Industrial Topics in Urban Labor System

Jaehyuk Park 1,2,3, Morgan R. Frank 4,5,6, Lijun Sun 7, Hyejin Youn 1,2,8*,

1 Kellogg School of Management, Northwestern University, Evanston, IL, USA
2 Northwestern Institute on Complex Systems, Evanston, IL, USA
3 Luddy School of Informatics, Computing, and Engineering, Indiana University, Bloomington, IN, USA
4 Department of Informatics and Networked Systems, School of Computing and Information, University of Pittsburgh, Pittsburgh, PA, USA
5 Connection Science, Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Cambridge, MA, USA
6 Digital Economy Lab, Institute for Human-Centered AI, Stanford University, Stanford, CA, USA
7 Department of Civil Engineering, McGill University, Montreal, QC, Canada
8 Department of Civil and Environmental Engineering at Northwestern University, Evanston, IL 60208, USA.

* hyejin.youn@kellogg.northwestern.edu

Abstract

Categorization is an essential component for us to understand the world for ourselves and to communicate it collectively. It is therefore important to recognize that classification systems is not necessarily static, especially for economic systems, and even more so in urban areas where most innovation takes place and is implemented. Out-of-date classification systems would potentially limit further understanding of the current economy because things constantly change. Here, we develop an occupation-based classification system for the US labor economy, called industrial topics, that satisfy adaptability and representability. By leveraging the distributions of occupations across the US urban areas, we identify industrial topics — clusters of occupations based on their co-existence pattern. Industrial topics indicate the mechanisms under the systematic allocation of different occupations. Considering the densely connected occupations as an industrial topic, our approach characterizes regional economies by their topical composition. Unlike the existing survey-based top-down approach, our method provides timely information about the underlying structure of the regional economy, which is critical for policymakers and business leaders especially in our fast-changing economy.

Introduction

From ancient civilization, human beings has long been classifying things around themselves: the edible or poisonous, or the dangerous or useful. Categorization does not only help our brain to learn and understand the outside world individually, but also equips us with efficient ways to share and maintain individually acquired knowledge with the community. The latter is an essential component for the advancement of science and technology, playing, therefore, a crucial role, if not indispensable, for a society to survive and thrive [1, 2]. The better we understand a system, the more sophisticated its
classification becomes, thus providing a better toolkit for further understanding. In biology, for example, taxonomy — the system of categorizing and describing species — does not just provide a list of species as a result of “the pioneering exploration of life on a little known planet” [3], but also helps to find testable scientific predictions [4]. Had not been Aristotle’s *scala naturae* (great chain of things) and Linnaean taxonomy, for example, it would have taken much longer time for Darwin and Wallace to develop the evolutionary theory from numerous empirical observations [5]. It is therefore reasonable to say that our scientific progress has been built upon classification systems.

There are two characteristics that a good classification system must satisfy. First, the classification system has to be adaptive to changes in the system. Indeed, many socioeconomic systems, including urban systems, are never static, but constantly creating novel services and products to increase diversity and productivity. When newly created services and products are truly innovative, we are often unable to place them in an existing classification scheme, and hence need either to create a new *ad hoc* category, or to revise the existing classifications to find their home [6, 7]. Second, a meaningful classification system must capture the variation at the most meaningful resolution for the required unit of analysis, and then arrange the variation to fulfill functional needs [6]. Take a furniture store, for example. When we walk into a store, furniture is primarily laid out by their functional purposes, such as chairs, tables, and beds, and then further down to by their styles and material types, in ways to fulfill our primary needs most efficiently.

Urban economy is best known for its fast pace of bringing about novel products and economic services [8, 9]. When created products and services are truly innovative, the contemporary classification is most likely to fail to fully appreciate novel features [6]. For example, the U.S. North American Industry Classification System (NAICS) is revised every five years [1], which is is not necessarily a timely revision. In addition, the revision needs to respect past classification decisions, for which it often misses the most valuable companies in the world as Libert et al. states in the following [10]:

Consider the five most valuable companies in the world, according to S&P: Apple, Alphabet (Google), Amazon, Microsoft, and Facebook, which we call the Fab Five. Despite the fact that these companies make money in different ways — Apple makes most of its money on hardware, Microsoft on software, and Facebook and Google from advertising — they do share a lot of similarities. But Information Technology doesn’t seem like the right category to group them into. The fifth member of the group, Amazon, is officially a Consumer Discretionary firm. There’s no denying that it is a retailer, but it also has a digital platform rather than physical stores, and nearly 50% of the units sold through its website are sold by third-party sellers. With that in mind, Amazon seems closer in DNA to Facebook than Walmart. Like Facebook, it created an open platform that anyone, anywhere in the world, can use.

The current industrial classification systems use physical firms or tradable goods as the fundamental unit while the global economy is increasingly driven by human capital with knowledge and skill, as a result of top-down decisions by the Economic Classification Policy Committee (ECPC) that creates categories to best serve tradable goods and businesses. For instance, the most widely used industrial classification, NAICS, is constructed based on the product of business establishments [11]. However, as the global economy is increasingly relying on knowledge and services, the importance of intangible inputs and outputs — such as the types of skills, occupations, and produced services — has increased in characterizing and analyzing the economic activity

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1[https://www.census.gov/eos/www/naics/index.html]
of a region [7]. In sum, the lack of occupation-based classification system limits the analysis of the economic structure of a nation or a region in terms of its distribution of human capital.

We apply a machine learning algorithm to identify the latent topic from the distributions of occupations across the US urban areas. The topic modeling algorithms has been widely to find a latent structure in large-scale documents, including recommendation system and computational social science. We identify industrial topics as latent clusters of occupations that characterize and relate the regional economies. The comparison between big and small cities shows the structural difference in the urban economy and the prevalence map of each topic reveals the distributional pattern of each industrial topic. Our method has a significant benefit when it comes to the temporal evolution of urban economy [12]. Furthermore, the change of our industrial topics over time provides us with the structural dynamics of the national economy through the lens of labor.

The computational approach in the characterization of a regional economy has significant academic contribution in both theory and methodology. Considering an industrial topic as a latent group of occupations, the topic offers a new holistic lens that links occupation and industry. We expect that the new lens can provide a new systematic approach to solve essential questions in the intersection of labor economics and economic structure, such as the local employment multipliers [13, 14, 15, 16]. Furthermore, the computational approach can provide a more economic and timely information about the underlying structure of the regional economy, compared to the existing survey-based top-down approach, which becomes more important for policymakers and business leaders in the fast-changing economy.

Results

Our approach begins with an analogy between a document and a regional economy. A document consists of the words inside. Accordingly, if we can find a set of words that are likely to locate in the same document, we can estimate the topic of the documents as the composition of the words. Moreover, by extracting multiple word sets from documents, we can see what topics exist across the documents, as well as what topics are over-represented in a certain document. Under this logic, computer scientists and linguists have worked on developing computational algorithms, topic modeling, to extract the topic — as a composition of words — from a large-scale set of documents.

Similarly, in a regional economy, different occupations are distributed unevenly, based on the strength of the regional economy. Hence, if we can find a group of occupations that frequently appear together in different regions, we can also call it an industrial topic. Furthermore, similar to the aforementioned document-topic relationship, the list of topics across all regions in a country can reveal the list of industrial topics that are regionally specialized, while we can also characterize a certain regional economy as a combination of those industrial topics.

Based on this correspondence, we apply Nonnegative Matrix Factorization (NMF) to the occupation distribution records of the metropolitan areas in the U.S., to extract an industrial topic as a group of occupations. Our approach using topic modeling method allows us to redefine the concept of the industry as the group of occupations, and to characterize the regional economic structures more organically and efficiently. In particular, since the topic modeling algorithm infers a latent topic based on locally allocated occupations, we focus on the extraction of the traded industries, defined as the industries concentrating in particular regions but sell products or services across regions and countries [17, 18]. A recent study finds that traded industries accounted for 36.0% of total U.S. employment, 50.5% of payroll, and about 91.2% of patenting activity in
Table 1. Four regions and their over-represented occupations

| Region                                      | Top Five Occupations (in order)                                                                 |
|----------------------------------------------|-----------------------------------------------------------------------------------------------|
| Los Angeles-Long Beach-Anaheim, CA          | Flight Attendants, Actors, Film and Video Editors, Media and Communication Equipment Workers, All Other, Media and Communication Workers, All Other |
| San Jose-Sunnyvale-Santa Clara, CA          | Computer Hardware Engineers, Software Developers, Systems Software, Semiconductor Processors, Software Developers, Applications, Electronics Engineers, Except Computer |
| Las Vegas-Henderson-Paradise, NV            | Gaming Cage Workers, Gaming Dealers, Gaming Supervisors, Gaming Service Workers, All Other, First-Line Supervisors of Gaming Workers |
| Washington-Arlington-Alexandria, DC-VA-MD-WV| Economists, Political Scientists, Legal Support Workers, All Other, Social Scientists and Related Workers, All Other, Flight Attendants |

The occupations having the highest TF-IDF scores of four urban areas are matched with prevalent industries of the regions.

2009 [18].

**Over-represented occupations in urban area**

All regional economies include local occupations that provide goods and services primarily to the local market, similar to the functional words that are frequently used across all different documents (e.g., articles, pronouns, and conjunctions). Restaurant servers and retail managers can be examples of local occupations whose employment size are known as roughly proportional to the regional population [17].

To mitigate the effect of local occupations and to normalize the size effect across regions, we re-weigh the employment size of each occupation in a region using Term Frequency–Inverse Document Frequency (TF-IDF). TF-IDF is a quantity assigned to each pair of a word and a document, which captures how important the word is to the document in a collection of documents [19]. In our application to the regional occupational distribution, the TF-IDF value increases proportionally to the number of times an occupation appears in the region. It is offset by the number of regions in all MSAs that have the occupation, which helps to adjust for the fact that local occupations appear more frequently in general (See Materials and methods for detail).

Our result shows that the TF-IDF scores successfully extract the over-represented occupations in a region. To validate how effective TF-IDF score is to extract the representative occupations in a region, we check the top five occupations in TF-IDF score for the four regions, whose specialized industries are well-known: Los Angeles-Long Beach-Anaheim, CA, San Jose-Sunnyvale-Santa Clara, CA, Las Vegas-Henderson-Paradise, NV, and Washington-Arlington-Alexandria, which is located across DC, VA, MD, and WV. As shown in Table 1, the over-represented occupations in the four regions are well-matched with the corresponding industries for which the regions are known. For instance, the occupations related to entertainment industry, such as film and video editors and media & communication workers, have high TF-IDF
scores in Los Angeles-Long Beach-Anaheim, CA — where Hollywood is, while the occupations in computer hardware and software industries have high scores in San Jose-Sunnyvale-Santa Clara, CA — where Silicon Valley locates. Similarly, the occupations with high TF-IDF scores in Las Vegas and Washington DC areas are also well corresponded to the specialized industries of the regions.

**Industrial topics**

Based on the TF-IDF score for each occupation across all metropolitan areas in the US, we extract the latent industrial topics using Nonnegative Matrix Factorization (NMF), one of the most widely used topic modeling algorithms. Here, according to our analogy between a regional economy and a document, we apply NMF to extract the industrial topic defined as a group of occupations that are likely to be located together (See Materials and methods for more detail).

Our results show that the topic modeling algorithm can successfully extract the
The name of each industrial topic is decided by analyzing overrepresented occupations in the topic. Similarly, the 2-digit NAICS codes are decided by matching the corresponding industry categories of overrepresented occupations.

The table below shows the industrial topics and their corresponding NAICS codes:

### Table 3. Industrial Topics and Matching NAICS Code

| Topic | Topic Name                                                                 | Corresponding 2-digit NAICS Code (% of Traded Industries) |
|-------|----------------------------------------------------------------------------|----------------------------------------------------------|
| 1     | Textile                                                                    | 31(98%)                                                  |
| 2     | Farming, Agriculture                                                       | 11(100%)                                                 |
| 3     | Oil and Gas                                                                | 21(100%)                                                 |
| 4     | Gambling                                                                   | 71(88%)                                                  |
| 5     | Shipping industry                                                          | 48(77%)                                                  |
| 6     | Software / Health and Medical Science / Insurance                          | 51(78%), 52(89%), 54(74%), 61(65%)                       |
| 7     | Livestocks / Agriculture, Animal, Life science                            | 11(100%), 31(98%), 54(74%), 61(65%)                      |
| 8     | Correctional Officers and Specialists                                      | 92(N/A)                                                  |
| 9     | Livestocks, Meat Processing                                                | 11(100%), 31(98%)                                        |
| 10    | Furniture, Textile                                                        | 31(98%), 33(98%)                                         |
| 11    | Chemical                                                                   | 32(98%)                                                  |
| 12    | Electrical, Computer, Aerospace Engineering                                | 54(74%), 33(98%)                                         |
| 13    | Nuclear Energy / Agriculture                                              | 22(70%), 11(100%)                                        |
| 14    | Metal and Plastic                                                          | 33(98%), 32(98%)                                         |
| 15    | Airline / Hospitality / Urban Services                                     | 48(77%)                                                  |

The correspondence between our industrial topics and the industries in NAICS reveals the essential features of our approach (Table 3). Our industrial topics cover most of the occupations in the traded industries, which is defined as “the industries of 2-digit NAICS code where more than 50% of its sub-industries (6-digit NAICS code) are categorized as the trade industry" (See more detail in Materials and methods). All corresponding industries in the existing system are the traded industries in which most of its businesses densely locate in a small number of specific areas, such as Agriculture, Forestry, Fishing and Hunting (NAICS code: 11) and Manufacturing (NAICS code: 31–33).

Nevertheless, not all industrial topics are clearly matched with one or two existing industry categories, and this discrepancy leads us to understand the concept of industrial category, not in the product-oriented but, in a labor-oriented way. First, since each industrial topic is described as the weight distribution of all occupations, it is unavailable to match an industrial topic to an existing industry category clearly. For example, even the industrial topics matched to one 2-digit NAICS code in Table 3—such as Topic 1, 2, 3, 4, 5, 8, 11, and 15, still those topics include, relatively low but, non-zero weights of the occupations related to other industries. It means that our
industrial topics provide us with additional information about the association between
the industrial topics, while still allowing us to characterize the core industry.

Also, the existing industry categories in the same industrial topic show the
relationships between the existing industry categories. For instance, the strong
relationships between (1) airline and hospitality industries (Topic 15), and (2) software,
medical science, and insurance industries (Topic 6) are well-aligned with the recent
study about a landscape of geo-industrial clusters in the global economy based on the
human capital flow [20]. Recent scholarly works about geo-industrial clusters have
shown the wide range of effects and advantages of having the clusters in the economic
growth or innovation in a region [21, 22, 23, 17, 24, 25, 26]. The concept of industrial
topics inferred by the occupational allocation pattern can be better applied to future
studies about geo-industrial clusters, than the existing industrial classification system.

Characterization of urban economy

Then, how does each industrial topic distributed across the country? Can the industrial
topics help us understand the structural pattern in the regional economy? The
application of the topic modeling algorithm on the occupational records provides not
only the occupational group of an industrial topic but also the topical composition of a
region (See more detail in Method and materials). This topical composition of a region,
described as the weights of all industrial topics, allows us to answer these questions and
characterize a regional economy in the labor-oriented perspective.

In terms of their employment size, we compare the distribution of industrial topics in
the 20 largest and smallest metropolitan areas. As presented in Fig. 1(a) and (b), the
comparison between the largest and the smallest regional economies shows a clear
difference in the economic structure depending on the size of a region. Large cities
commonly have a strong prevalence on Topic 6 (Software / Health and Medical Science /
Insurance) and 15 (Airline / Hospitality / Urban Services). However, the balance
between the two industrial topics is different for different areas, depending on their
economic structure. For example, while San Diego, Boston, and Baltimore areas have a
stronger prevalence of the hi-tech topic (Topic 6), Atlanta, Chicago, and Miami areas
have a stronger prevalence of the hospitality topic (Topic 15). Also, there exist the big
cities have a balanced prevalence in both topics, such as New York, Washington DC,
and San Francisco area. On the other hand, small cities have more variation in their
industrial specialization. Although we can observe a little tendency towards correctional
institutions (Topic 8) and metal and plastic manufacturing (Topic 14), still many of the
small cities their specialized industrial topics, including textile (Topic 1 for Rome, GA),
agriculture (Topic 2 for Hanford-Corcoran, CA), and even hi-tech industries (Topic 6 for
Corvallis, OR).

The geographical distribution of industrial topics provides us with both the
macro-level pattern of an industrial topic and the micro-level information about the
specialized areas across the country. On the macro-level, some industrial topics densely
concentrate in the regions that are close to each other, while other industrial topics
concentrate in multiple regions that are distant from each other across the country. For
example, the industrial topic for metal / plastic manufacturing (Topic 14, presented in
Fig. 1(c)) is prevalent in a very specific region of the country, that is famous for the
manufacturing industry in previous studies [27, 28]. This correspondence means that
the distribution of the occupations that are either directly or indirectly related to metal
and plastic manufacturing is still well-fitted to the concept of the economic cluster
[29, 17]. A few topics, including Topic 2, Topic 15, and Topic 13, have surprisingly large
spatial autocorrelation (as measured by the Moran’s I statistic. See Append Fig.1 and
Table 1) when compared to the spatial autocorrelation observed for the location
quotient of employment by NAICS code.
Atlantic City-Hammonton, NJ
Las Vegas-Henderson-Paradise, NV
Reno, NV
Gulfport-Biloxi-Pascagoula, MS
Lawton, OK

Fig 1. Distribution of industrial topics (a) and (b) Prevalent industrial topics in the ten largest cities (a) and ten smallest cities (b) in the U.S. (c) and (d) Prevalent regions for the industrial topics of metal & plastic manufacturing (c) and gambling (d). For visualization, we match the metropolitan areas in our dataset to their corresponding counties, using “CBSA to FIPS County Crosswalk” generated by the National Bureau of Economic Research. The maps for all other topics are presented in Supporting Information.

By contrast, the occupational distributions of the other industrial topics are similar to those of local industries, but on a bigger scale. In a city-level, the industrial topic for gambling (Topic 4), for example, is considered as a traded industry (Table 3), since it does not exist in all cities but concentrates in a small number of cities. However, at the national level, the industrial topic for gambling is sparsely spread in different parts of the country, as shown in Fig. 1(d). Although the levels of concentration are different, each part of the country has its representative area for gambling — such as Atlantic City in East, Las Vegas in West, Gulfport in South. The balanced distribution of the industrial topics that have been considered as traded industries proposes a critical message: the definition of local and traded industry is relative depending on the scale of our focus. We will talk about this implication more in Discussion.
Fig 2. Hierarchical clustering of top 50 cities based on industrial topic composition

Similarity of topical composition between large US cities provides the insights to understand urban economies and their groupings.

First, some cities very unique topical compositions. In particular, the topical composition of Las Vegas is unique, so distant from those of all other big cities. Considering Las Vegas is the only city in the 50 largest US cities among the cities...
specialized in the gambling topic (Fig. 1(d)), we can argue that the industrial topic of gambling (Topic 4) is more likely to be prevalent in the middle- or small-size cities rather than big cities. Not as much as Las Vegas, but some other cities, such as San Jose-Sunnyvale-Santa Clara, CA, New Orleans-Metairie, LA, and Virginia Beach-Norfolk-Newport News, VA-NC, also have the topical composition that is quite different from other big cities.

Second, understanding and comparing the urban economies based on topical composition can be utilized for future economic growth. From the perspective of policymakers or planners of a city, the hierarchical clustering provides the information about how likely the human capital resource of a city to become those of other cities that experience economic growth. For instance, if you are a mayor of Rochester, NY, then the comparison of topical compositions can provide the information that, for Rochester, it is easier to encourage the innovation in the industrial topics that are prevalent in Raleigh, NC than those prevalent in San Jose-Sunnyvale-Santa Clara, CA. Since the industrial topics are extracted from the occupational distribution, the “easier” means “more plausible to develop or convert the current human capital structure”, through providing job training programs or encouraging the migration of specialized human capital.

**Dynamics in industrial topics**

Due to its efficiency in the extraction of industrial topics from a corpus of regional occupation distributions, the industrial topics also can be used to trace the structural dynamics of regional economies across the country. How does the industrial structure

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Fig 3. Industrial topic dynamics from 2014 to 2018 The topics are linked when the cosine similarity of their occupational distribution vectors is higher than 0.5, and the name of the topics are manually assigned based on their representative occupations.
change over time? How consistent is the composition of the industrial topic? Can it also
detect a systematic change in the industrial structure? In this section, we explore the
potential of industrial topics to detect the change in the industrial structure by
comparing the industrial topics in different years.

For the comparison, we first extract the industrial topics from each year’s OES
dataset from 2014 to 2018. Then, we align the topics for different years, so that
the similar topics in different years have the same topic number. We do so by measuring the
cosine similarity of the occupational distribution vectors between the topics of different
years (See Materials and methods for detailed information). The range of cosine
similarity is from -1 to 1 — -1 when two vectors opposed, 0 when two vectors oriented
at 90° relative to each other, and 1 when two vectors with the same orientation —
although we here mostly focus on the positive score. In particular, we set a threshold
for the similarity, $\alpha$, to trace the dynamics of topics over time. For example, when
$\alpha = 0.5$, we assume that a pair of topics from consecutive years is the same or
significantly similar topics if the cosine similarity of their occupational distribution
vectors is higher than 0.5.

The majority of industrial topics are stable. Fig. 3 visualize the change of industrial
topics from 2014 to 2018 when $\alpha = 0.5$. The thickness of the link between the industrial
topics of consecutive years represents the similarity of occupational distribution. Most
industrial topics are consistent and linked to similar topics of the next year. Except
three industrial topics, 12 of 15 industrial topics did not experience a significant change
in their occupational distribution from 2014 to 2018.

Meanwhile, some industrial topics are merged and separated, depending on the
economic situation of the occupations that constitute the industrial topics. For example,
the two industrial topics related to oil and gas in 2014 (Topic 3 and 15) join together
into a single industrial topic in 2015 (Topic 3), as the employment in oil and natural gas
extraction and support activities in the United States declines [30]. By contrast, the
industrial topic of the occupations related to the nuclear energy industry (Topic 13) as
representative occupations emerges in 2018, which is well-aligned with the time when
U.S. nuclear electricity generation surpassed its previous peak [31]. Similarly, the new
industrial topic in 2018 related to the furniture industry (Topic 15), which concentrates
in the North Carolina area according to our regional analysis, can be explained by the
booming of the textile and furniture industry in this area [32, 33, 34].

Conclusion

Here, we proposed a bottom-up approach to identify the industrial topics that allows us
to detect the specialization of the regional economy from occupation distribution
records. In particular, we applied a topic modeling algorithm to extract the latent
allocation patterns of the occupational distribution. The proposed model has several
advantages over conventional analysis: (1) the model is flexible with new data (i.e., an
updated occupation employment data set), and (2) the model efficiently detects
structural change of the economy. Our result shows that the groups of occupations,
similar to the industry mix, also demonstrates a substantial geographic concentration.

As the first attempt to apply a topic modeling algorithm to defined and extract
industrial topics as a group of related occupations, our approach has limitations. First,
while our industrial topics are more flexible and adjustable to the contemporary
economic structure, still they are constrained by the less flexible list of occupations.
Our approach cannot detect the dynamics of industrial structure driven by new
occupations, for example, data scientists or AI specialists. This limitation can be
overcome by leveraging user-generated real-time-based skill or occupation information,
such as that from job searching and hiring services. Second, since we extract industrial
topics based on each region’s overrepresented occupations, our industrial topics underemphasize local industries, whose occupations evenly appear across regions in general. We expect local industries to be extracted using a different measurement for occupations from TF-IDF, separately from traded industries.

Nevertheless, our results agree with the recent clustering theory in regional science and urban economics, indicating that the regional economy does show clear clustering patterns. It helps us identify how the key industry sectors of cities are performing and how industrial signatures differ from city to city [35]. The extracted topics also show a clear geographical concentration. By tracing the change of each topic, we found that the weight of topics shows a great variation over the last four years. This change also corresponds to the development of cities. The topic distribution offers us a new feature to study a region’s economic performance. Our study indicates that the occupation components better reveal the structure of the regional economy. We hope our work could innovate more and new approaches and measures to define regional economy [36] and help research in city science [8, 37].

Materials and methods

Dataset

We analyze the occupational distribution using the Occupational Employment Statistics (OES) Survey data, which is a semi-annual survey conducted by Bureau of Labor Statistics to estimate employment and wage [38]. The dataset provides the number of employment and average wage for each occupation at the spatial level of Metropolitan Statistical Area (MSA).

The Occupational Employment Statistics (OES) data, collected by Bureau of Labor Statistics through a series of mail surveys, measure occupational employment and rates of wage and salary in non-farm establishments. The dataset also does not include self-employed persons. The OES data is available at different levels: nation as a whole, state, metropolitan/non-metropolitan area, etc. We refer readers to [http://www.bls.gov/oes/oes_emp.htm](http://www.bls.gov/oes/oes_emp.htm) for further details of the data set. In this study, we use the occupational employment and annual wage estimates at the level of MSA. In this study, we used the datasets during the five most recent years — from 2014 to 2018 — at the time of our analyses. As a result, our 5-year dataset includes the distribution of 829 occupations across 361 MSAs in the US from 2014 to 2018. Since there exist the MSAs newly appeared and disappeared during our target periods. For the consistency issue, we only include the MSAs whose major corresponding regions are consistently appeared throughout the period, while manually matching the old and new area codes. For instance, we match the area code “31084 - Los Angeles-Long Beach-Glendale, CA Metropolitan Division” in 2017 with “31080 - Los Angeles-Long Beach-Anaheim, CA” in 2018. The complete matching table is presented in Supporting information.

Term frequency–inverse document frequency (TF-IDF)

We use TF-IDF, “term frequency–inverse document frequency”, to score the importance of an occupation in a region based on how many employments the occupation has in that region and across all the regions. The intuition for this measure is: If an occupation appears frequently in a region, then it should be important and we should give that occupation a high score. But if the occupation appears in too many other regions, it’s probably not a unique identifier, therefore we should assign a lower score to that occupation. The math formula for this measure:
where $o, r, R,$ and $N$ represent an occupation, a region, all regions, and the total number of regions, respectively.

**Non-negative Matrix Factorization (NMF)**

Nonnegative Matrix Factorization (NMF) is one of the widely used topic modeling algorithms. NMF, also called *positive matrix factorization* [39] or *nonnegative matrix approximation* [40], is a computational technique to reduce dimensionality to analyze a high-dimensional data as a part based [41]. Along with other diverse applications, including those in astrophysics [42], bioinformatics [43], image processing [44], and recommendation system [45], NMF has been widely applied to topic extraction based on the allocation of words across a corpus of documents [44, 46].

The goal of NMF is to find a non-negative matrix which can approximately reproduce a given matrix, while having a lower dimension. Given a matrix $X$ with nonnegative elements, NMF algorithm aims to finds a decomposition of $X$ into two matrices — $W$ and $H$ having non-negative elements, such that

$$X \approx WH$$

$W$ and $H$ can be found by optimizing by the squared Frobenius norm, which is an extension of the Euclidean norm for matrices to calculate the distance, such that:

$$d_{Fro}(X, WH) = \frac{1}{2} \| X - WH \|_{Fro}^2 = \frac{1}{2} \sum_{i,j} (X_{ij} - WH_{i,j})^2$$

Similar to other dimension reduction methods, such as Principal Component Analysis (PCA) or Latent Dirichlet allocation (LDA), NMF requires to set the number of topics. Since our study focus on the traded industry, we set the latent number of topics as the number two-digit NAICS codes that are considered as traded industries. Delgado et al. recently calculate the percentage of sub-industries (6-digit NAICS code) classified as the traded industries, for each 2-digit NAICS code [18]. According to their calculation, 15 of 23 2-digit NAICS codes have more than 50% of their sub-industries that are traded industries. Hence, we set 15 as the latent number of topic here, although the number can be changed for future studies.

**Alignment of topics across years**

For the static analyses, we extract the industrial topics from the integrated dataset from 2014 to 2018. To trace the dynamics of the industrial topics during the five years, we extract the industrial topics separately using the dataset of each year.

The NMF algorithm does not guarantee that the order of the topics are kept for the similar datasets. That means, for example, the topic strongly related to the textile industry is marked as the first topic in the result for 2014 dataset, while the topic is marked as the third topic in the result for 2015. Hence, we align the order of the topics between years, by calculating the similarity between the topics in the consecutive years. In particular, we use the cosine distance between the occupational distribution vectors of the two topics in different years as the measurement of the similarity.
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**Supporting information**
| Rank | Topic  | Topic Label                                | Moran’s I |
|------|--------|--------------------------------------------|-----------|
| 1    | topic_1| Textile                                    | 0.808272  |
| 2    | topic_10| Furniture, Textile                         | 0.839089  |
| 3    | topic_14| Metal and Plastic                          | 0.903845  |
| 4    | topic_8| Correctional Officers and Specialists       | 0.926108  |
| 5    | topic_7| Livestocks / Agriculture, Animal, Life science | 0.931856 |
| 6    | topic_11| Chemical                                   | 0.963046  |
| 7    | topic_5| Shipping industry                          | 0.964980  |
| 8    | topic_12| Electrical, Computer, Aerospace Engineering | 0.976718 |
| 9    | topic_9| Livestocks, Meat Processing                | 0.997920  |
| 10   | topic_6| Software / Health and Medical Science / Insurance | 1.014528 |
| 11   | topic_3| Oil and Gas                                | 1.049666  |
| 12   | topic_4| Gambling                                   | 1.106953  |
| 13   | topic_13| Nuclear Energy / Agriculture               | 1.299990  |
| 14   | topic_15| Airline / Hospitality / Urban Services     | 1.356454  |
| 15   | topic_2| Farming, Agriculture                       | 1.379097  |

Table 4. Matching table of area codes For the areas whose codes and corresponding areas were slightly changed during the period, we manually match the area codes if their major corresponding areas are same.

Table 5. Detected topics ranked by spatial autocorrelation. Employment in Topic 2 (Farming, Agriculture), Topic 15 (Airline/Hospitality/Urban Services), and Topic 13 (Nuclear Energy/Agriculture) have especially large spatial autocorrelation compared to the expected spatial autocorrelation of the location quotient of employment for NAICS sectors.
Fig 4. Hierarchical clustering of top 50 cities based on industrial topic composition
Fig 5. The distribution of the Moran's I test statistic for spatial autocorrelation for the location quotient of employment by NAICS sector (blue) and the topics detected by our model (orange). A few of our detected topics exhibit greater spatial autocorrelation than would be expected based on the spatial autocorrelation of NAICS sector employment.