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Bridging the Gap: Integrated Occupational and Industrial Approach to Understand the Regional Economic Advantage

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Abstract: In the debates on regional economic analysis, scholars generally reach the consensus that the industrial frame and the occupational mix are not very accurate substitutes for each other. While industry concentration and mix are widely accepted as significant, the independent consideration of occupation has been shown to be important, especially for creativity-concentrated regions. However, neither the industrial nor the occupational mix is separately sufficient to be solely applied to understand the entire regional situation. This paper develops an integrated occupational and industrial structure (IOIS) at the state and also the national level in order to bridge the gap between separate industrial and occupational analytic results. The case of California is used to demonstrate that the integrated approach is a more effective way than either the single occupational or industrial analysis. The further application of this approach to data for the fifty states provides a general view of joint occupational and industrial development across the nation. This approach further links the occupational approach and the industrial development together by providing a new way to measure and identify the regional comparative difference to be able to implement more fruitful policy-making decisions.

Keywords: occupation; industrial structure; integrated approach; regional economics

1. Introduction

The industrial analytical framework has long been a top focus in research related to cities and regions. Ever since the 1950s, when trade was regarded as the major driving factor of regional productivity, regional industrial structure has always been the dominant model because the industrial output, or more specifically the products of regions and countries, has long driven the key questions guiding research in this field. As the role of human capital in economic development is increasingly gaining traction in the literature and policy realms, people's knowledge and problem-solving abilities provide a new perspective in which urban and regional competitiveness can be explored.

Since the pioneering work of Thompson and Thompson [1,2], the occupational mix has become an important factor in the regional economic analysis. From educational attainment to broader knowledge and skills, the occupational research frame has gained great interest among scholars. Of course, this debate has experienced several shifts in focus, as is described in the next section. In regional development analysis, scholars have generally reached the consensus that these two approaches offer differences in measuring the situations for a specific region. The industrial analysis is not enough to function as a replacement for occupational analysis. However, neither the industrial nor the occupational mix is enough to be solely applied to acquire the whole view of the regional economic image. The challenge is that the occupational perspective now plays an increasingly important part in regional development analysis while the industrial framework is still of significant influence. As a result, an integrated approach to view the regional industrial and occupational mix as a whole is needed.

2. Focus Shifts in Regional Economic Analysis

Regional economic analysis has experienced four major research approaches with their own focuses during the past several decades. The first is the focus on trade. Since the 1950s exports have been the focus of research on regional output, with scholars arguing that trade is the major element and contributor to regional productivity. In this period, the research approach is characteristic of firms gathering as industrial clusters for the shared benefit of convenient labor and resource supplies [3–11]. The second is the focus on human capital and division of labor as scholars became increasingly more interested in the role of human capital in regional development [12–24]. Ideas and innovation become more visible in the regional development agenda. Firms and labor cluster for more effective communication and idea exchanges, rather than just labor availability and natural resources. Scholars concerned themselves more with the clustering behavior of talent and human resource, rather than just the companies. The third is the focus on human capital in its own as separated from industrial frame and as measured by education. The indicator of education attainment is used by researchers to identify and group the human capital resources [22,25–27].

The fourth is the focus on occupational analysis. In the past ten years, the human capital through the measurement of skills and knowledge in practical work rather than just as educational attainment has been gaining momentum. The occupation-based regional analysis uses this approach and is the most recent approach to understanding regional prosperity. It was identified to target both occupational and industrial aspects of regional economic development [1,2,28–33]. Some researches further take more specifically skill measures other than education or skills to examine the human capital structure [24,34,35]. For example, Scott [24] proposes the dimensions of analytical, socially interactive, and practical capabilities—as recognized from the database of DOT (Dictionary of Occupational Titles published by the US Department of Labor in 1991).

Among the research focused on occupational development, Thompson and Thompson's [1,2] pioneering work suggests the turn from industrial to occupational analysis. Other researchers provided methodologies to aggregate occupational clusters [28,29] to serve as the practical tools for decision-makers and planners. Balfe and McDonald [28] grouped the occupations into clusters based on their education and vocational skills. Feser [29] aggregates the occupations from the perspective of broad knowledge to provide a way to explore the general value of occupational groups in regional economies. Markusen [30] comes up with occupational targeting and shows planners and decision-makers the advisable steps to identify the key occupations as networks of workers.

Some researchers identify how occupation analysis links with industrial development [31–33,36]. Barbour and Markusen [31] examine whether a region's occupational structure can be paralleled with the industrial structure and found that the approximation does not hold for specifically researched industries such as high-tech and information technology fields and suggest that the industries are not enough to determine the concentration and clustering of occupations. Mellander [37] distinguishes the knowledge industries and creative industry based on education and skills, respectively. Currid and Stolarick [32] contribute to the empirical work and specifically present the case of I.T. in Los Angeles to demonstrate the mismatch between the industrial and occupational analytical results. Nolan et al. [33] make efforts to reveal different occupational contents through the construction of an occupation-industry index even though the industrial mix is the same among metro regions. Gabe and Abel [36] find that knowledge occupations with unique characteristics are more likely to cluster than the general knowledge occupation across the US metropolitan regions.

In the debate on regional economic analysis, scholars think that the industrial frame and the occupational mix are not substitutes for each other. The independent consideration of occupation is especially important in regions with a high concentration of creativity-oriented industries and occupations. An integrated approach is needed to view the regional industrial and occupational structure as a whole. Industrial structure and occupational mix differ a lot—especially in certain industries and geographic areas. A comprehensive understanding of both is more important than just finding the gap. The integrated approach presented offers a potential solution.

This paper tries to develop such an approach of integrated occupational and industrial structure (IOIS). The detailed comparison in the case of California demonstrates that this approach does provide something new. It is also applied to data for the fifty states. The research is limited to the United States given data availability. The two-tier integrated approach using both occupational and industrial frameworks provides a new way to facilitate policy-making and refuel the prosperity of regions and cities.

3. Data and Methodology

3.1. Data Source

The research in this paper is based on three data sources. The first two are the Standard Occupational Classification system (SOC) in 2000 and 2010 by the Bureau of Labor Statistics and North American Industry Classification System (NAICS) in 2002 and 2007 from the Census Bureau. They provide the coding standards under which the industrial and occupational structures are organized. The third data source is the Public Use Micro-data (PUMS) files from the American Community Survey (ACS) released by the US Census Bureau. This single file contains data from 2006 to 2010. ACS PUMS has a single year of data, 3-years of combined data, and 5-years of combined data. The 5-year dataset covers the data from 2006–2010 in a single file, providing a larger sample which covers 5% of the total population compared with 3% in the 3-year dataset and 1% in the single year dataset. This 5-year database rather than a single-year or three-year file is selected to provide a larger sample. This data jointly provides both industry code and occupation code for working individuals. The industrial and occupational data from the PUMS includes the variables of NAICS code, SOC code, INDP (Census industrial code) and OCCP (Census occupational code). Each individual is also identified to specific geography. For this initial analysis, the geographic dimension is limited to the fifty states (plus Puerto Rico and the District of Columbia). The ACS PUMS file would also permit analysis at the metropolitan area or even county (for some counties). However, counting the individual crossing metropolitan units results in many instances where because of ACS sampling frames, the amount of "noise" in the counts is significant. To eliminate that as much as possible, only states will be used for this initial analysis. As the overall intention is to present, discuss, and validate the approach presented, and, since state level analysis is common practice, that level of analysis is a reasonable place to start. Eventually, this work can be supplemented with limited metropolitan level analysis.

The ACS PUMS files are especially useful for studying population and household groups for a specific use where published tables may be limited. In this five-year data file, the data previously available in OCCP and SOCP are now presented in 4 separate fields. OCCP10 and SOCP10 contain data for 2010 cases only, using the 2010 occupational classification system. OCCP02 and SOCP00 contain data for 2006, 2007, 2008 and 2009 cases only, using the 2002 occupational classification system. As for the data related to industries, the INDP and NAICS are also divided into four separate fields. INDP07 and NAICS07 contain data for 2008 to 2010 cases, using the 2007 industrial classification system. INDP02 and NAICS02 contain data for 2006 to 2007 cases only, using the 2002 industrial classification system. Therefore, the data for 2006 and 2007 are based on NAICS 2002 and SOC 2000, the data of 2008–2009 based on NAICS 2007 and SOC 2000, the data of 2010 based on NAICS 2007 and SOC 2010. (See Table 1).

Based on the above situation there is one problem. In the five-year data file from 2006 to 2010 the NAICS codes include both NAICS2002 to NAICS2007 and the SOC codes from SOC2000 and SOC2010. Based on the full concordance of NAICS 2007 matched to NAICS 2002 the changes are all in the same

NAICS two-digit codes after combining the same categories. Even at the three-digit-level, the changes in the codes and their contents are not big enough to influence the results seriously. Therefore, while at a finely-grained detailed level, the variation in coding could present a challenge, our summarization of the data (to two- and three-digit levels) eliminates the potential for any impact. Meanwhile the SOC codes had no substantial changes.

Table 1. Applied variables and codes of different years.

Years	Applied Variables	Applied Codes
2006–2007	INDP02 OCCP02	NAICS 2002 SOC 2000
2008–2009	INDP07 OCCP02	NAICS 2007 SOC 2000
2010	INDP07 OCCP10	NAICS 2007 SOC 2010

3.2. Constructing IOIS Matrix

Using two-digit NAICS codes, the cases are aggregated into the groups as the columns. The SOC codes are grouped to create the rows based on two-digit codes. Combined, they constitute a matrix with each cell representing the employment corresponding to both a two-digit NAICS code and two-digit SOC code. Given that PUMS is a weighted sample, the weights are applied to each individual before the individual cell totals are calculated to approximate the whole population, and the standard errors of estimation are shown in next section. The reason why the NAICS and SOC in the PUMS are used rather than the INDP and OCCP is that the industrial categories in INDP are too specific. One industrial category in the same major group often includes several different codes, even in a two-digit level. But the NAICS and SOC codes create meaningful group numbers and meet the intended requirements based on their links to the INDPs and OCCPs. This is the Integrated Occupational and Industrial Structure (IOIS) approach this paper constructs to represent the general occupational and industrial situations in states and the nation. In order to examine the industrial and occupational dimension in more details the matrix constructed as the IOIS is also completed for more digit levels (representing different levels of summarization) such as three-digit industrial NAICS code by two-digit occupational SOC code, two-digit industrial NAICS code by three-digit occupational SOC code, three-digit industrial NAICS code by three-digit occupational SOC code. The difference in the results is discussed in the next section.

The matrix shows the linkages between industries and occupations. It is also a manifestation of the integrated occupation/industry structure. The state of California's IOIS matrix for two-digit level NAICS and two-digit level SOC is in Appendix A. The national level numbers are in Appendix B. Due to the space limitation only the matrices of two-digit NAICS by two-digit SOC codes of California and the US are shown in the appendices. The two-digit NAICS code of 99 and the two-digit SOC codes of 55 and 99 are deleted because they do not represent actual employment. The state IOIS can be compared with the national IOIS to examine the variance and determine how large it is.

With the above matrices, we first make a quick and simple test of comparison in two-digit NAICS by two-digit SOC to determine the difference in employment percentage in every cell rather than discuss a specific comparison of every one of the actual numbers. California and D.C. are selected to compare with the whole US situation. These two are of a really different character. California is diversified with abundant resources and multiple economic functions while D.C.'s role is much simpler. When we compare the IOIS matrix of California with that of the US by means of simple subtraction (the US minus California), we find the range in the share difference is from −0.0065 to 0.0075. When it comes to D.C., it is from −0.0271 to 0.0297. Not even in the same order of magnitude, the different range of California suggests it has a similar IOIS with the whole nation while that D.C offers a sharply different framework compared with the US. Given the economic characters of California and D.C., it is expected that most of the other states should fall in the middle between these two.

This method provides for the difference, but does so by returning a whole collection of differences that then can be investigated. But the above method is somewhat problematic in matrix comparison because it is too simple, and lots of information is lost in processing the matrix values. Therefore, this paper proposes a different and more reasonable approach to better understand the comparison of the state IOIS with the national one.

In the above two-dimensional Matrix M_{io}, m_{io} corresponds to the employment of industry i and occupation o at the same time in actual numbers. Any element in the state Matrix M_r is expressed in r_{io} while that in the national Matrix M_n in n_{io}. This paper applies commonly used methods to normalize the matrices and determine their similarity. The first step is the normalizations of the state and national matrices to make them comparable (seen the Formulas (1) and (2)). After the normalization the matrices are expressed with R_{io} in state level and N_{io} in national level. Actually the Matrix R_{io} and Matrix N_{io} are highly dimensional vectors of $i \times o$ respectively. So in the next step the inner product of the two vectors as shown as s in Formula (3) is used to represent how similar they are. The inner product is handled with exponentiation of cube to inflate the variance among the v values. Based on this specific research, the cubic exponentiation is tested to be an adequate degree to make the variance more visible. It helps us better identify the variance values for the following analysis. Then we make the s subtracted by 1 to represent the variance (v) of the two matrices seen in Equation (4). It can be expressed as follows,

$$R_{io} = \frac{r_{io}}{\sqrt{\sum_i \sum_o (r_{io})^2}}, \tag{1}$$

$$N_{io} = \frac{n_{io}}{\sqrt{\sum_i \sum_o (n_{io})^2}}, \tag{2}$$

$$s = (\sum_i \sum_o (R_{io} \times N_{io}))^3 \ (0 \le s \le 1), \tag{3}$$

$$v = 1 - s \ (0 \le v \le 1). \tag{4}$$

In which, r_{io} represents the state employment and R_{io} is the normalized state employment; n_{io} is the national employment and N_{io} is the normalized national employment; i refers to a certain industry and o represents an occupation; s is the similarity; Finally v is the variance between the state and the nation. The variances of different code digit levels are shown and discussed in the next section, including two-digit NAICS by two-digit SOC, two-digit NAICS by three-digit SOC, three-digit NAICS by two-digit SOC, three-digit NAICS by three-digit SOC. In the setting of the above approach v is ranging from 0 to 1. When it is going close to 1 the variance is suggested to be bigger while it is becoming smaller when it is increasingly near 0.

Suppose we have the national and state matrices as $n_{io} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, r_{io} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ respectively. Noticeably, they are totally different from each other. Using the above formulas, we have $N_{io} = \begin{bmatrix} 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 \end{bmatrix}, R_{io} = \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{bmatrix}$ and finally $v = 1$. It is the biggest variance value, which in turn shows there is no similarity between the state and national occupational and industrial mix.

The same methods will also be applied in the single industry or occupation case as a one-dimensional matrix. The industrial and occupational mixes are both to be examined in two- and three-digit level, respectively. If the integrated industry and occupation structure matrix identifies a bigger variance between the state and national level than the single simpler matrix, we can say that the integrated approach has a more effective distinguishing ability. Or, at least it provides a different view, greater information and shows the result of existing regional differentiation.

The comparison of integrated occupational and industrial approach and the single approach is first conducted in the state of California. The case of California facilitates well to identify the difference between the two approaches given its vibrant and diversified economic activities. The human capital situation in the whole state fits well with the analysis focusing more on the occupational aspect. In a later analysis of more states, counterparts can be identified. Then, the integrated approach is applied to the fifty-state data to achieve a generalized view of the occupation and industry circumstances in other states and across the nation.

In order to further reveal if the states are spatially correlated in the variance values, Moran's I is added to conduct such an analysis. The three-digit industry by three-digit occupation results of the states are used to run Stata software. The geographical distance between the states are applied as the weights-matrix in the Stata software. The approaches of the global spatial autocorrelation and local spatial autocorrelation are both run. The former is to show if all the states have a spatial autocorrelation based on the variance of the regional IOIS feature from the national level. The latter is to tell us if in some areas there exists a certain spatial autocorrelation among some of the states. The scatterplot will help us better identify these states which gather spatially in the next section. After this, a more direct approach of the map with differentiated variance values of all the states is taken to reveal some regional similarities.

4. Results and Discussion

4.1. California Case

The variance between the two matrices mentioned above has been calculated. It is conducted at four different levels of detail: Two-digit NAICS by two-digit SOC, two-digit NAICS by three-digit SOC, three-digit NAICS by two-digit SOC, three-digit SOC and three-digit NAICS. The variances between California and national IOIS in four levels are as follows. (See Table 2).

Table 2. The variance between the state and national integrated occupational and industrial structure (IOIS) in four detailed level.

	Two-Digit NAICS	Three-Digit NAICS
Two-Digit SOC	0.0297	0.0349
Three-Digit SOC	0.0461	0.0501

If the single industrial or occupational structure is applied, it can be regarded as a simpler matrix with just one column or row. The results of these calculations are shown as Tables 3 and 4 below.

Table 3. The variance between the state and national industrial structure by NAICS.

	Two-Digit NAICS	Three-Digit NAICS
Industrial structure	0.0151	0.0310

Table 4. The variance between the state and national occupational mix by SOC.

	Two-Digit SOC	Three-Digit SOC
Occupational mix	0.0106	0.0214

If the integrated occupational and industrial structure as matrix has a larger variance between the state and national level than the single simpler matrix, we can infer that the integrated approach more effectively distinguishes the differentiation between state and the national economic industry/occupational structure. From the table results above, it can be seen that the variances of a single industrial or occupational structure in two-digit level are 0.0151 and 0.0106 respectively. But our integrated approach in both two-digit level shows the result of 0.0297. The difference grows even larger when it comes to more digit data analysis. The integrated approach reveals a bigger variance between the state and national level. It better recognizes the state variation when compared with the national situation.

The IOIS approach provides an integrated approach to explore the joint industrial and occupational distribution. The state integrated occupational and industrial structure is clearly different from that of the whole country, which reflects the state difference in occupational and by industrial content based on respective codes. It also provides a better way to see the national industrial and occupational linkages.

From the above comparison with the single industrial or occupational mix, the IOIS framework indeed provides a different result of v value. It reveals the state development status differs from the overall national economy in another way. Therefore, the state comparative difference shall be identified in this "another" way. It is a more comprehensive and exact way to grasp the view of state development, whether in conceptual or practical aspect.

4.2. From the Californian Case to 50 States in the US

Presented next are results for the fifty US states with Puerto Rico and D.C. using PUMS data from 2006–2010. These results are presented in Table 5. The appropriate sample weights are applied to calculate the values and are used to determine standard errors. (See the 2006–2010 Accuracy File for details on standard error calculations if needed). Given the use of state-level data, the standard errors are relatively low, and the details corresponding with the results in Table 5 are presented in Appendix C.

Table 5. Variance results between the 50 states of the US.

	I2O2	I2O3	I3O2	I3O3
Alabama	0.0370	0.0381	0.0393	0.0429
Alaska	0.1931	0.2017	0.1737	0.1948
Arizona	0.0410	0.0501	0.0393	0.0494
Arkansas	0.0598	0.0685	0.0778	0.0837
California	0.0297	0.0461	0.0349	0.0501
Colorado	0.0554	0.0623	0.0461	0.0557
Connecticut	0.0542	0.0579	0.0586	0.0619
Delaware	0.0456	0.0511	0.0474	0.0579
DC	0.4877	0.5627	0.4504	0.5714
Florida	0.0533	0.0497	0.0437	0.0426
Georgia	0.0276	0.0343	0.0221	0.0288
Hawaii	0.1661	0.1465	0.1507	0.1500
Idaho	0.0722	0.0994	0.0713	0.0980
Illinois	0.0184	0.0215	0.0217	0.0247
Indiana	0.1355	0.1032	0.0908	0.0753
Iowa	0.0911	0.1269	0.1066	0.1370
Kansas	0.0373	0.0584	0.0541	0.0687
Kentucky	0.0495	0.0471	0.0550	0.0556
Louisiana	0.0487	0.0544	0.0487	0.0528
Maine	0.0469	0.0623	0.0576	0.0777
Maryland	0.1104	0.1049	0.0749	0.0850
Massachusetts	0.0514	0.0611	0.0636	0.0740
Michigan	0.1274	0.1128	0.1509	0.1321
Minnesota	0.0380	0.0495	0.0431	0.0536
Mississippi	0.0565	0.0575	0.0723	0.0751
Missouri	0.0136	0.0197	0.0195	0.0255
Montana	0.1198	0.1527	0.0945	0.1329
Nebraska	0.0930	0.1759	0.1112	0.1671
Nevada	0.2163	0.2121	0.2564	0.2426
New Hampshire	0.0407	0.0496	0.0449	0.0524
New Jersey	0.0675	0.0763	0.0709	0.0863
New Mexico	0.0659	0.0650	0.0453	0.0529
New York	0.0605	0.0725	0.0737	0.0937
North Carolina	0.0237	0.0266	0.0264	0.0280
North Dakota	0.1867	0.3207	0.1998	0.3082
Ohio	0.0716	0.0693	0.0582	0.0600
Oklahoma	0.0291	0.0447	0.0419	0.0556
Oregon	0.0318	0.0490	0.0370	0.0607
Pennsylvania	0.0215	0.0312	0.0238	0.0320
Rhode Island	0.0395	0.0569	0.0635	0.0748
South Carolina	0.0346	0.0394	0.0380	0.0406
South Dakota	0.1866	0.2882	0.1852	0.2707

Table 5. *Cont.*

	I2O2	I2O3	I3O2	I3O3
Tennessee	0.0391	0.0373	0.0359	0.0374
Texas	0.0206	0.0273	0.0201	0.0276
Utah	0.0296	0.0949	0.0417	0.0948
Vermont	0.0577	0.0819	0.0899	0.1112
Virginia	0.0744	0.0811	0.0768	0.0839
Washington	0.0313	0.0457	0.0368	0.0569
West Virginia	0.0902	0.1016	0.0945	0.1070
Wisconsin	0.0891	0.0838	0.0636	0.0732
Wyoming	0.1957	0.2603	0.1647	0.2409
Puerto Rico	0.2721	0.3787	0.3361	0.4321

Notes: I2O2 equals two-digit NAICS by two-digit SOC; I2O3 equals two-digit NAICS by three-digit SOC; I3O2 equals three-digit NAICS by two-digit SOC; I3O3 equals three-digit NAICS by three-digit SOC. The same applies to the following text.

Descriptive variables such as mean, standard deviation, and maximum and minimum values are presented in Table 6. D.C. and Puerto Rico are excluded in the descriptive analysis, because they are not really of the state character.

Table 6. Descriptive Analysis of variance values across 50 state data files (D.C. and Puerto Rico excluded).

	I2O2	I2O3	I3O2	I3O3
Mean	0.0715	0.0866	0.0732	0.0889
Standard Deviation	0.0527	0.0670	0.0516	0.0647
Minimum	0.0136 (Missouri)	0.0197 (Missouri)	0.0195 (Missouri)	0.0247 (Illinois)
Maximum	0.2163 (Nevada)	0.3207 (North Dakota)	0.2564 (Nevada)	0.3082 (North Dakota)

The mean values of the variance at any data detail level are relatively high. Not surprisingly, the average state IOIS situation is very similar to the national IOIS. Based on the standard deviation of the variance values, the specific values for the various states are not so distant from the mean, and the industries and the occupations structures are distributed relatively evenly across the nation.

However, the results also show specific differences, by state, in the 50 state data files. The state of Missouri has the least variation in all the data detail levels except for the state of Illinois in three NAICS by three SOC codes, while Nevada and North Dakota are least like the national distribution. The analysis of data values above and below the mean is conducted in the three NAICS by three SOC detail level. Only 15 states have a greater variance from the national values than the mean. They are North Dakota, South Dakota, Nevada, Wyoming, Alaska, Nebraska, Hawaii, Iowa, Montana, Michigan, Vermont, West Virginia, Idaho, Utah and New York (ordered from most to least variance). These states have a larger difference in occupational and industrial structure compared with the national level. They have a more distinctive collection of industry and occupational pairing shares, due to either unique combinations of function or other specialized locational characteristics. The top three states with the least variance with the national level are Illinois, Missouri and Texas. These states look very similar to each other and to the whole nation.

From two-digit industrial by two-digit occupation to the three-digit industrial by three-digit occupation, the mean variance values experience changes with the adjustment of either industrial or occupation or both. As expected, the more detailed industrial or occupational codes used to construct the matrix and calculate the variance generate greater variation.

Now we move to the analysis of some specific states. When the occupational data level is becoming more detailed, there are some states with the variance value experiencing relatively large increase, for example, Iowa, Vermont, Maine, California, Rhode Islands, Kansas, Nebraska, Massachusetts, Oregon, Oklahoma, and Utah. The current occupational and industrial situations of these states are more outstanding and different from the national framework as the occupational aspect, and regional talent levels matter more, which might suggest that the human resources matter a lot for their current economic development. On the opposite side, there are states which are increasingly the same with the national IOIS and harder to differentiate themselves from the overall national level if the codes are more occupationally detailed, such as Indiana, Nevada, Virginia, Ohio, New Mexico, Florida, Kentucky, Tennessee, Alabama, South Carolina etc.

An aspect of Moran's I the results of the global spatial autocorrelation is shown in Table 7. The value of -0.016 with the significance of 0.870 reveals no significant spatial correlation among all the states in the statistical meaning, indicating there is no emerging regional gathering pattern in the nation, based on the variance of regional IOIS from the nation examined in our paper.

Table 7. Moran's I results (measures of the global spatial autocorrelation).

Variables	I	E(I)	Sd(I)	z	*p*-Value
Variance	−0.016	−0.020	0.024	0.164	0.870

However, the local spatial autocorrelation results, as shown in Table 8, provide us with some clues to grasp some regional clustering features based on the variance values examined in our paper. Some states are spatially correlated with a *p*-value lower than 0.1, indicating a statistical significance. The Moran's I value of South Dakoda and North Dakoda are positive, indicating these two states have a trend of clustering spatially based on the IOIS variance from the nation. Combining the illustration of the scatterplot in Figure 1 we can get a clearer view of the spatial clustering trend of the variance values. According to Moran's I definition of the spatial autocorrelation, the points in the first quadrant present some states with relatively high Moran's I values clustering together spatially. Specifically, around South Dakoda and North Dakoda there exist Wyoming, Montana and Nebraska. These points representing the five states are all in the first quadrant (as numbered in the figure), and they are indeed close and adjacent to each other in the real spatial layout. Other states with statistical significance involve DC and Puerto Rico. They are in the fourth quadrant, indicating there emerges differentiated and dispersed spatial trend around these two states. Because no clear spatial correlations in real meaning are visible about these two states, we will not conduct detailed analysis in this particular paper.

Table 8. Moran's I results (measures of the local spatial autocorrelation).

No.	Location	Ii	E(Ii)	sd(Ii)	z	*p*-Value *
1	Alabama	0.130	−0.020	0.121	1.231	0.218
2	Alaska	−0.010	−0.020	0.077	0.127	0.899
3	Arizona	0.005	−0.020	0.093	0.265	0.791
4	Arkansas	0.037	−0.020	0.101	0.561	0.574
5	California	−0.135	−0.020	0.201	−0.573	0.567
6	Colorado	−0.092	−0.020	0.151	−0.479	0.632
7	Connecticut	0.043	−0.020	0.187	0.334	0.738
8	Delaware	−0.098	−0.020	0.190	−0.415	0.678
9	DC	−1.251	−0.020	0.245	−5.015	0.000 **
10	Florida	0.110	−0.020	0.113	1.151	0.250
11	Georgia	0.144	−0.020	0.118	1.389	0.165
12	Hawaii	−0.004	−0.020	0.069	0.233	0.816
13	Idaho	−0.003	−0.020	0.120	0.138	0.890
14	Illinois	0.096	−0.020	0.109	1.056	0.291
15	Indiana	0.044	−0.020	0.117	0.549	0.583
16	Iowa	−0.025	−0.020	0.113	−0.049	0.961
17	Kansas	0.014	−0.020	0.119	0.281	0.779
18	Kentucky	0.071	−0.020	0.119	0.764	0.445
19	Louisiana	0.088	−0.020	0.121	0.890	0.374
20	Maine	0.029	−0.020	0.163	0.296	0.767
21	Maryland	−0.165	−0.020	0.249	−0.583	0.560
22	Massachusetts	0.050	−0.020	0.233	0.299	0.765

Table 8. *Cont.*

No.	Location	Ii	E(Ii)	sd(Ii)	z	*p*-Value *
23	Michigan	−0.030	−0.020	0.099	−0.105	0.917
24	Minnesota	−0.017	−0.020	0.100	0.028	0.977
25	Mississippi	0.061	−0.020	0.120	0.666	0.506
26	Missouri	0.088	−0.020	0.110	0.980	0.327
27	Montana	0.015	−0.020	0.103	0.337	0.736
28	Nebraska	−0.031	−0.020	0.121	−0.093	0.926
29	Nevada	−0.198	−0.020	0.192	−0.928	0.353
30	New Hampshire	0.056	−0.020	0.199	0.382	0.703
31	New Jersey	−0.000	−0.020	0.157	0.123	0.902
32	New Mexico	0.009	−0.020	0.097	0.299	0.765
33	New York	0.012	−0.020	0.165	0.194	0.846
34	North Carolina	0.012	−0.020	0.121	0.264	0.792
35	North Dakota	0.161	−0.020	0.110	1.644	0.100 **
36	Ohio	0.034	−0.020	0.118	0.454	0.650
37	Oklahoma	0.046	−0.020	0.095	0.692	0.489
38	Oregon	0.002	−0.020	0.163	0.131	0.896
39	Pennsylvania	−0.151	−0.020	0.157	−0.834	0.404
40	Rhode Island	0.046	−0.020	0.229	0.285	0.775
41	South Carolina	0.089	−0.020	0.110	0.983	0.326
42	South Dakota	0.170	−0.020	0.111	1.713	0.087 **
43	Tennessee	0.117	−0.020	0.105	1.300	0.194
44	Texas	0.081	−0.020	0.089	1.131	0.258
45	Utah	−0.005	−0.020	0.107	0.138	0.890
46	Vermont	−0.009	−0.020	0.169	0.063	0.950
47	Virginia	−0.040	−0.020	0.148	−0.135	0.893
48	Washington	0.000	−0.020	0.163	0.121	0.904
49	West Virginia	−0.002	−0.020	0.115	0.152	0.879
50	Wisconsin	0.023	−0.020	0.102	0.420	0.675
51	Wyoming	−0.066	−0.020	0.150	−0.305	0.760
52	Puerto Rico	−0.365	−0.020	0.072	−4.799	0.000 **

* 2-tail test, ** with an obvious statistical significance.

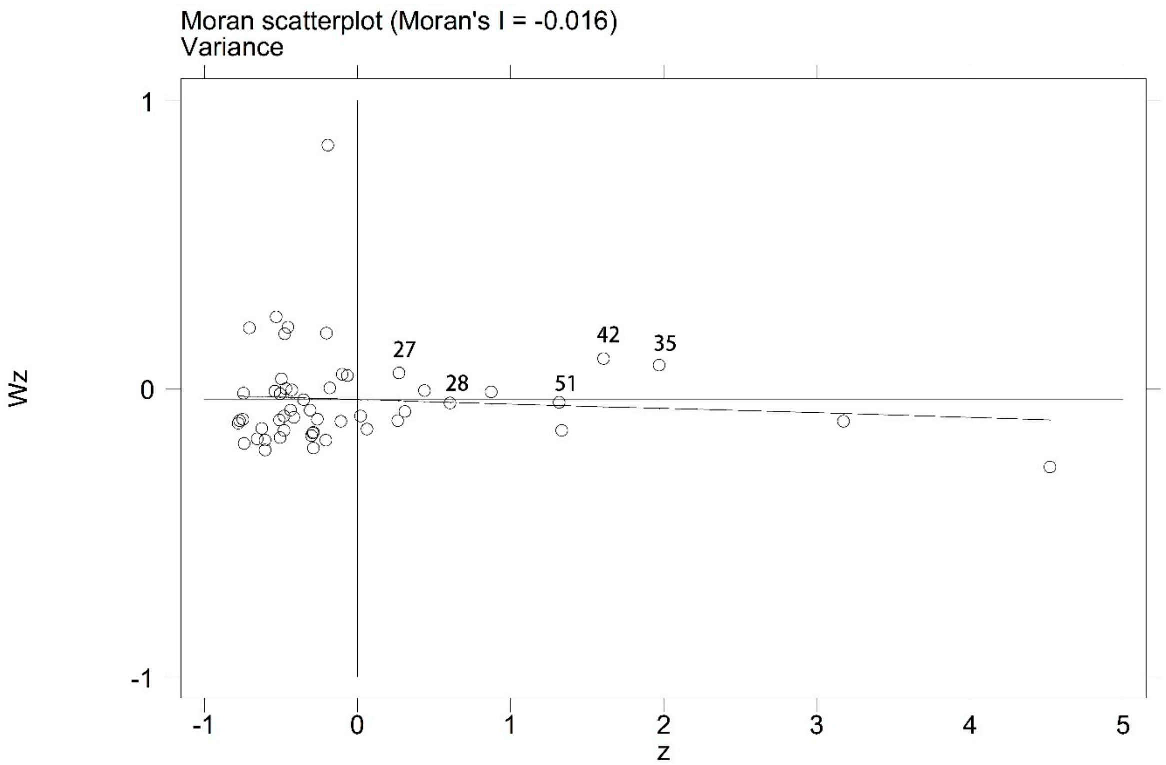

Figure 1. Scatterplot based on the variance values.

Besides the regional clustering feature with a statistical significance obtained from Moran's I analysis, we can also get a more direct sense of the regional appearance of IOIS from the map. Figure 2 shows the integrated occupational and industrial structural variant results in three by three digits. The map reveals some regional similarities in the amount of overall variance between each state and the national averages for the industry/occupation pairs. The southeastern US generally has smaller variance as do parts of the Midwest/rust belt and the southwest, including California; while the northern prairie states have industry/occupation distributions that are most different to the US averages. Some of the most populous US states (California, Texas, Illinois, Arizona, Florida, Georgia, Missouri) have a smaller variation with the US average. However, some of the more populated states (New York, New Jersey, Ohio, Virginia, Colorado, Michigan) show relatively higher variation with the US. Overall, the map shows that while there are some regional US patterns, some states still show individual variation.

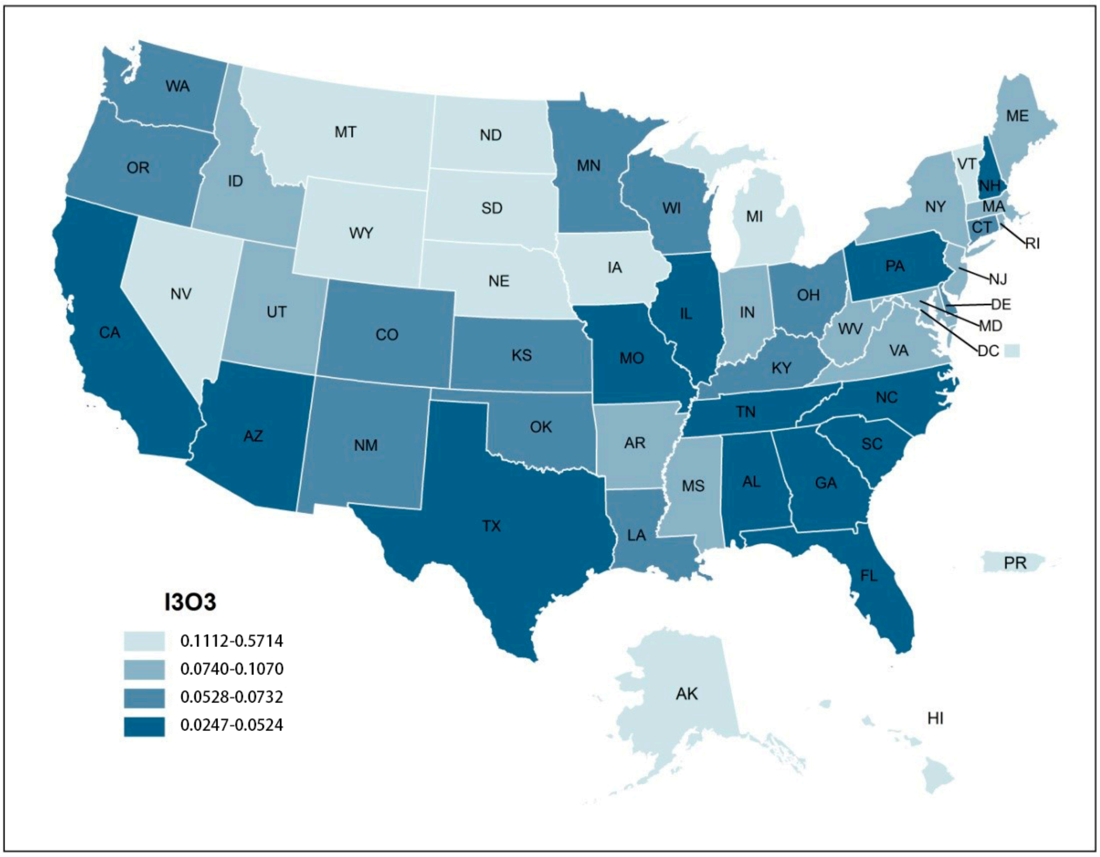

Figure 2. US States Industry/Occupation Variance by State.

5. Conclusions with Policy Implications and Further Work

The focus on the occupational mix in the regions and cities is nothing new. Researchers and planning practitioners have been making endeavors to integrate the occupational factor in economic development for the last several decades. The increasingly close linkages with the industrial analysis framework make occupations no longer just part of labor incentive research. The occupational analysis is supposed to be released out of the package and used broadly in the economic decision-making and agenda. The previous work in this field has done a lot to show the industrial and occupational analysis could not substitute each other. The gap and differences do, in fact, exist. Neither aspect will be neglected in effective planning practice. This paper constructs an integrated occupational and industrial structure (IOIS) to bind them together. It will lead to some policy implications in potential regional economic and human capital policy-making. Firstly, in regional perspective, the new integrated analytical approach will provide a more comprehensive and different view about the regional and national development situations. The state of California serves as the data source of the comparison between the integrated and single applied approach. It does demonstrate that the integrated approach reveals a bigger difference between the state and national level because the identified variance values increase when using the integrated approach. As a new perspective and method, it will serve as protentional policy information tools for the regional policy-making. It will better recognize the regional advantage and competitiveness compared with the national situation as a whole. Regions can gain an advantageous position by targeting more precisely in the development fields. This integrated framework provides a different option either in theoretical research or in practical plans. The occupation included a framework of the regional economy is of greater importance to the states which have an abundant human resource and creative talents, such as California. The single industrial analysis only provides the relatively fixed structure of the regional economy. And the single occupational analysis gives the limited information of the human resource pool. But the integrated framework tells us which kind of human resource is "alive" in the practical use corresponding to a certain industry. It helps the policy-makers bridge the industry requirement with the occupational supply by giving deeper insight into the regional development.

Secondly, in a national perspective, it is applied in the 52 state data files in PUMS. The overview of the national industrial and occupational status is provided. The snapshot shows most of the states have a highly similar occupational and industrial development with the national level. The occupations and industries are distributed relatively evenly across the nation. It needs further and detailed analysis in specific industries and areas to identify more potential benefits. In some sense, the results reflect that occupations play an even more important role in the industrial structure. An adjustment, made by gradually more detailed data level in terms of either occupations or industries, reveals that focusing more on occupational mix helps the state IOIS become more differentiated from the national level, while the industrial framework does less. The value change range is even bigger in the occupational aspect compared with the industrial one. It goes further to suggest the occupational aspect and human resources play an important role in achieving a unique regional advantage across the nation. From the variance results of the states, we learn that some states (such as Florida, Hawaii, Indiana, Michigan, Nevada) are not sensitive to the changes of more detailed occupational information. For example, their variance values even decrease when the I3O2 change to I3O3, indicating they grow more similar to the national average level. It might be an indication that under certain industrial frame, the human resource is in a disadvantageous position. In comparison, some states (such as California, Illinois, Maryland, to just name a few) have variance values increase from I3O2 to I3O3. These states have more available human capital potential. From the national point of view, it will help the policy makers mobilize the human resource and formulate labor incentive policies in a larger range more effectively.

The integrated industrial and occupational approach provided in this paper is just a start. Upcoming research shall be in more detailed and specific industrial and occupational groups to help with the policy-making of the urban and regional development. Because the occupational and human capital focus is mostly related to the industries containing the most knowledge and skill-intensified contents, the future research shall involve more efforts in the creative and knowledge industrial groups with the generalized ISIO approach. Of course, the creative industries refer to the broad sense, including design, software developing, art, performing, consulting and so on., all of which are of great significance to upgrade the industrial development and refuel the regional growth.

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Appendix A. IOIS Matrix of the State of California in Two-Digit NAICS by Two-Digit SOC Data Level in Actual Numbers, 2006–2010

Table A1. IOIS Matrix of the State of California in Two-Digit NAICS by Two-Digit SOC Data Level in Actual Numbers, 2006–2010.

	SOC																					
NAICS	**11**	**13**	**15**	**17**	**19**	**21**	**23**	**25**	**27**	**29**	**31**	**33**	**35**	**37**	**39**	**41**	**43**	**45**	**47**	**49**	**51**	**53**
11	53,650	3282	392	632	4009	55	118	214	589	129	10	5178	444	8126	5136	3418	15,737	311,783	1857	5958	7408	27,510
21	2974	1088	438	1691	1047	.	83	46	98	107	.	109	26	368	.	527	2283	.	12,075	3039	2805	36,56
22	17,581	8631	5354	13,546	3464	73	877	513	1220	550	22	1528	12	2635	24	R55	28,383	399	13,473	15,259	24,728	5322
23	175,806	28,694	2182	22,013	1085	44	725	309	3925	88	15	1763	69	8263	246	14,326	89,603	555	1 × 10ˆ6	55,808	25,074	31,032
31	32,495	10,763	2537	2010	4270	18	225	362	7650	190	14	658	5288	7506	554	26,340	38,224	7273	1944	11,875	207,498	55,346
32	54,291	16,168	6806	11,273	18,667	135	854	653	8144	1700	85	1201	99	3976	111	23,347	49,502	354	7922	14,338	161,756	43,318
33	183,286	57,607	72,101	157,704	9974	41	3033	1977	22,705	1748	312	3149	890	8161	335	48,156	134,661	112	22,892	41,620	408,768	46,594
3M	4891	1699	860	2164	178	.	.	140	633	66	32	207	139	926	.	2439	7477	32	584	1444	27,084	6861
42	56,048	36,473	10,129	3606	2647	81	763	997	6683	772	299	1127	2343	6882	602	233,093	133,498	16,633	4058	17,983	26,541	128,552
44	49,674	31,919	14,994	2190	1058	86	1042	1510	15,024	40,763	6802	5197	36,560	16,253	3922	842,501	246,454	1948	11,618	63,888	57,243	143,296
45	19,308	17,445	6339	644	602	242	228	1730	15,651	1023	218	5601	5304	9300	5906	412,216	148,076	251	1542	9977	15,927	37,591
48	35,006	9478	2769	2958	404	27	150	1075	978	199	317	4255	1184	5509	16,710	9978	76,811	191	3765	31,254	4716	326,106
49	17,483	2839	1715	1103	27	.	91	332	137	120	12	867	196	3961	104	4909	154,996	171	479	5032	5544	77,360
4M	3685	3786	712	159	46	58	62	703	1846	107	16	369	568	886	225	102,612	21,706	21	117	2521	1791	3200
51	90,126	24,274	51,915	18,671	2321	40	3788	13,972	14,4287	172	81	1957	4465	4205	9843	64,885	104,115	.	5190	46,970	14,287	12,892
52	151,592	209,499	36,478	1437	2385	1739	11,513	2194	3808	3126	331	4448	162	1581	576	157,072	299,222	50	613	2125	2232	831
53	124,599	32,571	3701	930	683	824	4359	448	2345	378	585	2924	3082	28,883	2615	196,589	76,204	67	7990	15,961	3927	16,376
54	205,477	211,746	195,583	137,364	66,446	1805	162,224	6035	123,909	24,604	5622	3123	561	5003	4852	49,947	248,069	235	7914	13,239	20,575	8097
55	4086	2233	1235	347	187	49	544	90	360	143	.	58	77	250	108	589	5243	.	83	101	182	302
56	61,414	36,390	9767	5156	2875	1293	4677	1839	8811	13,501	5992	104,356	3402	390,164	6410	47,274	152,762	2269	15,276	32,496	33,835	85,960
61	130,048	32,709	26,470	7319	31,402	41,064	1461	100,1046	34,975	27,023	5555	15,298	49,595	66,046	49,146	10,553	193,282	462	8033	13,186	5674	21,612
62	142,624	40,081	20,791	2816	37,432	135,837	3457	83,835	7586	680,847	323,303	7882	41,080	59,219	335,115	9481	351,657	94	3569	7694	16,606	18,263
71	31,238	16,825	3508	1399	1758	1305	821	11,141	135,328	1180	3432	29,285	40,627	43,042	129,618	38,877	46,878	604	3658	9727	3851	12,270
72	159,381	9798	1324	616	292	431	312	2805	3908	674	1394	6977	914,915	80,205	19,003	160,899	74,948	202	1945	5635	14,478	29,150
81	56,708	21,609	5986	2454	1727	71,882	2088	8695	13,478	3813	19,760	3930	7381	144,325	281,554	58,156	97,184	518	4352	162,169	72,828	65,263
92	81,187	83,684	35,987	29,713	20,611	38,559	40,152	14,621	9766	28,341	13,481	229,157	5450	20,738	31,051	3377	208,909	2965	17,001	40,207	9292	21,517

Appendix B. IOIS Matrix of the US in Two-Digit NAICS by Two-Digit SOC Data Level in Actual Numbers, 2006–2010

Table A2. IOIS Matrix of the US in Two-Digit NAICS by Two-Digit SOC Data Level in Actual Numbers, 2006–2010.

	SOC																					
NAICS	**11**	**13**	**15**	**17**	**19**	**21**	**23**	**25**	**27**	**29**	**31**	**33**	**35**	**37**	**39**	**41**	**43**	**45**	**47**	**49**	**51**	**53**
11	847,000	18,055	3949	4712	34,676	435	442	2275	3724	2095	657	21,480	4469	39,021	47,454	22,447	95,224	1 × 10ˆ6	13,208	28,848	40,623	120,867
21	79,327	31,311	11,083	43,188	24,305	70	4475	980	2338	1780	0	4355	1694	7026	235	11,378	69,985	228	314,951	66,260	54,470	103,242
22	144,307	67,749	43,347	106,632	26,584	535	5410	5140	9837	5059	79	13,024	443	26,769	214	21,001	262,060	1280	119,496	206,084	266,185	57,166
23	1,445,127	218,984	20,112	158,605	7435	740	5637	2756	29,819	2695	463	27,636	1971	61,963	3221	132,578	746,658	6133	9,204,169	598,165	243,444	363,352
31	233,423	81,484	25,248	29,138	39,134	208	2158	3366	30,793	3375	366	7179	35,000	63,521	2133	164,784	278,230	23,052	19,103	126,038	1,484,172	471,833
32	562,212	185,535	84,514	161,542	175,822	492	9454	7421	70,060	17,455	1740	14,411	2122	66,437	1621	220,950	562,505	9375	117,065	217,781	1,988,118	595,432
33	1,161,634	410,697	367,621	989,501	51,893	795	14,851	18,187	125,492	16,726	2411	25,660	3696	114,380	2204	361,454	1,065,870	989	251,485	505,573	4,666,107	700,516
3M	33,150	12,344	4605	13,201	1411	161	430	673	2947	322	268	1286	733	9888	293	17,862	45,704	127	5873	12,110	215,945	63,298
42	400,040	260,418	79,554	32,715	17,393	441	6609	6885	41,615	10,075	2424	8274	16,089	45,176	2953	1,779,781	985,294	60,662	38,325	198,142	207,272	1,008,606
44	389,787	241,865	101,132	16,648	8253	919	17,032	11,426	99,953	490,423	46,919	34,397	397,083	133,630	19,596	7,245,578	2,072,594	17,671	95,777	601,368	467,394	1,292,112
45	168,501	149,979	47,002	5545	4964	1098	2620	15,766	135,863	21,862	3025	44,023	68,257	101,000	44,821	3,819,559	1,373,493	2886	17,367	114,096	158,147	393,581
48	307,536	85,815	35,192	31,181	3412	1100	3539	10,976	8660	2777	2560	42,908	11,885	48,638	179,729	96,544	668,648	4970	64,701	325,410	69,309	3,117,644
49	164,823	29,205	18,285	10,669	1023	172	1052	2322	1445	1021	106	7769	725	36,869	850	36,010	1,252,794	1060	4291	45,079	40,456	568,052
4M	25,124	25,919	5644	860	617	145	354	4011	14,440	767	413	2897	5974	10,360	2153	779,271	162,775	174	1501	19,701	21,760	29,446
51	563,542	146,104	334,589	132,303	16,354	1636	16,204	139,077	664,700	1239	385	9904	38,212	31,816	49,231	531,421	855,145	141	17,556	384,565	109,960	78,119
52	1,340,730	2 × 10ˆ6	421,984	15,625	21,169	14,329	85,314	24,928	30,132	37,932	3214	38,669	3594	29,074	3787	1,389,574	2,896,675	168	5226	23,127	24,211	10,130
53	758,265	195,911	22,847	7366	3622	6968	27,335	3122	13,663	5290	6299	33,497	26,950	305,441	34,708	1,301,462	510,109	249	69,905	150,024	27,003	131,585
54	1,349,083	2 × 10ˆ6	1 × 10ˆ6	991,258	389,385	14,368	1,239,194	48,988	726,291	215,281	58,008	24,760	4516	41,594	46,576	360,111	1,875,090	3573	65,106	93,960	156,700	64,617
55	43,562	27,796	13,186	2560	1701	478	3923	773	2558	1368	303	1505	886	2131	523	5414	47,525	50	919	1953	2650	3227
56	485,123	280,008	90,341	37,161	20,950	13,695	33,305	20,125	48,648	125,002	79,758	665,961	35,585	3 × 10ˆ6	40,854	449,474	1,364,071	17,509	130,951	202,352	329,620	681,321
61	1,111,749	246,597	238,725	54,819	237,176	384,757	13,023	9,063,986	282,040	303,019	39,156	156,177	557,241	743,623	351,004	101,151	1,643,186	3386	79,632	132,996	60,635	346,493
62	1,289,298	338,811	167,811	23,727	228,796	1 × 10ˆ6	30,880	829,641	58,944	6,838,313	3,650,779	91,978	528,751	680,512	2,276,166	83,063	3,201,401	1770	47,861	96,250	213,860	184,382
71	210,014	81,029	18,853	8862	15,548	13,898	2733	97,624	773,426	8047	22,027	340,445	372,659	412,341	989,291	279,231	331,951	5953	26,964	82,999	28,603	99,720
72	1,402,381	80,965	11,322	4643	2827	7479	2724	27,986	35,137	5424	8310	69,938	8,605,685	769,346	215,606	1,252,807	635,670	1810	18,106	51,572	131,210	286,853
81	514,791	173,981	48,193	15,451	18,462	758,893	18,104	73,292	158,661	31,433	142,869	30,707	75,716	856,202	2,177,310	481,660	930,413	3112	36,446	1,273,193	571,557	450,793
92	841,951	738,358	304,787	204,626	193,890	387,304	332,932	124,825	83,087	246,013	68,632	2 × 10ˆ6	54,187	194,597	104,775	29,594	1,905,716	24,732	146,623	315,399	99,341	196,510

Appendix C. Details of Standard Errors Going with Variance results between the 50 states of the US

Table A3. Details of Standard Errors Going with Variance results between the 50 states of the US.

	I2O2	I2O3	I3O2	I3O3
Alabama	0.0015	0.0014	0.0015	0.0017
Alaska	0.0083	0.0097	0.0091	0.0103
Arizona	0.0015	0.0019	0.0016	0.0021
Arkansas	0.0023	0.0026	0.0028	0.0029
California	0.0004	0.0006	0.0005	0.0007
Colorado	0.0016	0.0022	0.0017	0.0023
Connecticut	0.0021	0.0024	0.0026	0.0026
Delaware	0.0047	0.0063	0.0050	0.0081
D.C.	0.0094	0.0114	0.0112	0.0138
Florida	0.0008	0.0008	0.0009	0.0009
Georgia	0.0008	0.0010	0.0007	0.0010
Hawaii	0.0049	0.0052	0.0055	0.0060
Idaho	0.0043	0.0055	0.0042	0.0054
Illinois	0.0008	0.0009	0.0008	0.0010
Indiana	0.0031	0.0023	0.0024	0.0021
Iowa	0.0030	0.0039	0.0030	0.0040
Kansas	0.0020	0.0032	0.0026	0.0037
Kentucky	0.0022	0.0019	0.0019	0.0021
Louisiana	0.0015	0.0017	0.0018	0.0018
Maine	0.0036	0.0040	0.0039	0.0051
Maryland	0.0021	0.0021	0.0021	0.0026
Massachusetts	0.0016	0.0020	0.0023	0.0026
Michigan	0.0022	0.0024	0.0028	0.0030
Minnesota	0.0016	0.0019	0.0016	0.0022
Mississippi	0.0022	0.0020	0.0024	0.0026
Missouri	0.0008	0.0011	0.0011	0.0014
Montana	0.0048	0.0072	0.0045	0.0071
Nebraska	0.0040	0.0063	0.0050	0.0062
Nevada	0.0051	0.0048	0.0058	0.0053
New Hampshire	0.0031	0.0041	0.0035	0.0049
New Jersey	0.0016	0.0018	0.0020	0.0024
New Mexico	0.0031	0.0039	0.0025	0.0037
New York	0.0011	0.0014	0.0014	0.0017
North Carolina	0.0007	0.0008	0.0007	0.0010
North Dakota	0.0082	0.0125	0.0081	0.0124
Ohio	0.0015	0.0016	0.0016	0.0018
Oklahoma	0.0012	0.0021	0.0017	0.0025
Oregon	0.0017	0.0028	0.0018	0.0032
Pennsylvania	0.0007	0.0010	0.0007	0.0010
Rhode Island	0.0036	0.0053	0.0050	0.0068
South Carolina	0.0014	0.0016	0.0017	0.0018
South Dakota	0.0090	0.0134	0.0084	0.0125
Tennessee	0.0016	0.0014	0.0015	0.0014
Texas	0.0006	0.0008	0.0005	0.0007
Utah	0.0021	0.0027	0.0024	0.0031
Vermont	0.0054	0.0074	0.0068	0.0086
Virginia	0.0017	0.0019	0.0021	0.0025
Washington	0.0010	0.0016	0.0012	0.0022
West Virginia	0.0031	0.0039	0.0035	0.0042
Wisconsin	0.0029	0.0026	0.0018	0.0022
Wyoming	0.0079	0.0097	0.0079	0.0112
Puerto Rico	0.0060	0.0077	0.0078	0.0088

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