Scholarly migration within Mexico: Analyzing internal migration among researchers using Scopus longitudinal bibliometric data

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Abstract

Migration of talent is a major driver of innovation. Large-scale bibliometric data have been used to measure international mobility of scholars. Yet, our understanding of internal migration among researchers is quite limited partly due to lack of data aggregated at a suitable sub-national level. In this study, we present a novel method and re-purpose bibliometric data using a neural network which provides a sub-national level for aggregating affiliation data. We analyze internal mobility based on over 1.3 million authorship records from the Scopus database to trace internal movements of over 150,000 scholars in Mexico and provide measures of internal migration such as net migration rates for all states over the period 1996-2019. Internal mobility is a rare event of a specific subset of active scholars. We document a core-periphery structure in the migration network of scholars' states centered around Mexico City, State of Mexico, Hidalgo, Morelos, and Queretaro which account for a major share of the total inter-state scholarly migration flows. Over the past two decades, the migration network has become more dense, but also more diverse, including greater exchange between states along the Gulf and the Pacific Coast. Our analysis of mobility events as a temporal network suggests that Mexican scholarly migration is experiencing a 'mobility transition' in which migration between urban centers is increasing in particular to and from a single metropolitan region.

Keywords: high-skilled migration, internal migration, science of science, brain drain, brain circulation,
1 Introduction

The academic exchange of ideas goes beyond physical borders. As such, many scholars are highly mobile and their work contributes to technological and economic advances of several places over their academic life course. A growing body of literature therefore focuses on the migration and mobility of scientists and its impact at the international level. However, even though the geographic distribution of scholars is both an outcome of regional disparities and a key source of inequality of opportunities for future generations, little is known about the drivers behind movements of researchers within country borders. Understanding these patterns can shed light on important regional deficits that identify areas of progress and opportunity for investment in human capital. From the public policy perspective, it is in the interest of regional governments to maintain a strong base of highly qualified scholars who can provide innovative and scientific solutions to public issues and collaborate with the private sector. In doing so, regional governments look for the underlying reasons for migratory movements of researchers and the associated sources of attraction at national and global levels. In order to identify these patterns, we propose an approach to study internal migration of scholars using Scopus bibliometric data. We present our methods to measure migratory movements and discuss, as an illustrative case, the resulting networks of scholarly migration in Mexico.

Although Mexico is an emerging system of science with several leading universities of Latin America, it is an under-studied case in scientometrics literature. Historically, Mexico had a policy to attract foreign researchers through scholarships and professionalization, which allowed it to be at the forefront of many Latin American countries [1]. Existing work on Mexico has focused on production and collaboration [2] or on particular fields such as computer science [3], physics [4] and health sciences [5].

Mexico is a particularly interesting case for exploratory analysis because a larger share of its mobile population moves internally rather than internationally while most existing discussions on migration and Mexico are about migration from Mexico to the US. Between 2005 and 2010, inter-state and intra-state migration accounted for 3.5% and 3.1% of the moving population respectively, compared to 1.1% for international migration [6]. Migration of Mexican researchers abroad, particularly the U.S., seems to be tied to differences in favorable conditions of the labor market [7] and changes in visa availability [8]. However, rather than focusing on a loss of talent, or brain drain, public policy can concentrate in harnessing the circulation of researchers who decide to return to Mexico [9], and similarly, internal movers who can strengthen the domestic academic network.

It remains unclear whether scholarly migration in Mexico has increased or slowed down in the last two decades as a result of special socioeconomic conditions, such as government spending on public institutions, social inequality, and alternative jobs in the private sector. Domestically, there has been a continued government effort to promote scientific research and development. A National System of Researchers (SNI in Spanish) is established in Mexico to track and reward academic and teaching contributions. Despite these policies,
limited data availability prevents any evaluation of current internal mobility of researchers.

This analysis intends to contribute twofold to the literature: first, by re-purposing bibliometric data to analyze internal rather than international migration, second by exploring migratory movements of scholars in Mexico. Although our substantive focus is on a specific country, the proposed methodological framework of re-purposing bibliometric data for internal migration is directly applicable to a broader context.

2 Data and Methodology

For analyzing international migration of researchers, many studies have relied on bibliometric databases. Recent studies offer proxies for place of residence [10], provide bilateral international migration flows [11], offer a methodological framework for dealing with multiple affiliations [12], and analyze movements of highly mobile researchers and return migration [13]. In particular, Scopus has been widely used to analyze international mobility [14, 15] due to its advantages compared to other bibliometric databases. For instance, Scopus provides a wider breadth of records in varied disciplines [16] and offers a more reliable author ID [17] which is suitable for tracking movements of individual researchers [18].

Large-scale bibliometric data allow us to identify migration of researchers in a way which has not been possible with traditional sources of migration data like censuses and surveys. Additionally, bibliometric data provide standardized data, which are suitable for comparative studies. The unit of the data is authorship record which is the linkage between an author and a publication. Our data involve 1.3 million authorship records of scholars who have published with Mexican affiliation addresses in sources covered by Scopus. Using the data, we analyze migratory events of over 150,000 researchers between 32 states of Mexico through the changes in their affiliation addresses over the 1996-2019 period.

3 Inferring states from affiliations

Prior to the analysis, the data were pre-processed to extract the state of each authorship record. For the majority of the data, the states can be extracted from the addresses by algorithmically looking up in a dictionary of Mexican cities and postcodes. These were records with fewer missing values for which predicting based on different input (such as postcode or city) consistently led to the same state. However, for a smaller but still considerable amount of the authorship data (where states cannot be extracted as easily), a more sophisticated method is required to identify the states reliably. In Subsection 3.1, we explain how we developed a neural network approach to address the issue while in Subsection 3.2 we discuss its application to extract the remaining states.

To the extent of our knowledge, the SNI is the only publicly available catalogue of researchers in Mexico. However, being in the SNI entails a rigorous application and permanence process which means that it captures a subset of all researchers in Mexico.
3.1 Developing a neural network

We use the states obtained through the algorithmic dictionary look-up method as training data for developing a neural network for inferring the states of the remaining part of the data. We use the Keras library \cite{19} with a tensorflow backend \cite{20} in the Python programming language.

To assign a state to each row of the input comprising of a city, an institution, and an address, we adopted an approach commonly used in sentiment analysis literature \cite{21} for predicting whether a sentence has a positive or a negative sentiment. Initially, we merge the city, the institution, and the address into one string for each row of the input. Then we convert this string into a feature vector using a bag of words method with term frequency inverse document frequency \cite{22} as the normalized frequency of a given word in a given row of the input relative to the frequency of that word in the whole data set. We use the words with the 3,000 highest relative frequencies as the input layer of the neural network. The number of layers and neurons of the neural network are depicted in Figure 1.

![Figure 1: A schematic representation of the neural network used for inferring states from affiliations](image)

The layers are densely connected and have a dropout rate of 0.25. The neurons of the first layers use a rectified linear unit \cite{23} as the activation function, the output layer uses a softmax activation function. The softmax \cite{24} activation function converts the activation of the output neurons into relative probabilities. The state that is assigned to the output neuron with the highest activation gets selected as the predicted state. We fine-tuned the number of layers, the number of neurons and the dropout rate manually to achieve a high accuracy on the test data while keeping the network as small as possible to avoid over-fitting.

We train this neural network with a random 80% sample of the data whose states were already obtained. Testing the trained network on the remaining 20% of the data results in an accuracy measured at 98.4%. In other words, on 98.4% of the test data, the neural network predicts the expected state. We also tested the accuracy on a subset of 2,248 manually tagged authorship records that were
unrecognizable with the algorithmic dictionary look-up approach. The neural network predicted the correct state in 85.6% of the records.

3.2 Using the neural network

We used this neural network to predict the states of the records for which states could not be reliably obtained using our first approach. In many cases there are more than one data point for inferring the location of a researcher in a given year. This feature of the data can be leveraged to increase the overall reliability of the predictions. More specifically, we omitted a small fraction (1%) of the total number of data points for which predicting a reliable state was particularly difficult even after using the neural network. For the purposes of identifying cases for this omission procedure, the lowest individual predictions scores of Keras were used.

In summary, the states for the majority of the authorship records were reliably extracted using an algorithmic dictionary look-up method. The states for the remaining authorship records were obtained using a neural network except for 1% of the authorship records which were discarded because their states could not be reliably extracted using either of our two methods.

After extracting states for authorship records, we obtain the most frequent state for each researcher in each year and format it as a tabular data structure in which rows represent individual researchers and columns represent different years. This data structure facilitates our analysis which involves creating networks from changes in states of individual researchers.

4 Results

4.1 General attributes of scholars in Mexico

One of the benefits of bibliometric data is that they enable us to conduct analysis at both individual and aggregate levels. For example, we can obtain a profile of the median scholar in Mexico by its mobility status and complement this information with macro-level migration rates for each state. The data resulting from the pre-processing discussed in the previous sections allows us to identify about 244,000 unique scholars in Mexico who have been active during the 1996-2019 period. However, a large share (58% or 142,000 authors) includes individuals who have only one authorship record, preventing us from inferring their internal migration patterns. These single-timed observations could be scholars moving abroad after publishing a single paper with a Mexican address or individuals not staying in academia as they only have a single-publication academic trajectory within Mexico. After removing the these observations, 101,000 authorship records are left and include 23,000 scholars who have moved at least once. That is, grouping individuals into moving and non-moving categories, the data show that only 22.7% of scholars who have published more than once have also moved between states during the period 1996-2019.
Two main characteristics of scholars are their academic age and their number of publications. The publication dates allow us to compute the number of years each researcher has been active. Academic age is obtained by subtracting the year of the earliest publication of an individual from that of the latest publication \[13\]. The median academic age of scholars in our data is 6 years, but mobile scholars have a median age of 9 years while their non-mobile counterparts have a median age of 5. Indeed, mobile scholars appear to be active for longer, which can be an artefact of having to build a more solid track record in order to get opportunities to transfer from one institute to another one. In terms of a crude productivity measure, the median mobile scholar has 6 publications whereas the median non-mobile scholar has 4 publications. Once again, this can be the result of the fact that mobile scholars have a longer career because it has taken them longer to accumulate networks to migrate to another state. At the same time, there could be a bias towards detecting mobility from researchers with more publications. While the Scopus database contains authorship records up to a certain date, the profiles of researchers are continuously evolving. Thus, the academic age and the number of publications can only be used to infer the presence of differences between these two groups, rather than the magnitude of such differences.

The individual level data can be aggregated to obtain a general picture of scholars in Mexico. Figure 2 shows two levels of aggregation used: states and regions of Mexico, which were determined by the geographic, economic and social similarities of each state. In total, we use five regions: i) Northern states along the Mexico-US border, ii) states in the Center with comparable economic status, iii) states along the Pacific Coast, iv) states benefiting from the industry and tourism of the Gulf of Mexico and the Yucatan Peninsula, and v) states surrounding Mexico City that share strong ties with the capital.

In terms of density of scholars within the general population, Figure 3 shows that the number of scholars per thousand people has increased over time for all states. However, there is little change in the ranking of per capita scholars such
that Mexico City, Morelos and Baja California consistently house the most scholars per capita, the opposite is true for Guerrero, Chiapas and Oaxaca. Differences in factors that attract scholars seem to accumulate to the extent that in 2018 the density of scholars in Guerrero is about 20 times smaller than that of Mexico City.

![Figure 3: Scholars per capita in Mexico](image)

**4.2 Measures of internal migration**

The data provide the history of movements over years, from which we can determine whether a scholar has been present in a different state within the last $s$ years. As the duration of conducting a research project and publishing it varies by discipline, not all scholars have a continuous and complete history of locations. As such, the time span used to define entries and exits to a state may penalize scholars in areas with a typically lengthy publication process. Therefore, we use a net migration rate, $M_{i,t,s}$, that takes into account different time windows of movements of scholars from state $i$ between years $t - s$ and $t$:

$$M_{i,t,s} = \frac{IM_{i,t-s} - EX_{i,t-s}}{N_{i,t}}$$  \hspace{1cm} (1)

Overall, the net migration rates are calculated as the difference between the entering ($IM_{i,t}$) and the exiting ($EX_{i,t}$) populations of state $i$ between $t$ and $t - s$ as a share of the total population of scholars ($N_{i,t}$) in a given time $t$. For instance, a 1-year ($s = 1$) net migration rate uses the difference between the number of scholars who have entered ($IM_{i,t-1}$) and those who have left ($EX_{i,t-1}$) state $i$ within the time period $(t - 1, t)$. Here on after, all rates are expressed per 1000 people.

In order to compare the magnitude of movements of scholars, Figure 4 shows interstate net migration rates from the National Council for Population.
(CONAPO) along with our net migration rates of scholars. Interstate \( (T) \) migration rates serve as a benchmark for movements of the general population. If we could filter the official CONAPO data based on education, we could estimate the movements and number of postgraduates and compute measure \( S \). However, this would most likely be a biased estimate as not all highly educated individuals publish (and vice versa). Using Scopus data, Scholars \( (S) \) shows that net migration rates of scholars vary, and can even surpass or mirror the interstate rates. Scopus data allow us to measure the numerator and denominators more adequately for net migration rates of scholars. In the absence of Scopus data, assuming that scholars’ movements behave similar to that of the general population would be an important limitation.

Figure 4: Comparison of migration rates in 2016. The letters in parentheses refer to the population stock used as a denominator for each of the rates. “T” refers to total state population whereas “S” indicates that the denominator is the stock of scholars in a given state. “Scholars \( (S) \)” refers to the 1-year migration rate using only data on scholars.

Figure 5 illustrates the range of net migration rates of researchers in 32 states of Mexico per thousand scholars, when using different temporal definitions to estimate the rates. First, we obtain measure \( T \) for a range of years such that \( s \in \{ 1 : 5 \} \). Then, the spread is produced by taking the minimum and the maximum migration rates amongst all time frames (1-5 years) at a given year. These then represent the lower and upper bounds. As previously mentioned, considering time frames allows us to include the diversity in research and publication process across fields. Therefore, these spreads can allude to the possible values that a rate can take when changing the time window.

\(^2\)The data used from CONAPO come from their 2015 Population Indicators and Projections. Interstate net migration rates for 2016 are projections from CONAPO. Yellow dots use Scopus data in computing state net migration rates.
Overall, there is heterogeneity in the dynamics of the migration rates. Campeche, Chiapas, and Aguascalientes show large spreads while some states oscillate around zero (Hidalgo, Guerrero, and Quintana Roo). There is no apparent trend in most cases, with the exception of Michoacan, Puebla, and Veracruz. Mexico City is the only state that has a period of over 5 years with a negative net migration rate, which suggests that, during that period, more scholars exited than entered Mexico City (with respect to migration internal to Mexico). Other states which show shorter periods of non-zero net migration rates are: Campeche, Jalisco, Queretaro, Morelos, and Veracruz.

Figure 5: Net migration rates for scholars by regions

Another perspective on movements of scholars is to focus on changes relative to the state of the first publication. Figure 6 contains plots by state of academic origin of the share of mobile scholars that have moved to states. Each row groups the states of academic origin within a region. For instance, the first plot of Figure 6 shows that scholars who started off in Baja California mostly migrated to states within the Northern region during the period 1996-2019.
Figure 6: Share of mobile scholars by destination and origin state. Panels show the state of origin of a scholar and the intensity of movements to other regions by year.
Figure 6 suggests that there is a degree of selectivity in the inter-state movements given a state of origin. Scholars with an academic origin from northern states tend to move within the region, with the exception of Nuevo Leon. Although the Center states are surrounded by all the remaining groups, there appears to be a strong attraction between Center states to Mexico City and surrounding areas as well as the Pacific Coast. Most of the mobile scholars originating in one of the states along the Pacific Coast or the Gulf of Mexico also prefer Mexico City and the surrounding states. The least diverse outcomes come from the mobile scholars who began their career in Mexico City and surrounding states: most move within the region. Overall, the origin-destination analysis suggests that regardless of the state of origin, Mexico City and its surrounding states are favorite destinations. Nevertheless, there are still differences within the states of certain rows. For instance, the pattern illustrated for Chiapas looks different from that of the other seven states of the Pacific coast region.

The flexibility of bibliometric data allows us to calculate additional migration rates. The Migration Effectiveness Index ($MEI$) and the Aggregate Net Migration Rate ($ANMR$) \cite{25}, measure the effect of migration in the redistribution of a population within the country. The former is a measure of the turnover within a population while the latter is a migration rate standardized by this turnover rate. Formally,

$$MEI_{t,s} = \frac{100}{\sum_i (IM_{i,t-s} + EX_{i,t-s})} \sum_i |IM_{i,t-s} - EX_{i,t-s}|$$ (2)

$$ANMR_{t,s} = \frac{100}{\sum_i N_{i,t}} \frac{0.5 \sum_i |IM_{i,t-s} - EX_{i,t-s}|}{\sum_i N_{i,t}} = 100(M_{t,s})(MEI_{t,s})$$ (3)

where $i$ denotes a state or region and $s$ is the time window of interest.\footnote{We extend the time-invariant measure in \cite{25} into a time series.}

The numerator of the $MEI$ contains the total sum of differences between the number of scholars entering ($IM_{i,t-s}$) and exiting ($EX_{i,t-s}$) a given state (or region) $i$. Its denominator has a similar syntax except that the movements are added together. Intuitively, the $MEI$ measures the net migration balance in an area as a share of the total number who moved either from or away from the zone. The $ANMR$ shares the same numerator as the $MEI$, however it is weighted by the total population of scholars ($N_{i,t}$). It is an indicator of population redistribution which can be high when the net migration level is higher than the actual combined flow of entering and exiting scholars. By changing the denominator to the population of scholars, the $ANMR$ becomes an indicator of the general effect of the number of moving scholars on the population, as shown in its second specification.

Figures 7 and 8 show the impact measures for the period 1996-2019 using different time horizons to measure the number of scholars entering and exiting a region. In general, the country $MEI$ in Figure 7a shows a downward trend.
Figure 7: Migration Effectiveness Index, over time, and for different temporal definitions of migration (see main text for details on the index).

Figure 8: Aggregate Net Migration Rate, over time, and for different temporal definitions of migration (see main text for details on the index).
which suggests that redistribution of scholars may be decreasing over time. The MEI also increases with wider time windows as more migration events can be detected. In order to compare within-region redistribution of scholars, Figure 7b shows the MEI by the main regions in Mexico. All the MEI measures are highly volatile except that of Mexico City and its surrounding states. In comparison to the rest of the states, the low MEI from Mexico City suggests a lower redistribution of scholars within this region.

As expected, the ANMR measurements illustrated in Figures 8 show similar results as those in the MEI. However, the ANMR values suggest that the turnover of scholars as a share of the population is much lower and is stable for Mexico City and the surrounding states. Overall, these results jointly suggest that the net migration level to the area of Mexico City is lower than the total volume of mobile scholars in that region, and therefore there is a low population redistribution.

5 Internal migration as a network

The data from scholars who have moved between different states can be used to create a migration network by representing each state as a node and creating a directed edge \((i,j)\) for each mobility event from state \(i\) to state \(j\). Creating such a migration network enables us to analyze the system of scholarly internal migration in Mexico as a whole.

5.1 Networks and their temporal dynamics

Figure 9 (a) shows the direction and magnitude of migratory movements of scholars in Mexico between 1996 and 2019. The states that receive and send the most scholars include the capital city and its surrounding states (State of Mexico, Puebla, and Morelos), as well as states that contribute the most to national GDP such as Nuevo Leon, Guanajuato, Jalisco and Michoacan. Overall, Mexico City appears to be the main destination and origin of mobile scholars. This may be due to its political and economic importance as well as because it houses many large national universities and research institutes.

Subpanels (b-d) of Figure 9 highlight the period movements of scholars between states. Overall, the migration network of researchers has not only become more dense but also more diverse over the past two decades. For instance, in more recent years, states along the Pacific coast (red) show a greater exchange (purple edges) with states along the Gulf of Mexico and the Yucatan Peninsula (blue).

5.2 Assortativity of networks over time

Degree assortativity of a network captures the correlations between the degrees of adjacent nodes [26]. In many social networks, there is a tendency between nodes of similar degree to connect (assortative mixing by degree) while in many
In directed networks, the correlation can be measured in four different ways by using either in- or out-degree for source and target nodes (in-in, in-out, out-in, and out-out). We measure out-in assortativity of directed graph $G$ using Eq. 4:

$$r(G) = \frac{\sum_{j,k} (e_{j,k} - q_{j}^{in} q_{k}^{out})}{\sigma_{in} \sigma_{out}}$$  \hspace{1cm} (4)$$

In Eq. 4, $r(G)$ is the out-in degree assortativity coefficient for directed graph $G$. $e_{j,k}$ is the probability that a randomly chosen directed edge leads into a vertex of in-degree $j$ and out of a vertex of out-degree $k$. The term $q_{j}^{in}$ ($q_{k}^{out}$)
represents the excess in-degree (out-degree) distribution \( \sigma_{\text{in}} \) of directed graph \( G \) and \( \sigma_{\text{out}} \) is the standard deviation of the distribution \( q_{\text{in}}^j \) \( (q_{\text{out}}^k) \).

Figure 10 illustrates \( r(G) \) for 23 cross-sectional one-year migration networks. As it can be seen in Figure 10, the degree assortativity coefficient of the networks has generally increased over time during the period 1996-2019. This increase in assortativity can be explained as the gradual transformation of the network from a dissortative mixing pattern \( (r(G) = -0.45) \) to a random (less dissortative) mixing pattern \( (r(G) = -0.1) \).

In the first few years of the period under study, movements were mostly from low out-degree nodes (states with small outgoing flow) to high in-degree nodes (states with large incoming flow) and from high out-degree nodes to low in-degree nodes. The in- and out-degree of the nodes are highly correlated (i.e. the adjacency matrix of the directed networks are very close to that of a symmetric matrix) and therefore all four types of degree assortativity measures show the same increase with minor differences (in-in, in-out, and out-out plots are not shown to avoid redundancy). Therefore, we can say that the majority of flows in the first few years were from small academic states to large academic states or vice versa.

In the last few years, however, the degrees of adjacent nodes are hardly correlated. The mixing patterns of the networks in more recent years feature less dissortativity and instead a circulation of researchers between the states irrespective of their degrees. This suggest that the mixing pattern of the network is affected by a relative increase in mobility between states of similar size (small to small and large to large) in the past two decades.

5.3 Community structure induced by the dynamics of flows

For detecting communities in networks, there are different approaches (and algorithms) which according to Fortunato and Hric belong to five categories: optimization, statistical inference, dynamics, consensus clustering, and spectral
methods. As the edges in our migration networks represent flows between states, we expect that detecting and analyzing communities based on the dynamics of the flows may reveal a more meaningful structure. *InfoMap* is a popular algorithm from the dynamics category for detecting communities [29] which relies on random walk dynamics in the network and the intuition that a the hypothetical random walker stays a longer time in dense regions of the network. For running InfoMap, we use the *MapEquation* software package [30, 31] to detect how the flows between states lead to formation of network communities between them.

For this purpose, we create an alluvial map [30] of the network flows and communities over time which is illustrated in Figure 11. The order of the communities is based on their number of nodes and the height of each community is proportional to its total flow. The structure of these communities clearly show a dense core with a relatively few nodes accounting for the majority of the total flows and an outlying loosely connected periphery made up of relatively many nodes having a small portion of the flows. Such a network structure is referred to as a core-periphery structure [32].

As it can be seen in Figure 11, there are 11 communities in the migration network in 1996. The core was made up of 13 states: Chiapas, Mexico City, State of Mexico, Guerrero, Hidalgo, Jalisco, Morelos, Oaxaca, Puebla, Queretaro, Tlaxcala, Veracruz de Ignacio, Zacatecas. The other communities in 1996 were smaller and made up of at most three states (as shown in Fig. 11). Some communities have a stable flow over different years and therefore do not break into smaller groups over time. For instance, the community shown in dark blue is made up of Baja California and Baja California Sur in 1996 which never break into smaller groups. However, some other states join it at some point such as Guerrero (breaking off the core and joining the blue community) in 1997 and Sonora in 1998.

The dynamics of flows in some other communities is more volatile and therefore their nodes change communities over time. For instance, Chihuahua, Nuevo Leon, and San Luis Potosi form a 3-node community in 1996 which is shown in dark red. The three nodes diverge into different groups and eventually in 2018 each of them is a part of a different community. In 2018, the number of communities increases to 18 and the core community becomes smaller both in terms of total flow (represented by height) and the number of nodes which reduces to 7. Five states which remain in the core are Mexico City, State of Mexico, Hidalgo, Morelos, and Queretaro, while the two states Guanajuato and Michoacan join the core.

6 Discussion: A scholarly migration transition?

The changes observed in patterns of scholarly migration between states can be looked at from the perspective of a migration transition model [33]. Similar to the Demographic Transition [34], Zelinsky identifies five phases whereby spatial and time-specific characteristics (economic, social, and historical) determine mobility patterns [35] in the context of general migration considering different
Figure 11: Communities of the states over time featuring a core-periphery structure
origins, destinations, and direction of migratory events. Although the model is based on a general population of migrants, the observed network patterns imply that it may have a bearing on mobile sub-populations such as scholars. The initial patterns of migration between rural and urbanized states (Figure 9 (a)) and the dissortative mixing pattern (10) we witnessed for the first few years of the period under study suggest that Mexican scholarly mobility has experienced the phase of a late transitional society [33]. Indeed, at this stage migration relatively increases between urban centers. This, in turn, results in circular migration within a single metropolitan region of the network.

Considering that most structural patterns in the network of scholarly migration in Mexico feature the characteristics of a late transitional society, we would speculate that the advanced society in Zelinsky’s model [33] is the forthcoming stage of the migration transition for Mexico. Migration between urban centers and individual urban agglomerations continues in the advanced society stage such that a lattice of major and minor metropoles will emerge in the network of migratory movements. The core-periphery structure of the network documented in Figure 11 seems to be analogous to the expected lattice of major and minor metropoles suggesting a likely transitioning of Mexico’s internal scholarly migration into something analogous to the advanced society stage.

Zelinsky’s model of migration transition is not directly applicable to the case of scholarly migration, and overstretching the model outside of its scope should be avoided. Here we present this analogy to highlight that there are no comprehensive theories for migration of scholars, especially in the context of internal migration and its relationships to international migration which is in part due to lack of data. The methodological framework proposed in the current study aims to facilitate organizing data and information about scholars that can be used to evaluate the likelihood of alternative hypotheses and to build the foundations of a theory of scholarly migration.

7 Summary and future directions

By studying changes in the migration flows and rates of scholars between the 32 Mexican states, we develop methodological approaches to study internal migration of scholars using bibliometric data, and offer a general perspective on trends and patterns for Mexico. We also analyze general traits of scholars such as their number of years of active publication and the main states of origin and destination.

Our results suggest that there is heterogeneity in the direction and magnitude of migratory movements among scholars while Mexico City and its surrounding states appear frequently on the paths of mobile researchers. Our work highlights that longitudinal bibliometric data offer valuable insight into internal migration patterns of scholars when coupled with an algorithmic method for producing a sub-national level of aggregation.

Standard demographic measures, such as net migration rates, are essential for quantifying migratory movements, but a more comprehensive picture
of scholarly migration is obtained when network approaches are deployed as well. Demographic and network approaches complement each other in providing a more comprehensive view on the dynamics of scholarly migration which is consistent with the transitional nature of migration systems. The combination of methods and data that we present opens new opportunities for developing a theoretical framework for understanding scholarly migration within country boundaries.

Declarations

Availability of data and material

The bibliometric data used in this study is proprietary and cannot be released. Scopus data is owned and maintained by Elsevier.

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Authors’ contributions

AMG has done the majority of data processing, analysis, and writing of the manuscript. SA has designed the project and contributed in data processing and network analysis. TT has contributed in the design and implementation of the neural network. EZ has supervised the whole project. SA, TT, and EZ have contributed to the writing of the manuscript.

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