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The Method of Reflections and U.S. Occupational Employment

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Abstract

This paper applies the method of reflections to location quotients in the labor markets of U.S. cities. A location quotient is an occupation's share of a city's employment relative to the national average, like a country's revealed comparative advantage. The method of reflections relates the *diversity* of U.S. cities (how many occupations do they have?) to the *ubiquity* of occupations (how many cities have them?).

We find that incorporating information about the ubiquity of occupations changes the diversity rankings of U.S. cities in interesting ways. Compared to using location quotients, the method of reflections provides results that are more strongly correlated with wages in U.S. cities. When looking at the change in wages from 2006 to 2017, the relationships are in the expected directions: cities that become more diverse tend to have greater increases in wages, while occupations that become more ubiquitous tend to have smaller increases (or even decreases) in wages. This paper does not make an argument about the causal relationship between city diversity and occupational ubiquity, but it discusses some of the suggestive patterns in these results.

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Introduction

This paper applies the method of reflections, an economic analysis of country complexity that uses international trade data, to location quotients in the labor markets of U.S. cities. We find that incorporating information about the ubiquity of occupations changes the diversity rankings of U.S. cities in interesting ways. Compared to location quotients, the method of reflections provides results that are more strongly correlated with wages in U.S. cities. When looking at the change in wages from 2006 to 2017, the relationships are in the expected directions: cities that become more diverse tend to have greater increases in wages, while occupations that become more ubiquitous tend to have smaller increases (or even decreases) in wages.

Location Quotients

A location quotient measures the concentration of a particular occupation in a particular city, relative to the concentration of that occupation in the country overall. "Concentration" means the employment in that occupation divided by total employment in all occupations. Location quotients carry information about which jobs are concentrated in which cities, and how different cities host unique sets of jobs compared to national averages. The calculation of a location quotient is exactly analogous to the calculation of a revealed comparative advantage in international trade. Here we use data from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics.[1]

Mathematically,

$$X_{ro} = number\ of\ jobs\ in\ region\ r\ in\ occupation\ o$$

$$Location\ Quotient_{ro} = \frac{X_{ro}}{\sum_o X_{ro}} \Big/ \frac{\sum_r X_{ro}}{\sum_{r,o} X_{ro}}$$

For example, in 2017, people employed as "economists" were 0.37 percent of all employees in Washington DC (there were 9,240 economists in a total Washington DC workforce of 2.5 million).[2] However, people employed as economists were only 0.01 percent of all employees in the United States (there were 16,050 economists in a total U.S. workforce of 120 million). This gives "economists in Washington DC" a (very high) location quotient of 0.37 / 0.01 = 37.

There is a wide range in the variety of occupations found in different U.S. cities. A simple but revealing calculation looks at a city and sums the number of occupations it hosts with a location quotient of greater than or equal to one.[3] Larger U.S. cities tend to have more occupations with a location quotient greater than or equal to one, even though location quotients use a city's total population in the

[1] BLS collects data from employers, but not from self-employed workers.

[2] "Economists" are code 19-3011 in the BLS's standard occupational classification system.

[3] Some of the metropolitan and non-metropolitan area names are shortened for clarity. For example, the full BLS listings are: Minneapolis-St. Paul-Bloomington, MN-WI; Los Angeles-Long Beach-Glendale, CA Metropolitan Division; Baltimore-Columbia-Towson, MD; Portland-Vancouver-Hillsboro, OR-WA; New York-Jersey City-White Plains, NY-NJ Metropolitan Division; Phoenix-Mesa-Scottsdale, AZ; San Diego-Carlsbad, CA; Chicago-Naperville-Arlington Heights, IL Metropolitan Division; Houston-The Woodlands-Sugar Land, TX; etc.

denominator. For example, Portsmouth, NH ranks highest among U.S. cities with total employment below 100,000, but still has just 189 occupations with a location quotient greater than or equal to one. That is less than half of the figure for Minneapolis. (Equivalently, the only cities that host more than 189 occupations with a location quotient greater than or equal to one have at least 100,000 total employment.) This is a revealing point about the distribution of occupations in U.S. cities: larger cities have a *more-than-proportionate* variety of occupations.[4]

Table 1 U.S. cities by number of occupations with a location quotient ≥ 1 in 2017

(Top 10)		*(Bottom 10)*	
City	**Number of occupations**	**City**	**Number of occupations**
Minneapolis, MN	388	Dalton, GA	70
Los Angeles, CA	375	Columbus, IN	69
Baltimore, MD	375	Midland, MI	67
Portland, OR	374	Arecibo, PR	67
New York, NY	363	Walla Walla, WA	66
San Diego, CA	355	Danville, IL	66
St. Louis, MO	353	Kokomo, IN	58
Phoenix, AZ	352	San German, PR	56
Boston, MA	349	Hinesville, GA	49
Chicago, IL	349	Guayama, PR	40

Source: BLS Occupational Employment Statistics, author’s calculations.

Method of Reflections

In the context of international trade, the method of reflections is from César Hidalgo and Ricardo Hausmann’s work on product space and economic complexity.[5] Hidalgo and Hausmann look at different exports from different countries and relate the diversity of a country (how many different products does that country export?) to the ubiquity of an export (how many different countries export that product?). Some very diverse countries export many products, while some very ubiquitous products are exported by most countries. Countries that export few products usually export only ubiquitous products, but highly diversified countries are the only ones to export certain rare products.

Hidalgo and Hausmann’s insight is that country diversity and product ubiquity can be combined recursively.[6] This yields a measure of economic complexity, which is found to be both correlated with a country’s level of income and predictive of future growth. This analysis has been extended by Ourens

[4] Many studies of networks find that the value of a network increases at a greater-than-linear rate with each additional node in the network. Shutters et al., “Urban Occupational Structures as Information Networks,” 2018.
[5] Hidalgo and Hausmann, “The Building Blocks of Economic Complexity,” June 30, 2009.
[6] “Recursively” means that elements of the set are defined in terms of other elements of the set. See below for a more detailed example of the method of reflections.

(who finds that method of reflections indicators are good predictors of long-term growth),[7] Felipe et al. (who compare economic complexity with other indices of technological complexity),[8] and others.

In this paper we apply that analytical method to U.S. cities and occupations, instead of countries and exports. It combines the information in city diversity (how many occupations a city hosts) and occupational ubiquity (how rare an occupation is). For a city, we calculate the ubiquity of the occupations that it hosts, and incorporate the diversity of the other cities that host such occupations, then the ubiquity of the occupations in those cities, and so on. For an occupation, we calculate the diversity of the cities that host it, and incorporate the ubiquity of the other occupations that those cities host, then the diversity of cities that host those occupations, and so on. The motivating question is whether the patterns of occupations in U.S. cities are analogous to the patterns of revealed comparative advantage in countries, where ubiquitous occupations can be found in most U.S. cities while diverse cities host even rare occupations.

We use a matrix of occupational concentration. For region r and occupation o,

$$M_{ro} = \begin{cases} 1\ if\ Location\ Quotient_{ro} \geq 1 \\ 0\ otherwise \end{cases}$$

(In the above example, the location quotient of economists in Washington DC is easily 1.) We then sum over rows and columns to calculate the diversity of region r and the ubiquity of occupation o:

$$Diversity_r = k_{r,0} = \sum_o M_{ro}$$

$$Ubiquity_o = k_{o,0} = \sum_r M_{ro}$$

Here, $k_{r,0}$ is the 0th order diversification of region r and $k_{o,0}$ is the 0th order ubiquity of occupation o.

We then calculate iteratively:

$$k_{r,N} = \frac{1}{k_{r,0}} \sum_o M_{ro} * k_{o,N-1}$$

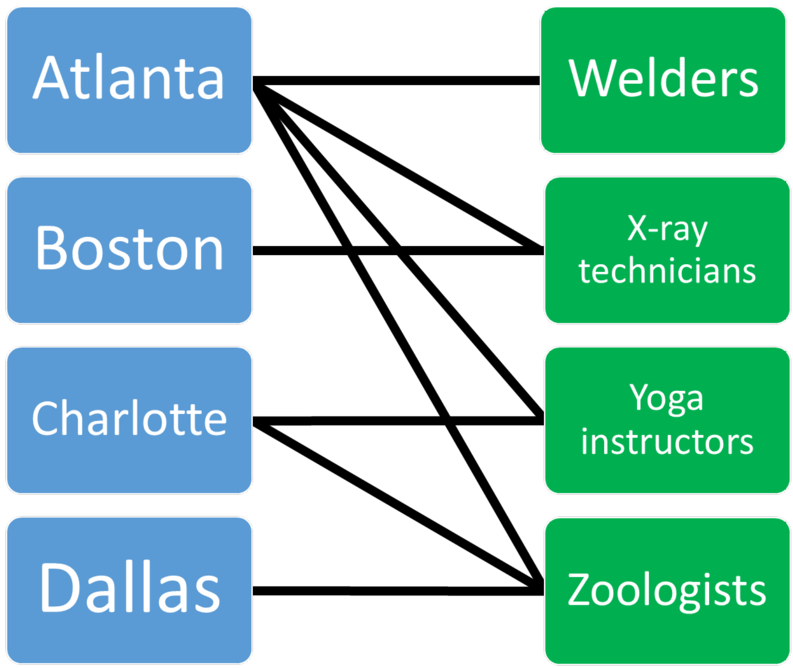
$$k_{o,N} = \frac{1}{k_{o,0}} \sum_r M_{ro} * k_{r,N-1}$$

Analogous to Hidalgo and Hausmann, the even-numbered variables ($k_{r,0}$, $k_{r,2}$, $k_{r,4}$, etc.) measure the occupational diversity of different U.S. cities. The odd-numbered variables ($k_{o,1}$, $k_{o,3}$, $k_{o,5}$, etc.) measure the ubiquity across U.S. cities of different occupations.

[7] Ourens, "Can the Method of Reflections Help Predict Future Growth?" 2013.
[8] Felipe et al., "Product Complexity and Economic Development," March 2012.

(A more detailed example of the method of reflections)

This example is from Hidalgo and Hausmann's "Supplementary Material for the Building Blocks of Economic Complexity," using U.S. cities and occupations instead of countries and exports. Say there are four cities (Atlanta, Boston, Charlotte, and Dallas) and four occupations (Welders, X-ray technicians, Yoga instructors, and Zoologists). A hypothetical method of reflections network might look like:



We can describe the network like this:

Regional diversity	***Occupational ubiquity***
$k_{r(Atlanta),0} = 4$	$k_{o(Welders),0} = 1$
$k_{r(Boston),0} = 1$	$k_{o(X-ray\ technicians),0} = 2$
$k_{r(Charlotte),0} = 2$	$k_{o(Yoga\ instructors),0} = 2$
$k_{r(Dallas),0} = 1$	$k_{o(Zoologists),0} = 3$

Next we calculate the first iteration:

Average ubiquity of a region's occupations (first iteration)	***Average diversity of an occupation's host regions (first iteration)***
$k_{r(Atlanta),1} = \left(\frac{1}{4}\right)(1+2+2+3) = 2$	$k_{o(Welders),1} = \left(\frac{1}{1}\right)(4) = 4$
$k_{r(Boston),1} = \left(\frac{1}{1}\right)(2) = 2$	$k_{o(X-ray\ technicians),1} = \left(\frac{1}{2}\right)(4+1) = 2.5$
$k_{r(Charlotte),1} = \left(\frac{1}{2}\right)(2+3) = 2.5$	$k_{o(Yoga\ instructors),1} = \left(\frac{1}{2}\right)(4+2) = 3$
$k_{r(Dallas),1} = \left(\frac{1}{1}\right)(3) = 3$	$k_{o(Zoologists),1} = \left(\frac{1}{3}\right)(4+2+1) = 2.33$

The second iteration uses the average first iteration values:

Average ubiquity of a region's occupations (second iteration)	***Average diversity of an occupation's host regions (second iteration)***
$k_{r(Atlanta),2} = \left(\frac{1}{4}\right)(4+2.5+3+2.33) = 2.96$	$k_{o(Welders),2} = \left(\frac{1}{1}\right)(2) = 2$
$k_{r(Boston),2} = \left(\frac{1}{1}\right)(2.5) = 2.5$	$k_{o(X-ray\ technicians),2} = \left(\frac{1}{2}\right)(2+2) = 2$
$k_{r(Charlotte),2} = \left(\frac{1}{2}\right)(3+2.33) = 2.66$	$k_{o(Yoga\ instructors),2} = \left(\frac{1}{2}\right)(2+2.5) = 2.25$
$k_{r(Dallas),2} = \left(\frac{1}{1}\right)(2.33) = 2.33$	$k_{o(Zoologists),2} = \left(\frac{1}{3}\right)(2+2.5+3) = 2.5$

Here, the most diverse city is Atlanta, which has all four occupations. Boston and Dallas have only one occupation each. However, the one occupation in Boston, X-ray technicians, is relatively rare: Atlanta is the only other city with that occupation. In contrast, the one occupation in Dallas, Zoologists, is more common. The iterations incorporate this information: when we calculate $k_{r,2}$, Boston has a higher value than Dallas, reflecting the fact that Boston's occupation is relatively non-ubiquitous and found only in more diverse cities.

Findings

We use the BLS Occupational Employment Statistics for May 2017. We look at 422 U.S. cities and 738 occupations, which excludes occupations that are only present in fewer than 10 cities.[9] We calculate the location quotient for each occupation in each city, set that location quotient equal to one if it is greater than or equal to a threshold value of one (and zero otherwise), and calculate the method of reflections up to the 18th iteration for cities and the 17th iteration for occupations.

See the attached Excel spreadsheet for these calculations.

City Diversity

The following table shows the top ten and bottom ten cities by their diversity rank using the method of reflections at the 18th iteration ($k_{r,18}$). "Diversity rank" means that the city with the highest $k_{r,18}$ value is first, the city with the second-highest $k_{r,18}$ value is second, and so on.

Table 2 Top 10 and bottom 10 cities by diversity rank using the method of reflections ($k_{r,18}$)

(Top 10)	***(Bottom 10)***
Washington, DC	Goldsboro, NC
New York, NY	Elmira, NY
San Francisco, CA	Gettysburg, PA
Seattle, WA	Hinesville, GA
Boston, MA	Michigan City, IN
Los Angeles, CA	San German, PR
Chicago, IL	Bay City, MI
Atlanta, GA	Kokomo, IN
Minneapolis, MN	Rome, GA
San Diego, CA	Danville, IL

Source: BLS Occupational Employment Statistics, author's calculations.

The following table shows the biggest changes between city rankings using location quotients (described earlier and shown in Table 1) and city rankings using the method of reflections at $k_{r,18}$. Rankings do not capture the magnitude of the differences between cities, but they do convey interesting information. Overall the two rankings are closely correlated, but the differences are revealing. The method of reflections finds that certain occupations are especially strong contributors to diversity, so some cities rise significantly in the rankings: they host relatively few occupations, but the occupations they do host are relatively rare. Conversely, cities that host many occupations can drop in the rankings if those occupations are relatively ubiquitous, as method of reflections incorporates information about that ubiquity.

[9] "Present" here means that the occupation has a location quotient greater than or equal to one.

Table 3 Top 10 and bottom 10 cities by change in rank (location quotient to method of reflections)

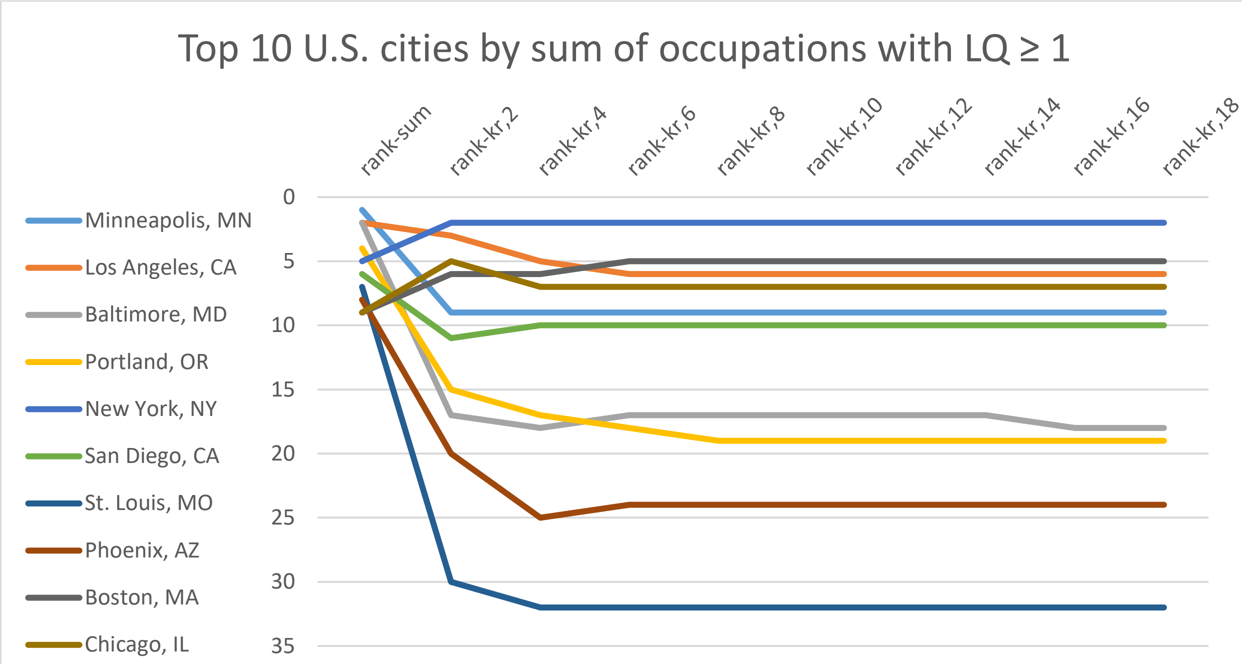
(Biggest increase in rank)		***(Biggest decrease in rank)***	
California-Lexington Park, MD	From 408th to 110th	Fort Smith, AR	From 202nd to 291st
Ithaca, NY	From 367th to 148th	Prescott, AZ	From 232nd to 322nd
Elkhart, IN	From 370th to 201st	Grand Junction, CO	From 224th to 314th
State College, PA	From 365th to 203rd	Redding, CA	From 222nd to 312th
Corvallis, OR	From 341st to 180th	Mount Vernon, WA	From 253rd to 346th
Salinas, CA	From 295th to 144th	Florence, SC	From 227th to 323rd
Bloomington, IL	From 319th to 170th	Staunton, VA	From 305th to 403rd
Carson City, NV	From 399th to 253rd	Youngstown, PA	From 116th to 218th
Kahului, HI	From 297th to 152nd	Owensboro, KY	From 270th to 381st
Napa, CA	From 313th to 174th	Kingsport, TN	From 143rd to 254th

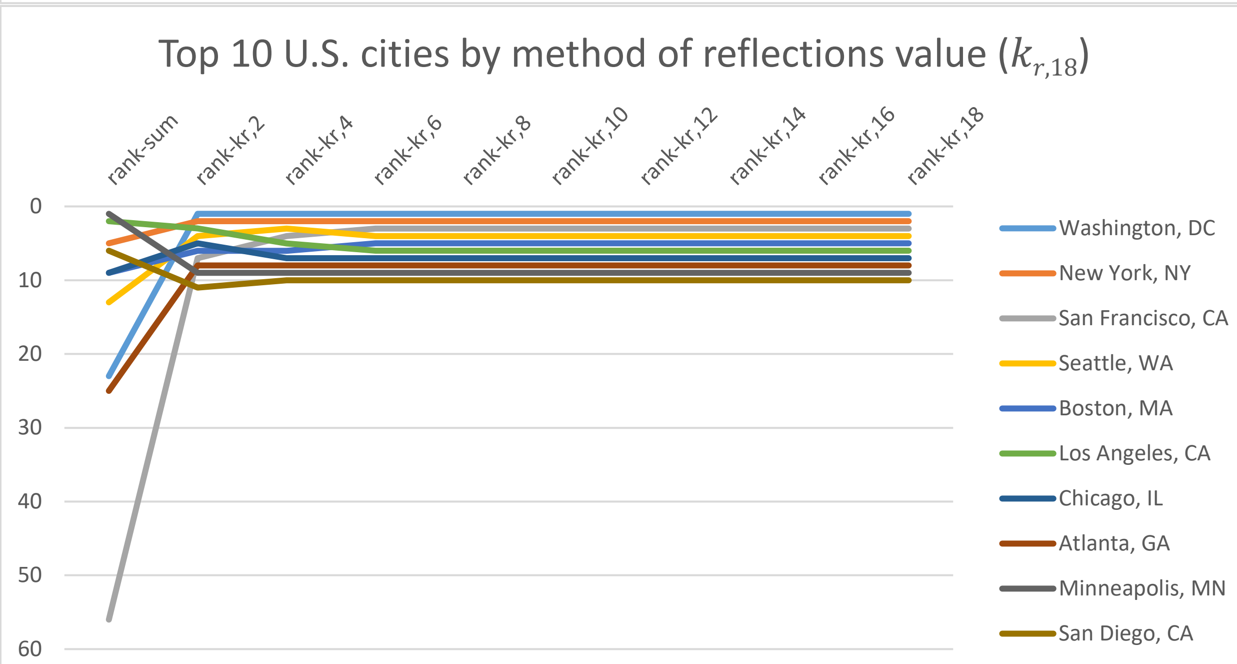
Source: BLS Occupational Employment Statistics, author's calculations. Note that increasing in rank here means going from a high number to a low number- for example, increasing from the 408th most-diverse city (where 407 cities are more diverse) to the 110th most-diverse city (where only 109 cities are more diverse).

To illustrate this process more fully, figure 1 shows the top ten U.S. cities ranked in two different ways. First, by the number of occupations they host with a location quotient greater than or equal to one. Second, by their rank using the method of reflections value at $k_{r,18}$. Some cities change significantly in the rankings. San Francisco, for example, was ranked 56th among U.S. cities when counting the number of occupations hosted with a location quotient greater than or equal to one. It had only 268 such occupations, compared to 388 in Minneapolis. However, after incorporating information about the rarity of those occupations, San Francisco rose to third place. The city had more than the national average of six of the ten most rare occupations, including genetic counselors, artists, fashion designers, dancers, and mathematicians (see Table 4).[10] In contrast, St. Louis was ranked seventh among U.S. cities when counting the 353 occupations it hosted, but fell to 32nd when using the method of reflections. The city had more than the national average of fourteen of the twenty most ubiquitous occupations (cashiers, tellers, cooks, police officers, maintenance workers, mail carriers, water treatment plant operators, etc.), but only one of the ten most rare (dancers). The following figure 2 shows all U.S. cities starting with rankings by location quotient and going through rankings in method of reflections iterations. Select cities are highlighted, to show how places like Austin TX and Cape Coral FL rise in rank while Winston-Salem NC and Topeka KS fall in rank when we consider the rarity of the occupations they host.

[10] These are BLS categories: "artists" refers to artists and related workers not listed elsewhere (27-1019); fashion designers design clothing and accessories, creating original designs or adapting fashion trends (27-1022); and dancers perform dances on stage, for broadcasting, or for video recording (27-2031).

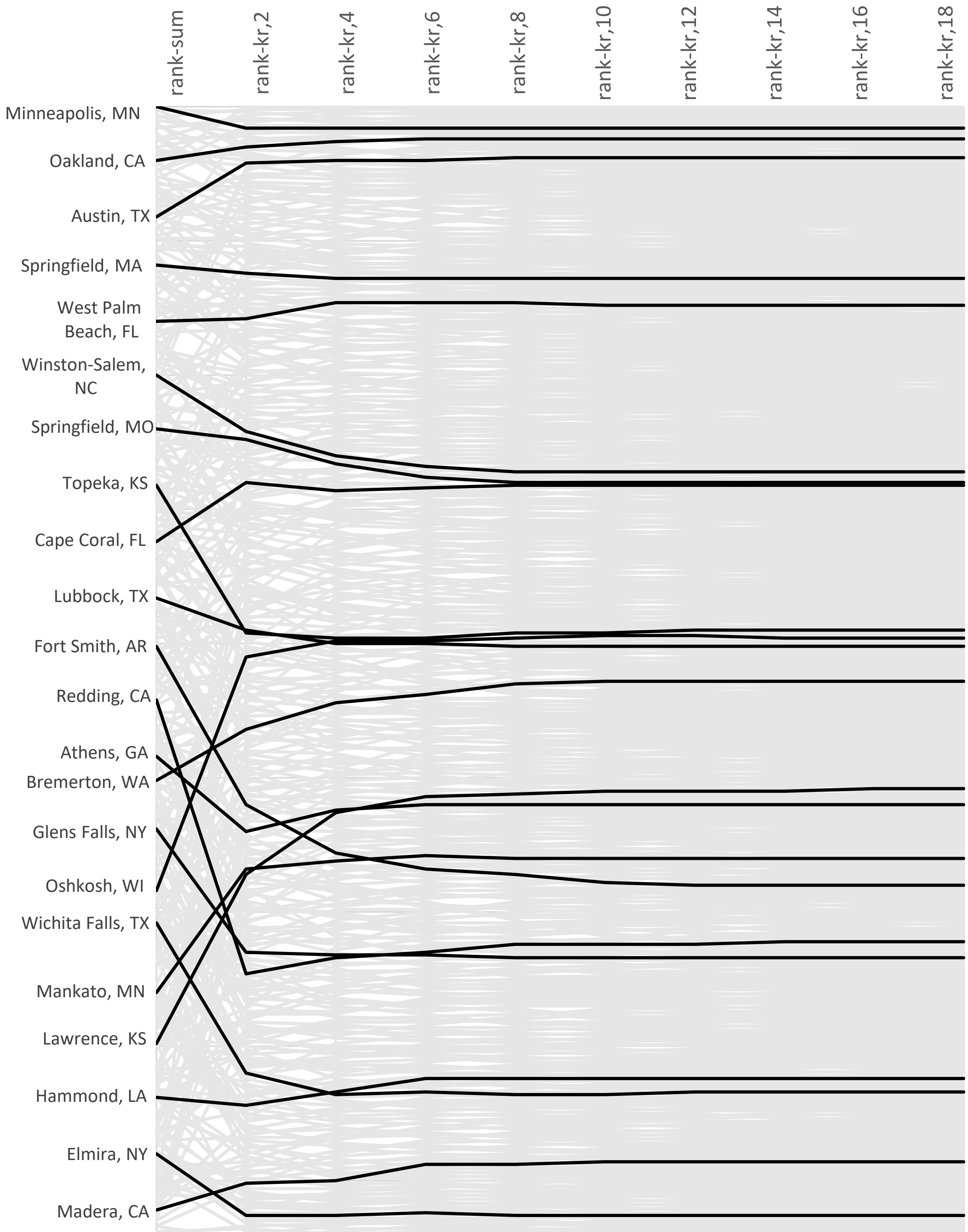
Figure 1 Top ten U.S. city rankings by location quotients and by the method of reflections





Source: BLS Occupational Employment Statistics, author’s calculations.

Figure 2 Select U.S. city rankings in method of reflections iterations



Source: BLS Occupational Employment Statistics, author's calculations.

Occupational Ubiquity

We use the method of reflections to quantify the rarity of occupations in the United States. The following table shows the top ten and bottom ten occupations by rarity using the method of reflections at the 17th iteration.

Table 4 Top 10 and bottom 10 occupations by rarity rank using the method of reflections ($k_{o,17}$)

(Top 10, most rare)	*(Bottom 10, most ubiquitous)*
Genetic counselors	Parts salespersons
Sociologists	Postal service mail carriers
Geography teachers, postsecondary	Maintenance and repair workers, general
Artists and related workers, all other	Police and sheriff's patrol officers
Fashion designers	Welders, cutters, solderers, and brazers
Flight attendants	Industrial machinery mechanics
Door-to-door sales workers, news and street vendors, and related workers	Cooks, institution and cafeteria
Dancers	First-line supervisors of retail sales workers
Mathematicians	Tellers
Architecture teachers, postsecondary	Cashiers

Source: BLS Occupational Employment Statistics, author's calculations.

The following table shows the biggest changes between occupational ubiquity rankings using location quotients and occupational ubiquity rankings in the method of reflections at $k_{o,17}$. The method of reflections finds that certain occupations rise significantly in the rankings, as the cities that host them are especially diverse. For example, in 2017 post-secondary physics teachers were somewhat rare in the United States using the location quotient calculation: they ranked as the 232nd most rare occupation. But post-secondary physics teachers were especially likely to be found in very diverse cities. Eight of the ten most diverse cities hosted post-secondary physics teachers with a location quotient greater than or equal to 1 (Washington DC, New York NY, Seattle WA, Boston MA, Los Angeles CA, Chicago IL, Minneapolis MN, and San Diego CA), while post-secondary physics teachers were not in any of the 268 least-diverse cities. Post-secondary physics teachers were only somewhat rare, but they tended to be *co-located* with very rare occupations. So, when incorporating information about city diversity using the method of reflections, post-secondary physics teachers rose in the rankings to become the 77th most rare occupation.

In contrast, metal and plastic patternmakers were among the rarest occupations in the United States based on location quotients, as only ten cities hosted that occupation. But many of those ten cities were not very diverse: they included Lancaster, PA (the 103rd most diverse U.S. city), Peoria, IL (194th), Waterloo, IA (244th), and Anniston, AL (319th). Metal and plastic patternmakers were very rare, but they tended to be *co-located* with very common occupations. So metal and plastic patternmakers fell from a rarity ranking of 1st using location quotients to 403rd using the method of reflections.

Table 5 Top 10 and bottom 10 occupations by change in rank (location quotient to method of reflections)

(Biggest increase in rank)		*(Biggest decrease in rank)*	
Compensation/benefits managers	From 291st to 85th	Logging equipment operators	From 249th to 653rd
Database administrators	From 328th to 138th	Helpers for extraction workers (such as drillers and derrick operators)	From 55th to 496th
Sociology teachers	From 273rd to 98th	Agricultural equipment operators	From 173rd to 616th
Administrative law judges	From 255th to 83rd	Roustabouts (repairers of oil field equipment)	From 173rd to 623rd
Nuclear medicine technologists	From 423rd to 255th	Agricultural workers, other	From 10th to 482nd
Insurance underwriters	From 362nd to 194th	Textile winding machine setters (who operate machines that wind textiles)	From 22nd to 509th
Interior designers	From 362nd to 197th	Rotary drill operators, oil/gas	From 55th to 550th
Accountants	From 315th to 150th	Derrick operators, oil/gas	From 18th to 545th
Curators	From 245th to 80th	Service unit operators, oil/gas/mining	From 123rd to 659th
Training and development managers	From 339th to 175th	Farmworkers and laborers, crop/nursery/greenhouse	From 164th to 717th

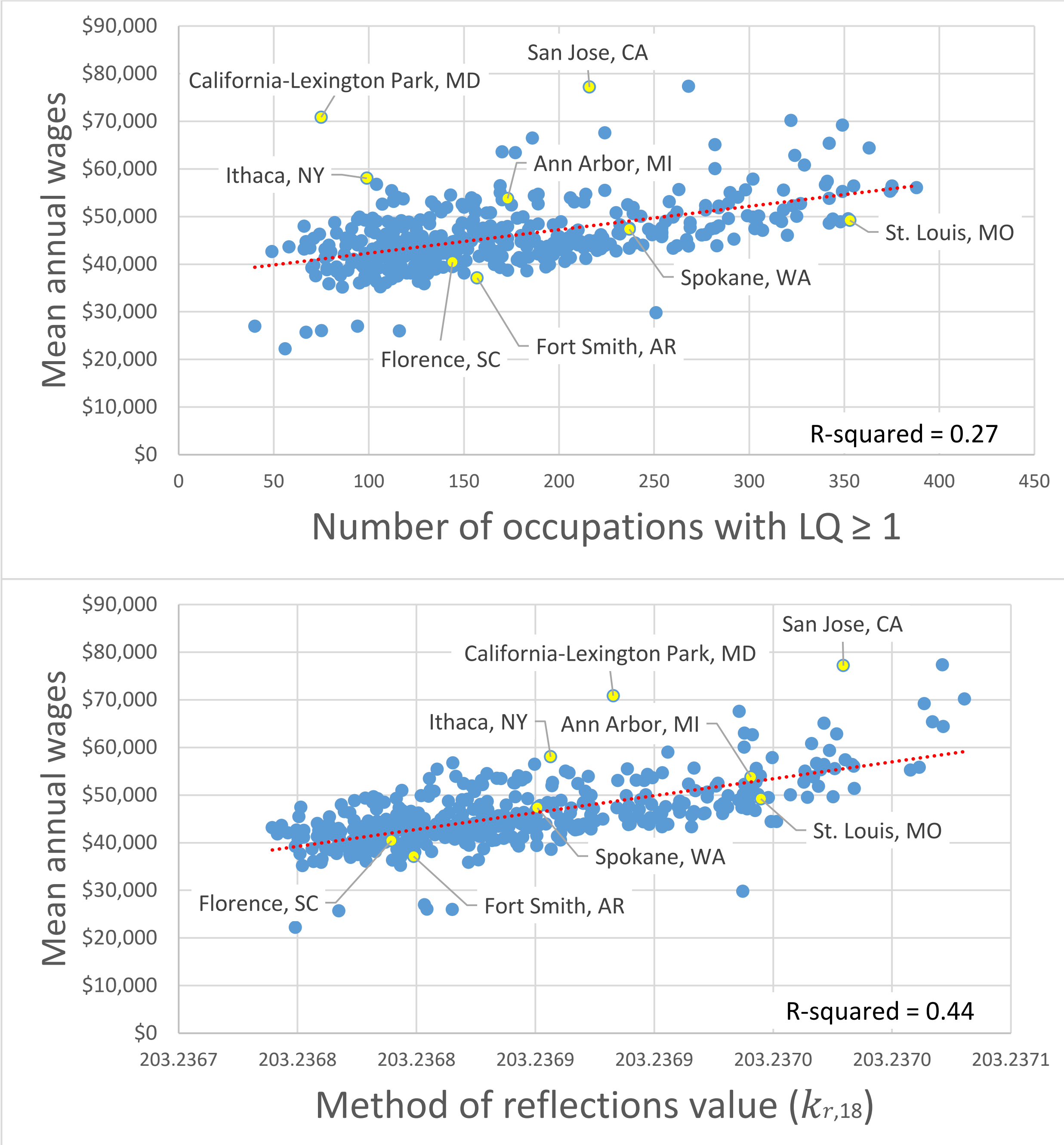
Source: BLS Occupational Employment Statistics, author's calculations. Note that increasing in rank here means going from a high number to a low number- for example, increasing from the 291st most-rare occupation (where 290 occupations are more rare) to the 85th most-rare occupation (where only 84 occupations are more rare).

Relationship with Wages

We look at the mean annual wages in different U.S. cities using BLS Occupational Employment Statistics for May 2017. We graph these wages against two different values: first, the city's number of occupations with a location quotient greater than or equal to 1. Second, the city's diversity value calculated using the method of reflections (using $k_{r,18}$).

Both relationships are statistically significant at 99 percent. However, we obtain a better fit by using the method of reflections value instead of the location quotient value. Regressing a city's mean annual wages on its location quotient gives an R-squared value of 0.27, while regressing a city's mean annual wages on its method of reflections value gives an R-squared value of 0.44. This suggests that the method of reflections may be capturing relevant information about the labor dynamics in U.S. cities. Specifically, while U.S. cities with many occupations tend to have higher wages, cities with especially rare occupations also tend to have higher wages, and the latter relationship appears stronger.

Figure 3 Mean annual wages, location quotients, and the method of reflections



Source: BLS Occupational Employment Statistics, author's calculations.

Some cities are labeled for illustrative purposes. For example, in 2017, California-Lexington Park MD had the third-highest mean annual wage in the United States: $70,860. It had only 75 occupations with a location quotient greater than or equal to one. However, this set included many relatively rare occupations: mathematicians, financial analysts, database administrators, software developers, computer and information research scientists, etc. Using information about the rarity of these occupations helped the city climb the ranks: out of 423 U.S. cities, it was 408th by the number of occupations it hosted, but 110th using the method of reflections.

In contrast, Spokane WA had 237 occupations with a location quotient greater than or equal to one (and a mean annual wage of $47,320). But it didn't host any of the 116 rarest occupations; the most rare occupation it had with a location quotient greater than or equal to one was camera operators (ranked 117th). It did have more than the national average of seven of the ten most ubiquitous occupations: tellers, cooks, industrial machinery mechanics, welders, maintenance and repair workers, postal service mail carriers, and parts salespersons. Spokane WA fell from 81st by the number of occupations it hosted to 237th using the method of reflections.

Comparison to 2006

We compare 2017 calculations of diversity to 2006. Some U.S. cities are not directly comparable because of the BLS's change in sample and metropolitan area definitions, including New York NY and Bethesda MD. For all occupations in the United States, the average change in mean annual wages from 2006 to 2017 was 29.2 percent (from $39,190 to $50,620).

Table 6 Changes in regional diversity ($k_{r,18}$) and changes in mean annual wages from 2006 to 2017

Top 10 (became relatively more diverse)	**2006-2017 change in wages**	***Bottom 10 (became relatively less diverse)***	**2006-2017 change in wages**
Seattle, WA	36.9%	Sebastian, FL	14.6%
San Francisco, CA	41.3%	Punta Gorda, FL	19.8%
Washington, DC	32.5%	Brunswick, GA	24.2%
Salt Lake City, UT	30.9%	Bay City, MI	14.8%
Boston, MA	32.8%	Hot Springs, AR	25.8%
Atlanta, GA	25.6%	Danville, IL	33.2%
Austin, TX	29.9%	Longview, WA	25.0%
Ann Arbor, MI	16.0%	Guyama, PR	11.4%
Los Angeles, CA	29.3%	Rome, GA	28.6%
Durham, NC	31.4%	Lynn, MA	14.5%

Source: BLS Occupational Employment Statistics, author's calculations.

We also compare 2017 calculations of occupational ubiquity to 2006. The change in city diversity from 2006 to 2017 is positively correlated with the change in mean city wages (for all occupations). The relationship is not perfect but is statistically significant at 99 percent.

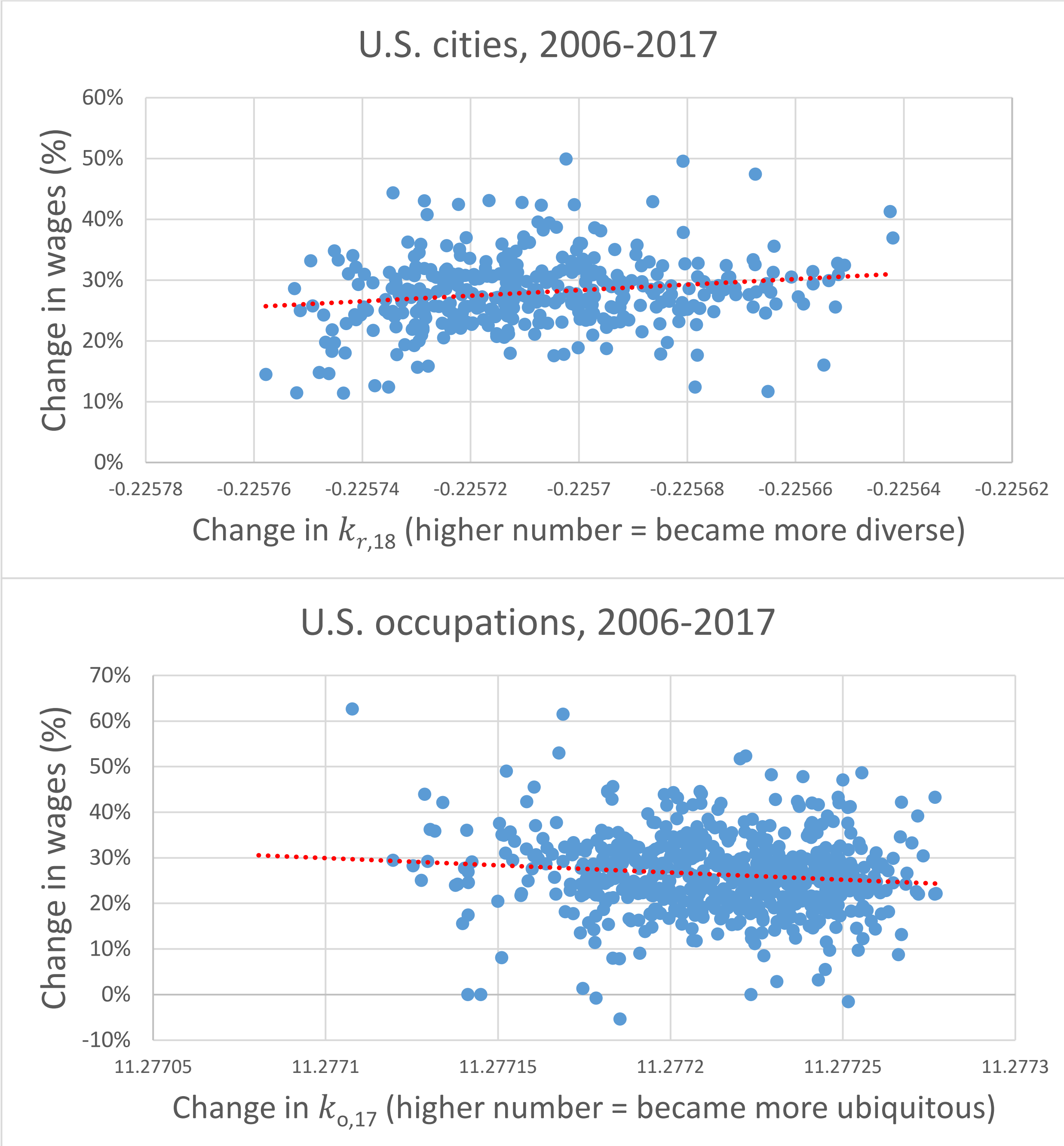
Table 7 Changes in occupational ubiquity ($k_{o,17}$) and changes in mean annual wages from 2006 to 2017

Top 10 (became relatively rarer)	**2006-2017 change in wages**	***Bottom 10 (became relatively more common)***	**2006-2017 change in wages**
Funeral directors	62.6%	Patternmakers	20.5%
Drilling and boring machine tool setters	29.2%	Skin care specialists	18.9%
Postmasters	36.0%	Cooling and freezing equipment operators	29.3%
Cutters and trimmers	24.6%	Occupational health technicians	21.6%
Pourers and casters	29.1%	Health technicians	22.0%
Painting and decorating workers	31.0%	Supervisors and managers of firefighters	
Tool grinders	20.5%	Psychiatric technicians	18.5%
Short order cooks	28.6%	Athletic trainers	25.1%
Carpenter helpers	28.6%	Extruding machine setters (who operate machines that draw materials into tubes, hoses, etc.)	16.1%
Agricultural inspectors	15.7%	Agricultural workers, all other	43.2%

Source: BLS Occupational Employment Statistics, author's calculations.

Additionally, the change in occupational ubiquity is negatively correlated with the change in wages over all U.S. cities. This is the expected direction, as occupations that became more ubiquitous had smaller increases (or even decreases) in their average wages. Again, the relationship is not perfect, but it is statistically significant at 99 percent.

Figure 4 Changes in wages, city diversity, and occupational ubiquity from 2006 to 2017



Source: BLS Occupational Employment Statistics, author's calculations.

Conclusion

This paper does not draw a conclusion about the underlying factors driving the location of occupations in different U.S. cities (analogous to the role of capabilities in Hidalgo and Hausmann's work), and it does not make an argument about the causal relationship between changes in city diversity or occupational ubiquity and changes in wages.[11] It simply applies a calculation from international trade literature to U.S. labor markets and finds interesting patterns in the results. Measuring city diversity and occupational ubiquity can generate detailed evidence of the ongoing changes in labor markets, driven by forces like education, technology, and international trade.[12]

The analysis presented in this paper may be useful for "taking the temperature" of cities and occupations. Changes in diversity or ubiquity may be signals of broader phenomena driving growth, wages, productivity, and tradability. For example, one way to quantify the effects of recessions on cities is to calculate not just the absolute loss of jobs but the changes in city diversity. This also may help illuminate the distribution and velocity of geographic inequality, as cutting-edge economic activities like biotech and neuroscience are increasingly concentrated in a small number of large cities with mutually reinforcing characteristics (like dense social networks and research universities).[13] Next steps may include analyzing the underlying trends and the directions of causality. Other potential applications are tracking how industrial or tax policies affect cities and occupations in the method of reflections, using this analysis on labor markets in other countries, and exploring whether and how cities should prioritize certain occupations by providing missing inputs and targeted policies.

[11] In international trade, the method of reflections gives guidance on development: countries may be able to grow, transform, and become more productive by moving strategically into new industries. For example, one application suggests Uganda should try to shift into the production of agrochemicals and construction materials. Hausmann et al., "How Should Uganda Grow?" January 2014.

[12] This paper uses a specific definition of city diversity (how many occupations a city hosts with location quotients ≥ 1). One study finds that *cultural* diversity, based on the heterogeneity of responses to questions about values and beliefs, has a positive effect on economic development. Ashraf and Galor, "Cultural Diversity," 2011.

[13] Balland et al, "Complex Economic Activities Concentrate in Large Cities," 2020.

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