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Urbanization favors high wage earners

Shade T. Shutters [1,2 ✉], J. M. Applegate [1,2], Elizabeth Wentz[3] and Michael Batty[4]

As cities increase in size, total wages grow superlinearly, meaning that average wages are higher in larger cities. This phenomenon, known as the urban wage premium, supports the notion that urbanization and the growth of cities contribute positively to human well-being. However, it remains unclear how the distribution of wages changes as cities grow. Here we segment the populations of U.S. cities into wage deciles and determine the scaling coefficient of each decile's aggregate wages versus city size. We find that, while total wages of all deciles grow superlinearly with city size, the effect is uneven, with total wages of the highest wage earners growing faster than all other deciles. We show that this corresponds with the predominance of high-wage jobs in larger cities. Thus, the effects of urbanization are mixed -- it is associated with higher average wages but with increasing inequality, thus inhibiting prospects for long-term sustainability.

INTRODUCTION

Urban scholars have long known that workers in larger cities earn higher average wages than workers in smaller cities, a phenomenon known as the urban wage premium[1,2]. Over a century ago, Alfred Marshall[3] referred to this phenomenon as economies of agglomeration or scale, while the biologist Haldane, amongst others, defined this effect in both animals and humans as positive allometry[4]. Among cities, researchers have shown that both wages and incomes increase superlinearly as a power function of population size[5–9], meaning that average incomes and wages are higher in larger cities. Findings such as these have contributed to the view that urbanization can be a positive contributor to human well-being[10–12]. Yet, in both human and natural systems, inequality of resource distribution is known to increase with time and development[13,14] suggesting that while larger cities may bring higher average wages, they may also exhibit higher levels of inequality.

Such inequality is not only "a threat to economic progress, social cohesion and political stability"[15], it also negatively impacts a city's prospects of becoming sustainable[16]. However, the relationship between inequality and sustainability is complex[17–20]. The relationship is seemingly mediated through levels of social trust, with higher levels of inequality decreasing social trust, which in turn decreases sustainable behaviors. Yet social trust is also known to increase with higher levels of aggregate income. Thus, growth may offset some of the negative impacts of increased inequality[21]. Furthermore, increased inequality is correlated with higher levels of innovation[22], which is an important contributor to future sustainability. This further complicates the relationship between inequality, growth, and sustainability.

Our goal in this study is to better understand the nature of this complex relationship between city size and inequality. While studies have shown that inequality of wages, incomes, and other indicators of prosperity exists between cities of different sizes[5,15,23–25], we seek to understand how inequality within cities varies as a function of city size. We do this by examining how the distribution of wages within cities changes with size.

Researchers have previously addressed this question by analyzing descriptive metrics of distributions, such as GINI coefficients[6,14] or the ratios of different distribution percentiles[26,27]. Here, we use power-law scaling analysis to search for systematic regularities of wage distributions as a function of city size. Power-law scaling has been used to characterize the relationship between city size and aggregate urban measures such as wages, income, housing prices, infrastructure, crime, innovation, information networks, professional diversity, etc.[5–9,28–32] In this study, we focus on wages.

While others have examined the power-law scaling behavior of aggregate wages[5,33], it remains unclear how the distribution of wages changes with increasing city size. This distribution can give important clues about the relationship between city size and wage inequality. To do so we divide the populations of 382 U.S. metropolitan statistical areas (MSAs) m into wage deciles d so that the lowest 10% of wage earners are in decile one and the highest 10% of wage earners are in decile ten. We then calculate the power-law scaling coefficient of a decile's total wages $W_{m,d}$ versus the MSA's population P_m

$$W_{m,d} = aP_m^\beta. \tag{1}$$

We take β to be the magnitude of a decile's urban wage premium and compare how the wage premium is realized across different classes of wage earners.

Previous studies have used a similar method to examine how distributions of personal income changes with city size[7,28]. These studies divide urban populations into fixed bins based on an individual's personal income and then fit the number of workers in each income bin against city size as a power law. Thus, while this method compares the number of workers per income bin versus population, our method compares total wages per population decile versus population. This is a critical distinction as the use of fixed bins, for either wages or income, is significantly affected by differences in cost of living among cities (see Supplementary Discussion and Supplementary Fig. 1 for further discussion of this method).

[1]School of Complex Adaptive Systems, Arizona State University, Tempe, AZ 85287, USA. [2]Global Climate Forum, 10178 Berlin, Germany. [3]School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ 85282, USA. [4]The Centre for Advanced Spatial Analysis, University College London, W1T 4TJ London, UK. ✉email: shade.shutters@asu.edu
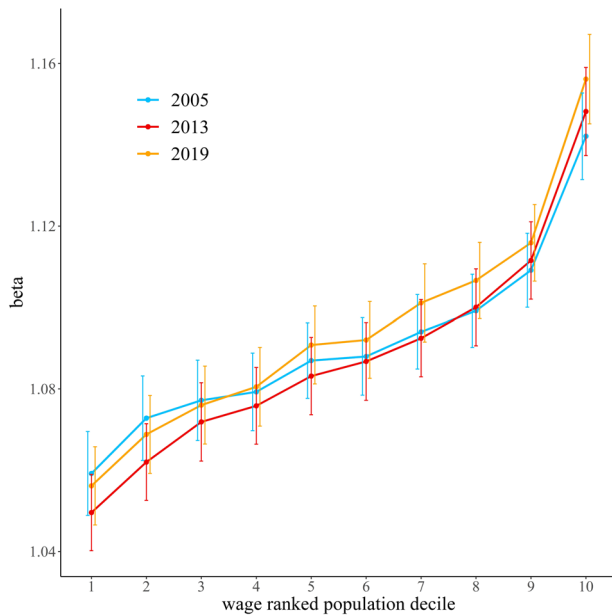
Fig. 1 Urban wage premium among U.S. metropolitan areas (MSAs) by wage ranked population decile. Deciles represent one tenth of an area's population after they are ranked in order of annual wages. Each point indicates the exponent β (beta) of a single power-law regression of a decile's aggregate wages versus city size. Error bars represent the standard error.

RESULTS AND DISCUSSION

We find that power-law scaling coefficient of decile wages versus population size varies significantly across wage deciles (Fig. 1). In all years studied the wage premium for the tenth decile of wage earners is significantly higher than any other decile and decreases monotonically across deciles. In 2019 the tenth decile exhibited $\beta = 1.16$, while the aggregate wage premium across all wage earners was $\beta = 1.11$.

The pattern across deciles remained remarkably stable over our study period of 2005–2019. The scaling coefficient of the tenth decile did increase slightly from 1.142 in 2005 to 1.156 in 2019. Similar increases were exhibited in deciles 5 through 9, while βs for deciles 1 and 2 decreased slightly.

Examining other decile characteristics, we find the proportion of workers with a college degree increases substantially with higher wage deciles while the proportion of female workers decreases from over half of workers in the lowest wage decile to about one fourth of workers in the highest decile (Table 1).

Scaling exponents of deciles

Despite the adverse effects of increased inequality[15] and the UN's Sustainable Development Goal to "reduce inequality within and among countries"[34], inequality has continued to increase globally over the past 25 years[23,35]. Phenomena cited as drivers of this inequality include globalization, technology change, and the decline of labor unions[36]. Our study suggests that these various drivers manifest disproportionately in larger cities. This complicates the role of urbanization in enhancing human well-being as it creates a trade-off between the opportunity for higher wages that come with larger cities and increasing inequality of those wages.

Concentration of high-wage jobs in larger cities

To explain results we focus on the fact that cities require the presence of particular economic building blocks before they can grow more complex, and typically more lucrative, industries[29]. The degree to which those industries require others to build upon is

Table 1. 2019 power-law scaling exponents for MSA decile total wages vs. MSA size, with mean annual decile wages and other select attributes (wages in thousands of $).

Population decile	β	Mean Wages	% female	% with degree
1	1.056	15.4	52.9	15.6
2	1.069	24.9	50.9	16.3
3	1.076	31.6	49.6	21.0
4	1.081	38.3	48.1	27.4
5	1.091	45.8	46.6	35.1
6	1.092	54.3	45.2	42.2
7	1.101	65.0	42.3	48.8
8	1.107	79.3	39.5	55.9
9	1.116	102.6	33.9	65.3
10	1.156	232.9	25.8	78.3

reflected in the power-law scaling coefficient β' of an MSA's employment in an industry $E_{m,i}$ versus the MSA's size P_m

$$E_{m,i} = aP_m^{\beta'}. \tag{2}$$

Superlinear scaling (i.e. $\beta > 1$) indicates that industries tend to appear more in cities that have reached a population size capable of supporting both the emerging industry and its prerequisites. When calculating 2019 scaling coefficients for each 2-digit industry in the PUMS data, our results echoed those of Youn et al.[29] which showed that management, professional, and scientific consulting services had the highest scaling coefficients (See Supplementary Table 1 for industry scaling results).

We apply that same technique to occupations using the U.S. Census Bureau's 2-digit occupational groups. Growth in some occupations requires the existence of prerequisites, such as other occupations or a minimum city size, forming a hierarchy of increasingly complex occupations[37,38]. As with industries, the degree to which occupations depend on prerequisites is reflected in the scaling exponent β'' of an MSA's employment in an occupational $E_{m,o}$ versus the MSA's size P_m

$$E_{m,o} = aP_m^{\beta''}. \tag{3}$$

The larger an occupation's scaling coefficient, the larger the population required to support that occupation. Table 2 presents 2019 power-law scaling coefficients of all 2-digit occupation groups across MSAs.

The pattern shown in Fig. 1 suggests that those occupations emerging in larger cities also bring higher wages relative to occupations that do not require larger city size. This is supported by a positive correlation between an occupation's scaling exponent and its average wages across MSAs (R2 = 0.46, excluding military occupations).

Higher scaling coefficients in the top wage deciles are also partly a result of the fact that mean wages of some occupation groups increase with city size[25]. In other words, not only do higher wage occupations concentrate in large cities, but workers in the same occupation group earn higher wages in larger cities. We quantify this effect by calculating the scaling coefficient β''' of total occupational wages $W_{m,o}$ in an MSA versus total occupational employment $E_{m,o}$ in an MSA for each 2-digit occupation group o

$$W_{m,o} = aE_{m,o}^{\beta'''}. \tag{4}$$

Results show that this effect is particularly pronounced in legal ($\beta''' = 1.14$), sales ($\beta''' = 1.09$), management ($\beta''' = 1.09$), and arts ($\beta''' = 1.08$) occupations. Again, the relationship between an occupation group's power-law coefficient and the group's mean wages is positive (R2 = 0.60, excluding military occupations). (See

Table 2. Comparison of 2019 power-law scaling exponents for MSA 2-digit occupation employment vs. MSA size, with mean annual wages (in thousands of $).		
2- digit occupation group	β''	Mean Wages
23-Legal	1.329	138.7
15-Computer and Mathematical	1.327	95.8
27-Arts, Design, Entertainment, Sports, and Media	1.261	72.2
13-Business and Financial Operations	1.208	89.3
17-Architecture and Engineering	1.164	93.3
39-Personal Care and Service	1.131	34.0
19-Life, Physical, and Social Science	1.125	83.6
11-Management	1.112	105.4
41-Sales and Related	1.078	69.6
37-Building and Grounds Cleaning and Maintenance	1.059	33.9
43-Office and Administrative Support	1.045	46.7
35-Food Preparation and Serving Related	1.045	29.1
21-Community and Social Service	1.029	52.4
29-Healthcare Practitioners and Technical	1.023	92.2
25-Educational Instruction and Library	1.014	57.5
31-Healthcare Support	1.014	33.7
33-Protective Service	1.012	62.3
47-Construction and Extraction	0.993	50.6
53-Transportation and Material Moving	0.982	44.0
49-Installation, Maintenance, and Repair	0.939	53.7
51-Production	0.906	46.3
45-Farming, Fishing, and Forestry	0.688	32.9
55-Military Specific	0.645	50.7

Table 3. 2019 power-law scaling exponents for MSA employment by educational attainment level vs. MSA size, with mean annual wages (in thousands of $).		
Educational attainment level	Beta	Wages
Professional degree[a]	1.260	169.8
PhD	1.196	128.6
Master's degree	1.191	101.7
Bachelor's degree	1.150	82.7
Some college or associate degree	0.984	52.7
High school or less	0.969	42.1

[a]Professional degrees include doctorates other than PhDs, such as law degrees (J.D., L.L.B) and medical/dental degrees (M.D., D.D.S.), and certain master's degrees such as architecture (M. Arch).

Supplementary Table 2 for full occupation results and Supplementary Table 3 for the same wage scaling analysis applied to industries).

There are likely many factors that contribute to the pattern of inequality shown in Fig. 1. We show that increasing wage inequality is related to the fact that more lucrative occupations both occur more frequently and pay higher wages in larger cities. Overall, our results use individual-level microdata to confirm a general trend identified in many other studies—that wages are higher in larger cities, that those higher wages are concentrated among the highest wage earners, and that this increases wage inequality in larger cities.

The impact of education level

While we have shown that higher inequality is related to the asymmetric concentration of high wage jobs in larger cities, this creates a new question of why high wage jobs concentrate in larger cities. Some have suggested that workers earn a premium in larger cities because they acquire valuable skills through knowledge spillovers that they could not acquire in smaller cities[25]. Others have suggested that larger cities offer more opportunities for high skilled workers to be matched with a job requiring high skill levels and that once a city has established a large concentration of high-skilled workers, they will continue to attract high-skilled workers away from smaller cities[39]. This latter assertion is supported by the fact that workers with a college education not only concentrate more in larger cities[40,41], but that they have continued to do so through multiple generations[14,24].

Because education level is positively correlated with wages[40,41], we analyzed the 2019 power-law scaling coefficient of workers by educational attainment level to examine whether college education also plays a role in higher inequality levels in larger cities. Results in Table 3 show that not only do the numbers of college educated workers scale superlinearly with MSA size, but the scaling coefficient increases with the typical time required to complete each degree type. Thus, β is approximately linear for workers with some college or an associate degree, $\beta = 1.15$ for workers with a bachelor's degree, and $\beta = 1.26$ for workers with a professional degree. Thus, not only do high wage jobs concentrate in larger cities, so too do workers with advanced education levels.

Furthermore, the number of workers with a high school education or less scales sublinearly with MSA size suggesting that not only do larger cities offer more opportunities work high-skilled workers, but they also offer diminishing opportunities for less skilled workers. This phenomenon likely exacerbates the appearance of higher levels of inequality in larger cities.

Stability of our findings over time

We conducted our analysis for every year from 2005 to 2019, showing three years of results graphically in Fig. 1. During this period the pattern of inequality across deciles remained qualitatively fixed and scaling exponents of individual deciles changed little over time. However, our study period is too short to conclude that the pattern we find among wage deciles holds over longer periods of time.

On the contrary, a large body of literature examines a broad transition starting in the late 1970s and continuing through the 1980s in which larger cities began to diverge from smaller cities in several characteristics, including interregional inequality[23,26,42–44]. This transition has also appeared in a recent long-term study of aggregate wage scaling of urban areas, with small cities having a higher wage premium than large cities prior to the mid-1990s[45]. Thus, there is ample indication that the trend we observe among wage deciles has looked qualitatively different in the past.

Future directions

This study lays the groundwork for several tantalizing future research directions. First, we note that our study excludes part-time and partial-year workers. Our goal was to do an initial study without the complications and possible distortions of these categories of workers. Yet, these workers, by earning less than their full-time counterparts, likely exacerbate effects of inequality and could be integrated in future studies.

Second, we briefly discussed the impact of differences in prices among cities on different scaling calculations. While we show in Supplementary Fig. 2 that prices do not affect the patterns uncovered in our analysis, it does change the magnitude of power-law scaling coefficients in our study and can significantly

alter the results of other methods used to analyze wage and income distributions. Thus, further research is needed to better understand the impact of regional price differences on measures of inequality.

Finally, we propose that power-law scaling analysis of occupational and industrial employment versus city size may be supplemented by a similar analysis of skills. Do particular skills concentrate in larger cities and are those skills associated with higher wages? Addressing such questions will likely enhance our understanding of the drivers of inequality both between and within cities.

METHODS

Data

We take wage and population data from the American Community Survey, Public Use Microdata Set (PUMS) published by the U.S. Census Bureau[46]. These data include approximately 400 individual-level attributes collected annually from 1% of the U.S. population. From these data we extracted each individual's employment status, annual wages, sex, and educational attainment for the years 2005–2019.

Individuals represented in the PUMS dataset are assigned to spatial units called Public Use Microdata Areas (PUMAs), which are designed to encompass approximately 100,000 residents and which correspond to no other generally used geographical unit. Therefore, we use the mapping of PUMAs to U.S. metropolitan statistical areas (MSA) from iPums.org[47] to assign individuals to MSAs and to calculate the total population of each MSA.

Synthesizing complete MSA populations

Each individual in the PUMS dataset is assigned an expansion factor, or weight, which estimates the total number of people in the individual's PUMA having the same attributes, including wages. Those weights were adjusted by the PUMA-to-MSA crosswalk factor to estimate a total number of people per MSA at each wage value, occupation, industry, and educational attainment level. We then used the weighted n-tiles algorithm of the R package *hutils*[48] to expand our sample and place every individual of an MSA into a population decile ordered by wages.

From this expanded dataset we extracted only individuals in the workforce that worked 50–52 weeks in the previous 12 months and that ordinarily worked 35 or more hours per week. This avoids distortions, particularly in lower wage deciles, due to part-time and partial-year employment. Note that PUMS data does not designate anyone under age 16 as employed even if they are employed.

With the resulting dataset, we calculated total wages by decile for each MSA, the log of which was regressed against the log of the MSA's total population to calculate a decile's power-law scaling coefficient β.

To better understand our main result, we further calculated the power-law scaling coefficient of number of MSA workers in each 2-digit occupation, in each 2-digit industry, and in each educational attainment category versus MSA population. In each case we used the US Census Bureau's categories for occupations, industries, and educational attainment levels.

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AUTHOR CONTRIBUTIONS

S.T.S. and J.M.A. conceived of the project, acquired the data, and performed the analysis. S.T.S., J.M.A., E.W., and M.B. wrote and revised the paper.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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Correspondence and requests for materials should be addressed to Shade T. Shutters.

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