Barnett and Nam (2021)). In particular, I add climate change, safety, and social and economic inequality factors not considered in the previous international migration network studies. I test the relationship between most factors or drivers of migration decisions introduced in Czaika and Reinprecht (2020). Furthermore, my approach provides a deeper understanding of international migration by identifying how migration is different from tourism.

Also, my study contributes to understanding the process of forming international migration networks, from individual migration decisions to migration flows at the country level. Even if the data used in this paper is macro-level, explanatory variables in the model explain drivers to migrate to other countries. In particular, we can measure the causal effects of the explanatory variables on network formation using the logistic model, including network structural variables. Thus, my model provides a deep understanding of the international migration network formation in terms of network structural factors as well as non-network structural factors.

Although my study suggests the integrated model, including network structural factors, to explain the formation of international migration or tourism networks, it still has room to be developed. First, we need a deeper understanding of what network structure or centrality measures mean by social and economic in the international migration or tourism networks. I observe the effect of network structure in the international migration or tourism networks in this study, but its social and economic meaning needs to be clarified due to the complexity of interactions in the networks. Studies to interpret centralities and network structural measures in economic theory have been conducted[17], and my results also need to be interpreted based on economic theory, including network structure or centralities. Additionally, we need more future data to measure climate change's effect on migration and tourism. This study shows the possible negative effects of climate change on migration and tourism in the future. Climate change is a global phenomenon, and Most countries have started to discuss climate change recently (see Footnote 4). Thus, to identify the effects of climate change on migration and tourism, we need more future data, including the effects of climate change policies in countries.

[17]Bloch, Jackson and Tebaldi (2023) interpret network centralities using a traditional economic model approach. They show that network centralities can be used to characterize nodes' positions in networks. However, the interpretation of nodes' positions can be different by the kinds of networks.

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