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Wage Premiums Across the Rural-Urban Continuum: What Constitutes a "Good Job"?

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Abstract

Much like how beauty is in the eye of the beholder, there is no single definition of what constitutes a "good job." What makes a given job "good" in relation to other jobs can differ in rural vs. urban areas: a job that pays relatively well compared to other available jobs in a rural area may not compare as favorably in more urbanized areas, and vice versa. While plenty of research has been done regarding wage differences in urban and rural areas, most studies have focused on how wages vary across the urban-rural continuum within specific jobs, with relatively little attention paid to how wage premiums can vary across occupations within particular communities. This study examines variations in wage premiums across five major occupational categories in metropolitan, micropolitan, and noncore US counties and tests whether population size and levels of education are good predictors of wage premiums in each size class. The results indicate that certain categories of occupations do pay relatively better or worse according to the degree of rurality, although population size and education were not exceptionally good at predicting wage premiums.

Keywords: Rural-urban Continuum; Metropolitan Areas, Micropolitan Areas; Rural Areas; Wage Premiums

1. Introduction

What sorts of jobs are "good jobs"? The answer will depend on whom one asks, as well as what the asker means by "good" (i.e., prestigious, remunerative, enjoyable, or all of the above). To simplify the question, we might choose to define an especially "good job" in a local context as one that pays more than or about the same as other typical jobs in a given area. Even then, asking the question in metropolitan and nonmetropolitan areas will likely yield different responses. There has been plenty of scholarly work focusing on earnings within given jobs and across various points along the urban-rural continuum, arguing that workers' earnings are generally higher in more urbanized areas than in more rural areas, even for the same jobs. However, literature that compares earnings across occupations and within areas of similar population is relatively more difficult to find, which suggests that this topic might become a fruitful area for new research. To that end, I have carried out some preliminary work to explore the subject and provide basic insights into this problem.

2. Conceptual Framework

2.1 Justification: What Are the Issues Concerning Jobs and Occupations in Rural Areas Compared to Urban Areas?

Some readers may wonder why it is worthwhile to include rural areas when one might just as easily restrict analysis to different sizes of urban areas. However, recent political upheavals in the US and Europe resulting from waves of nationalism and populism—particularly among residents of rural areas—have sparked an interest in the "forgotten" rural working-class among policymakers, journalists, and researchers. Tired of feeling ignored in favor of cosmopolitan "elites," rural voters have expressed their anger at the ballot box.

In the US, much of this frustration arises from a scarcity of what might be considered "good" jobs in small towns. Throughout most of the country's history, opportunity in rural areas was found primarily in agricultural work, as well as in natural resource extraction. However, increased mechanization and other technological advances caused employment in these industries to fall over time (Freudenburg, 1992). In the middle decades of the 20th century, manufacturing shifted out of cities and into nonmetropolitan areas as firms searched for cheaper labor, and initially it seemed as though manufacturing would form the new basis of the rural economy. In fact, in the 1960s and 1970s, manufacturing actually grew faster in nonmetro areas than in metro areas, but as the Fordist era came to a close, manufacturing also fell into decline, as many firms moved their production to cheaper locations overseas (Bloomquist, 1987; Falk & Lobao, 2003). Even though structural shifts have pushed the US economy as a whole towards services and away from primary and secondary sector economic activity, rural areas still rely on primary and secondary sector employment to a greater extent than urban areas.

From the 1980s on, employment in the service sector has grown in rural areas, making up a greater proportion of rural jobs. McGranahan (2003) describes the expansion of services as "a mixed blessing," since "the sector generally provides good jobs for the well-educated, but for others, the jobs may be part-time, temporary, low-pay, and without meaningful benefits—much worse than those found in the manufacturing sector" (142-143). High- and low-paying service jobs can be found in places at every level of the rural-urban hierarchy: lawyers and convenience store clerks alike are needed everywhere from the biggest cities to the smallest towns. However, high-paying work in producer services and other knowledge-intensive service fields tends to be concentrated in metro areas near the top of the urban hierarchy (Shearmur & Doloreux, 2008), and is underrepresented in rural areas (Glasmeier & Howland, 1993). It should be noted that producer services do exist in rural areas (as described in Beyers & Lindahl, 1996), but Corcoran, Faggian, and McCann (2007) explain in their study of human capital migration in Australia that most college graduates in rural areas work in healthcare and educational occupations. The lion's share of service jobs in rural areas are generally of the low-skill variety and offer low wages, which in many ways makes them a poor substitute for the natural resource and manufacturing jobs they have replaced. As such, jobs that might not necessarily be considered "good" in urban areas could actually rank among the "better" jobs in rural areas.

2.2 What Constitutes a "Good" Job in Rural vs. Urban Areas?

Most existing research on wage variation by occupation in rural vs. urban areas has focused on earnings within occupations and across size classes, rather than the other way around. What this approach reveals is that generally, workers in urban areas earn more than workers in rural areas, even within the same occupation. As McLaughin and Perman (1991) remark, "workers' characteristics and jobs can be identical, but workers are rewarded differently because of the structure and operation of the local labor market" (358). This is especially true of knowledge-intensive service occupations, which experience greater wage premiums in urban areas for a variety of reasons, including better matching (Costa & Kahn, 2000; Brown & Scott, 2012) and higher returns to education in urban areas (Goetz and Rupasingha, 2004). Furthermore, it has been established that larger cities tend to have more high-skill jobs than smaller cities, and smaller cities tend to have more high-skill jobs than small towns (Scott & Mantegna, 2009; Abel, Gabe, & Stolarick, 2014); similarly, jobs in rural areas tend to rely more on physical abilities and strength than on knowledge and skill (Abel, Gabe, & Stolarick, 2014). While these findings are vital to understanding how labor markets differ in rural areas compared to cities, they do not provide much information on how wages differ within specific places. In other words, we may know that doctors in urban areas earn more compared to doctors in rural areas and cashiers in urban areas earn more relative to cashiers in rural areas, and we might safely assume that in either case doctors earn more than cashiers. But it is less clear how much better off an urban doctor is compared to an urban cashier and whether a relationship of the same magnitude exists between rural doctors and rural cashiers.

Some existing studies have incorporated elements of a within-size class approach to wage premiums, but none have fully explored it in a US/North American context. Gabe (2011) explores wage premiums associated with creativity, but his analysis focuses on urban areas and does not differentiate between city sizes. Bacolod (2017) remarks that men benefit more from agglomerations than do women, even though women are concentrated in fields that gain more from agglomeration, but she too considers only US metropolitan areas. In examining urban wage premiums and human capital transfers, Gould (2007) finds evidence to support the notion of urban wage premiums for white-collar workers, but not for blue-collar workers, and in doing so he comes closest to addressing the question posed in this paper. Glaeser and Maré (2001) compare earnings in metro and nonmetro areas to investigate the cause of urban wage premiums, but they do not consider earnings within metro and nonmetro areas. Similarly, Baum-Snow and Pavan (2012) account for wage differences and job matching across city sizes without discussing differences within cities of similar sizes. Arraes, Menezes, and Simonassi (2014) investigate earnings differentials within occupational categories for

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regions of Brazil, but these regions are sorted geographically rather than by size. The apparent dearth of literature comprehensively examining within-size class wage premiums suggests that more research on this topic is needed.

The two primary aims of this paper are 1) to calculate and compare local wage premiums for different occupational categories across the urban-rural continuum and 2) to determine whether higher education and total population are good predictors of these local wage premiums. More specifically, I hypothesize that management, business, science, and arts occupations will prove to be the most lucrative overall, but to a greater extent in metro counties compared to micro and noncore counties. On the other hand, natural resources, construction, and maintenance occupations, as well as production, transport, and material moving occupations, are expected to be associated with lower wage premiums in metro counties relative to micro and metro counties, even if they do not necessarily correspond to lower-than-median earnings in all cases. Since sales and service occupations can be found in relative abundance in both rural and urban areas, it is expected that their relationship to median earnings will be fairly neutral. Finally, since higher education and larger populations are both associated with higher wages, I hypothesize that increases in both variables will predict higher-than-median earnings, even within the metro, micro, and noncore size classes.

3. Data and Methods

The analysis consisted of two main steps. First, local wage premiums were calculated for five distinct occupational categories in all 3108 counties and county-equivalents in the 48 contiguous US states. Results were then separated by size class in order to compare premiums across categories according to rurality. For the second step, an OLS linear regression model was constructed to determine whether education levels and population were good predictors of premiums for different occupational categories and size classes. A detailed description of data sources, variable choices, and methods used is presented as follows.

3.1 Data Sources

All data used in this analysis were obtained from the 2014 5-year estimates of the US Census Bureau's American Community Survey (ACS). The advantage of using ACS data relative to other sources (e.g., the Current Population Survey) is that its 5-year estimates include data for even the smallest rural counties, which may be suppressed due to privacy concerns or may not be collected at all in other cases.

The area studied includes all 3108 counties and county-equivalents, including independent cities, in the 48 contiguous states. Counties were chosen as the unit of observation because in the US, the county level is often the smallest scale at which reliable economic data is available for rural areas. Also, the fact that counties have fixed administrative boundaries that rarely change make them more stable over time than, say, census tracts or metropolitan and micropolitan statistical areas, whose boundaries change as populations change. Alaska and Hawaii were excluded from this analysis based on their uniqueness compared to other states: "nonmetropolitan" places in the Alaskan wilderness or in the tiny Hawaiian Islands are not strictly comparable to nonmetropolitan areas in Kansas or in Georgia.

To reflect each county's degree of rurality, counties were divided into three subgroups based on the current (2010) definitions of metropolitan statistical areas and micropolitan statistical areas devised by the Office of Management and Budget (OMB). Counties belonging to a metropolitan statistical area were classified as "metro," while those belonging to a micropolitan statistical area were classified as "micro" and those which belong to neither a metropolitan nor a micropolitan statistical area were classified as "noncore." The OMB definitions state that metropolitan statistical areas include a central county or counties containing an urban core with a population of 50 000 or greater, as well as all adjacent outlying counties having "a high degree of social and economic integration with the central county or counties as measured through commuting" (OMB 2010, p. 37252). Similarly, micropolitan statistical areas include a central county or counties with an urban core of 10 000-49 999 and any adjacent outlying counties with strong ties to the central county or counties. A "noncore" county is a county that does not contain an urban core with a population of more than 9 999 and is not considered an outlying county of any metro- or micropolitan statistical area. While both micropolitan and noncore counties are considered nonmetropolitan areas, micropolitan areas are more urbanized than noncore areas, so in this context, "nonmetropolitan" is not necessarily equivalent to "rural"; according to Isserman (2005), this false equivalence is part of the "county trap" compromising much rural research. To reflect this distinction, counties were divided into the three categories described above rather than simply splitting them into metropolitan and nonmetropolitan areas. Grouping counties into three size classes rather than separating them into metro vs. nonmetro areas or into core-based statistical areas (i.e., metropolitan and micropolitan statistical areas) vs. non-core-based statistical areas also yields somewhat more detailed information about how variables of interest—in this case, occupational wage premiums—vary at different levels of rurality.

Median earnings data by occupation was used to calculate wage premiums. Compared to an industry-based approach, an occupational perspective provides more information about the skills needed and types of tasks performed by a given worker (Burns and Healy 1978). As an example, a scientist who develops new technology, the janitor who cleans her lab, and the assembly-line worker who manufactures the finished product might all be classified as working in the defense industry, but they all do very different types of work. In the case of the ACS occupational categories, the scientist's job falls under the "management, business, science, and arts occupations," while the janitor's job is classified under "service occupations" and the assembly-line worker's job is categorized under "production, manufacturing, and materials moving occupations." Some industries may pay better than others, but the necessary tasks within a given job are likely fairly consistent across industries, which means that the scientist, the janitor, and the assembly-line worker could expect to earn roughly the same amount if they took the same jobs in a different industry.

In addition to median earnings data, data on levels of higher education and total county population were also included because these variables might be connected to a county's median earnings. Higher education levels were measured by the percentage of the population age 25 and up with a bachelor's degree or higher. Since higher levels of human capital are associated with higher wages, it seemed likely that areas with relatively more college-educated workers would be associated with higher wage premiums in some occupational categories. Basic count data (with no exclusions based on age or labor force participation) was used to account for each county's total population. It was decided not to limit the population measure to include only the working population in order to determine whether higher total population (both working and non-working) in a county is associated with higher earnings.

3.2 Methodology

The R statistical software was used to divide median earnings for each of the five occupational categories within a county by the county's overall median earnings. A score higher than 1 means that median earnings for that occupational category are greater than the overall median earnings, whereas a score that is less than 1 means that the category's median earnings are below the overall median. These results are henceforth referred to as wage "premiums," even though scores below 1 might logically be considered penalties (or other opposites of a premium). Within each occupational category, results were sorted by size class (i.e., metro, micro, or noncore) and the maximum and minimum values, the mean, and the median were calculated for each size class.

After calculating the premiums by occupational category and sorting the data by size class, an OLS regression model was constructed to determine whether the level of higher education in a county and the logarithm of a county's total population were good predictors of these premiums. Log population was included rather than population itself so that the coefficients in the regression results would be easier to interpret. The model construction is as follows:

$$\widehat{premium}_i = b_0 + b_1 education_i + b_2 logpopulation_i + e_i$$

where the percentage of a county's population age 25 and up with a bachelor's degree or higher and the log of a county's total population were included as the independent variables and wage premiums for a given occupational category served as the dependent variable. The model was run separately for each size class and each occupational category so that the estimated premiums for each occupational category would be computed using only data from areas in the same size class.

4. Results

4.1 Part 1

Tables containing the summary statistics calculated in the first part of the analysis, as well as frequency histograms, can be found in Table 1 and Figure 1.

Table 1. Descriptive statistics of wage premiums by size class and occupation

Table 1a: Management, business, science, and arts occupations						
	Metro (N=1160)		Micro (N=637)		Noncore (N=1311)	
Max	Radford city, VA	2.38	Zapata County, TX	2.33	Hall County, TX	2.38
Mean	-	1.51	-	1.49	-	1.44
Median	-	1.5	Saint Mary Parish, LA	1.49	Switzerland County, IN	1.42
Min	Oliver County, ND	1.05	McPherson County, NE	0.87	Daggett County, UT	0.37

Table 1b: Service occupations						
	Metro (N=1160)		Micro (N=637)		Noncore (N=1311)	
Max	Armstrong County, TX	0.99	Lassen County, CA	1.18	Terrell County, TX	2.49
Mean	-	0.52	-	0.55	-	0.56
Median	-	0.52	Labette County, KS	0.54	Gilmer County, GA	0.55
Min	Poquoson city, VA	0.26	Sully County, SD	0.19	Wheeler County, NE	0.18

Table 1c: Sales occupations						
	Metro (N=1160)		Micro (N=637)		Noncore (N=1311)	
Max	Owyhee County, ID	1.25	Tyrrell County, NC	1.19	Mora County, NM	2.09
Mean	-	0.83	-	0.84	-	0.84
Median	-	0.83	Baldwin County, GA	0.84	Corson County, SD	0.84
Min	Golden Valley County, MT	0.52	Los Alamos County, NM	0.44	Lexington city, Virginia	0.18

Table 1d: Natural resources, construction, and maintenance occupations						
	Metro (N=1160)		Micro (N=637)		Noncore (N=1310)	
Max	St. Helena Parish, LA	1.88	Norton city, VA	2.42	Schleicher County, TX	2.44
Mean	-	1.1	-	1.18	-	1.17
Median	-	1.11	Geary County, KS	1.17	-	1.14
Min	Falls Church city, VA	0.38	Kenedy County, TX	0.64	Mora County, NM	0.24

Table 1e: Production, transportation, and material moving occupations						
	Metro (N=1160)		Micro (N=636)		Noncore (N=1309)	
Max	West Feliciana Parish, LA	1.61	Logan County, NE	2.33	Culberson County, TX	3.05
Mean	-	0.97	-	1.05	-	1.07
Median	-	0.97	-	1.05	O'Brien County, IA	1.06
Min	Radford city, VA	0.35	Los Alamos County, NM	0.36	Hinsdale County, CO	0.15

Figure 1

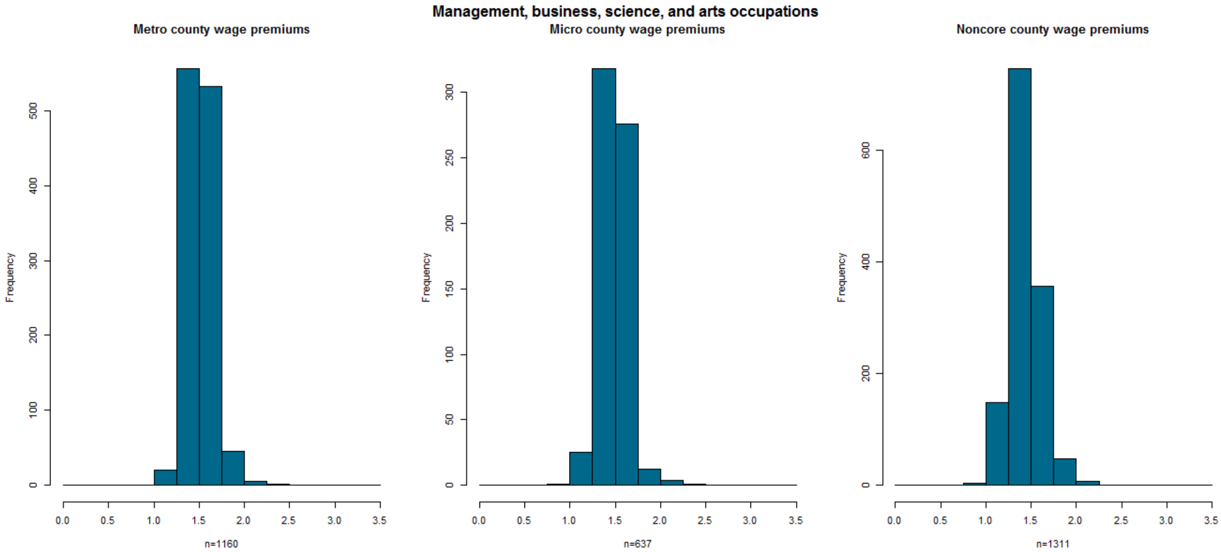

Figure 1a. Management, business, science, and arts occupations

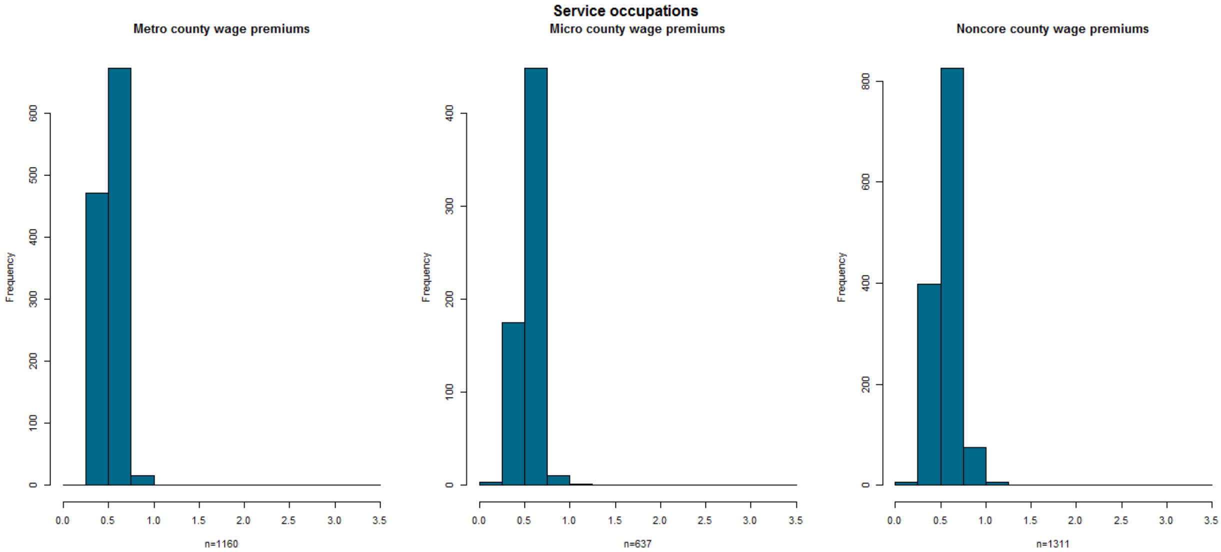

Figure 1b. Service occupations

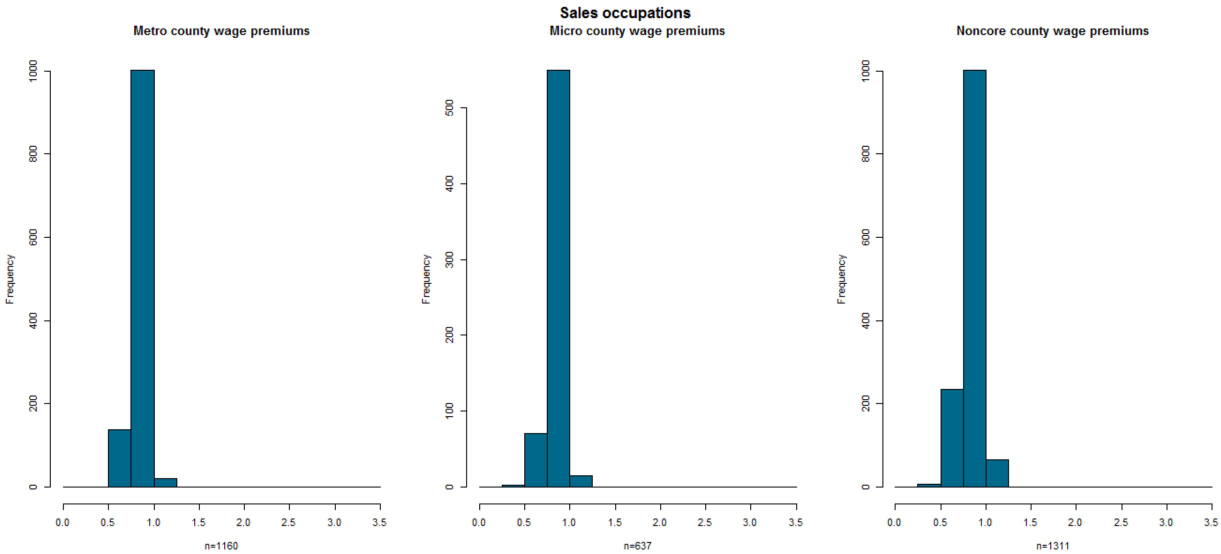

Figure 1c. Sales occupations

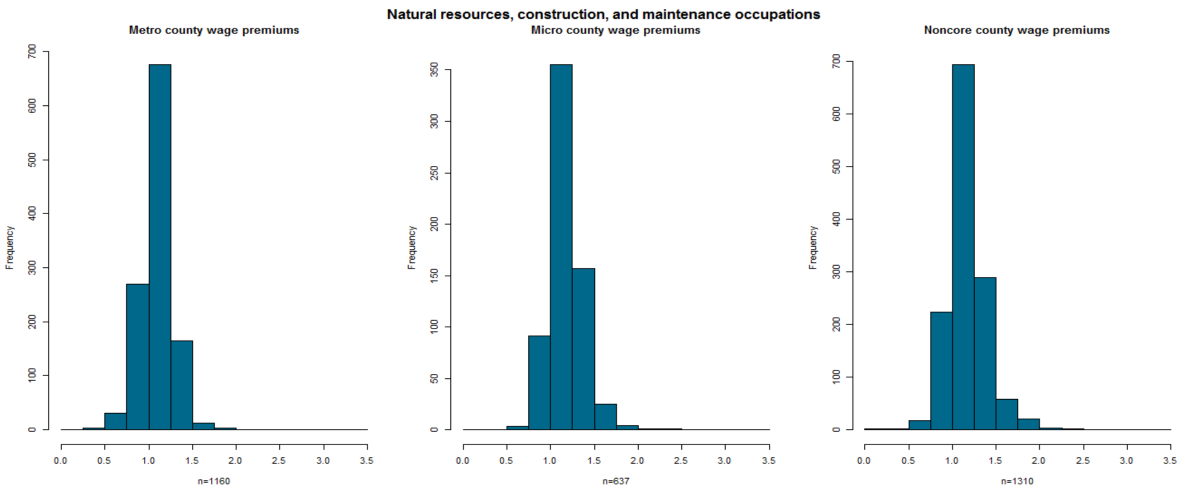

Figure 1d. Natural resources, construction, and maintenance occupations

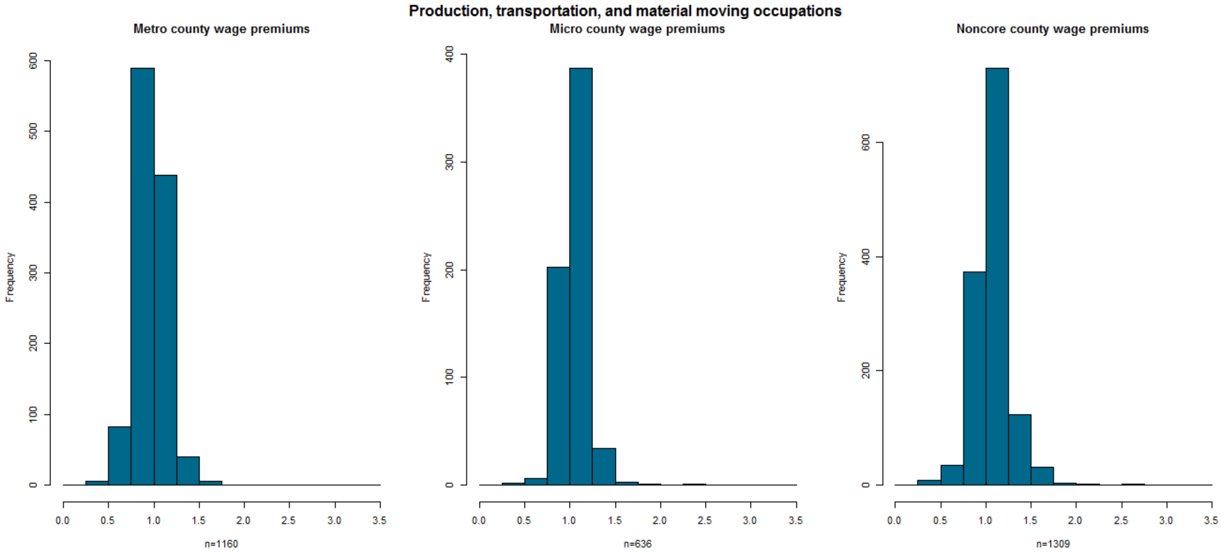

Figure 1e. Production, transportation, and material moving occupations

In the case of management, business, science, and arts occupations, the maximum premiums for metro, micro, and noncore areas ranged from 2.33 to 2.38, which suggests that even in areas where management occupations pay the most compared to local median earnings, the highest management premiums do not vary much according to the degree of rurality. However, the minimum management premium among metro counties (1.05) was much higher than the minimums in micro (0.87) and noncore (0.37) counties. Across all size classes, the mean and median ranged from 1.42 to 1.51. These results reveal that management occupations are generally associated with higher-than-median earnings across the board, with the maximum premiums hitting a cap just below 2.4x local median earnings. The smallest premiums varied dramatically by size class, though, with minimums decreasing along with size. This suggests that management premiums range from high to decent in metro counties, bottoming out at slightly above local median earnings, while premiums are less reliably good in micro and noncore counties.

Service occupations exhibited the opposite pattern relative to metro areas, where even the highest premiums (0.99) were still less than the median. The mean and median for metro, micro, and noncore counties ranged from 0.52 to 0.56, which suggests that broadly speaking, service jobs are not especially lucrative anywhere. The minimums for micro counties (0.19) and noncore counties (0.18) were quite low, as was the minimum for metro counties (0.26), but the maximum premiums for micro (1.18) and noncore (2.49) counties were distinctly higher than the metro maximum, though, which indicates greater variability as places decrease in size, even if they are not a good bet in any case.

Similarly, sales occupations were generally less lucrative across metro, micro, and noncore counties, with the mean and median premiums hovering around 0.84 in all cases. The range of premiums was narrowest for metro areas, with a maximum of 1.25 and a minimum of 0.52, increasing slightly for micro areas, and expanding dramatically in noncore areas.

For all size classes, the typical premiums for natural resource, construction, and maintenance occupations were slightly higher than local median earnings, with means ranging from 1.1 to 1.18 and medians ranging from 1.11 to 1.17. The highest minimum occurred among micro counties (0.64), and the lowest minimum occurred among noncore counties (0.24). The maximum premiums increased with the degree of rurality, with the metro maximum at 1.88, the micro maximum at 2.42, and the noncore maximum at 2.44.

Lastly, production, transportation, and material moving occupations generally tended to pay better relative to local median earnings as rurality increased, with both the mean and median increasing from metro to micro to noncore counties. The highest maximum (3.05) occurred among noncore counties, although they also exhibited the lowest minimum (0.15). The micro maximum (2.33) and minimum (0.36) were both higher than in metro areas.

4.2 Part 2

Tables containing my full regression results can be found in Table 2.

Table 2. Regression results

Table 2a: Management, business, science, and arts occupations

	Dependent variable: wage premiums		
	Metro	Micro	Noncore
	(1)	(2)	(3)
Metro % postsecondary education	-0.002***		
	(0.0004)		
Log metro population	0.047***		
	(0.003)		
Micro % postsecondary education		0.001	
		(0.001)	
Log micro population		0.056***	
		(0.006)	
Noncore % postsecondary education			0.0002
			(0.001)
Log noncore population			0.051***
			(0.005)
Constant	1.018***	0.900***	0.964***
	(0.031)	(0.067)	(0.052)
Observations	1,160	637	1,311
R^2	0.179	0.112	0.071
Adjusted R^2	0.177	0.109	0.069
Residual Std. Error	0.123 (df = 1157)	0.131 (df = 634)	0.168 (df = 1308)
F Statistic	125.943*** (df = 2;	39.901*** (df = 2;	49.733*** (df = 2;

	1157)	634)	1308)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2b: Service occupations

	Dependent variable: wage premiums		
	Metro	Micro	Noncore
	(1)	(2)	(3)
Metro % postsecondary education	-0.004***		
	(0.0003)		
Log metro population	0.011***		
	(0.002)		
Micro % postsecondary education		-0.002***	
		(0.0005)	
Log micro population		0.010**	
		(0.004)	
Noncore % postsecondary education			0.0002
			(0.001)
Log noncore population			0.051***
			(0.005)
Constant	0.506***	0.490***	0.964***
	(0.019)	(0.047)	(0.052)
Observations	1,160	637	1,311
R^2	0.200	0.040	0.071
Adjusted R^2	0.199	0.037	0.069
Residual Std. Error	0.077 (df = 1157)	0.092 (df = 634)	0.168 (df = 1308)
F Statistic	144.755*** (df = 2; 1157)	13.332*** (df = 2; 634)	49.733*** (df = 2; 1308)

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 2c: Sales occupations

	Dependent variable: wage premiums		
	Metro	Micro	Noncore
	(1)	(2)	(3)
Metro % postsecondary education	-0.003***		
	(0.0002)		
Log metro population	0.010***		

	(0.002)		
Micro % postsecondary education		-0.0004	
		(0.0004)	
Log micro population		-0.005	
		(0.004)	
Noncore % postsecondary education			-0.001
			(0.001)
Log noncore population			-0.0003
			(0.004)
Constant	0.794***	0.892***	0.852***
	(0.018)	(0.042)	(0.036)
Observations	1,160	637	1,311
R^2	0.115	0.004	0.001
Adjusted R^2	0.114	0.001	-0.0004
Residual Std. Error	0.071 (df = 1157)	0.082 (df = 634)	0.115 (df = 1308)
F Statistic	75.215*** (df = 2; 1157)	1.305 (df = 2; 634)	0.751 (df = 2; 1308)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2d: Natural resource, construction, and maintenance occupations

	Dependent variable: wage premiums		
	Metro	Micro	Noncore
	(1)	(2)	(3)
Metro % postsecondary education	-0.008***		
	(0.001)		
Log metro population	-0.002		
	(0.004)		
Micro % postsecondary education		-0.003***	
		(0.001)	
Log micro population		0.004	
		(0.009)	
Noncore % postsecondary education			-0.006***
			(0.001)
Log noncore population			0.020***
			(0.007)
Constant	1.316***	1.190***	1.073***

	(0.039)	(0.093)	(0.068)
Observations	1,160	637	1,310
R^2	0.225	0.016	0.033
Adjusted R^2	0.224	0.013	0.032
Residual Std. Error	0.154 (df = 1157)	0.183 (df = 634)	0.215 (df = 1307)
F Statistic	168.184*** (df = 2; 1157)	5.109*** (df = 2; 634)	22.646*** (df = 2; 1307)

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 2e: Production, transportation, and material moving occupations

	Dependent variable: wage premiums		
	Metro	Micro	Noncore
	(1)	(2)	(3)
Metro % postsecondary education	-0.008***		
	(0.0004)		
Log metro population	-0.026***		
	(0.003)		
Micro % postsecondary education		-0.003***	
		(0.001)	
Log micro population		-0.022***	
		(0.007)	
Noncore % postsecondary education			-0.006***
			(0.001)
Log noncore population			-0.018***
			(0.006)
Constant	1.468***	1.333***	1.342***
	(0.029)	(0.076)	(0.064)
Observations	1,160	636	1,309
R^2	0.475	0.034	0.030
Adjusted R^2	0.474	0.031	0.029
Residual Std. Error	0.114 (df = 1157)	0.146 (df = 633)	0.206 (df = 1306)
F Statistic	524.183*** (df = 2; 1157)	11.280*** (df = 2; 633)	20.274*** (df = 2; 1306)

Note: *p<0.1; **p<0.05; ***p<0.01.

Coefficients for both education and log population were quite close to 0 in most cases but were often highly statistically significant ($p<0.05$ or better) across metro, micro, and noncore areas, which suggests that these variables have a very small but meaningful association with wage premiums. On the other hand, the adjusted R-squared values were generally quite low, rarely exceeding 0.2, which indicates that these models are not a good fit for the data and are not likely to be useful in predicting wage premiums.

Among the management, business, science, and arts occupations regressions, the postsecondary education variable was only significant in the case of metro counties, where it unexpectedly had a very significant, slight negative relationship to wage premiums (-0.002, $p<0.01$). However, log population also had a highly significant, slight positive relationship to wage premiums among metro, micro, and rural counties. The best-fitting model was the one including metro counties, with an adjusted R-squared value of 0.18, while the lowest R-squared belonged to the model for noncore counties (0.07).

The service occupations regressions also showed a slight but significant ($p<0.01$) negative impact of higher education levels on median wages in the case of metro and micro counties, although postsecondary education was still not significant for noncore counties. As before, log population had a small (0.01-0.5) but highly significant ($p<0.05$ or better) association with wage premiums. The highest (0.2) R-squared value again belonged to the model for metro counties, and the lowest (0.04) belonged to the micro county model.

The regressions for sales occupation produced the most abysmal fit, with R-squared values ranging from 0.11 for the metro model at the highest to -0.04, which is equivalent to 0, at the lowest. The coefficients for both postsecondary education and log population were only significant ($p<0.01$) for the metro regression, though their effects were still weak (-0.003 and 0.01, respectively).

In the case of natural resources, construction, and maintenance occupations, postsecondary education had a weakly negative (-0.008 to -0.003) but highly significant ($p<0.01$) relationship to wage premiums for metro, micro and noncore counties. Log population was only significant ($p<0.01$) in nonmetro counties, though its effects were slightly positive (0.02). The fit remained poor, with R-squared values ranging from 0.22 at best (metro) to 0.02 at worst (micro).

Unexpectedly, the metro model for production, transport, and material moving occupations yielded the highest R-squared value of all at 0.47, although the R-squared values for micro and noncore counties were much lower at 0.03. Again, postsecondary education was highly significant ($p<0.01$) and weakly negative (-0.008 to -0.003) across all size classes, but here this was also true of log population.

5. Discussion

5.1 Interpretation

The results of both parts of this analysis provide more convincing support for some of the hypotheses described above than they do for others. For example, these findings indicate that management, business, science, and arts occupations are indeed generally associated with higher wage premiums for across metro, micro, and noncore counties, with a more pronounced effect in metro counties. Similarly, although natural resource, construction, and maintenance occupations or production, transport, and material moving occupations were not expected to be associated with higher-than-median wage premiums, the results do support the hypothesis that they are associated with lower premiums in metro counties compared to micro and noncore counties. On the other hand, service and sales occupations generated lower premiums across size classes than had originally been anticipated.

The regression results turned out to be even more mixed than the wage premium results. The fact that postsecondary education levels turned out to be inversely related to the estimated wage premiums in metro counties for all occupational groupings directly contradicted my expectations, as did the fact that its coefficients frequently had negative values in micro and noncore counties. Total population did turn out to be positively associated with higher estimated premiums, though, which was consistent with my hypotheses. It was not expected that this simple model would fit the data well, but it was surprising how poorly postsecondary education levels and total population predicted wage premiums. Nevertheless, the fact that both variables were highly significant much of the time confirms that they are strongly related to wage premiums, even if their effects are small. Even though only some of the hypotheses were supported by the data, these results still yield insights that might benefit from further study.

5.2 Limitations

An obvious criticism is that the broad ACS occupational categories lump together a wide range of jobs, which means that much of the variation within categories is ignored. For example, farmers and construction workers are both included in the category of "natural resources, construction, and maintenance occupations." One might expect farmers in the countryside to earn more than they would in cities and construction workers to earn more from building skyscrapers than barns, but this cannot be determined from the data used here. In another example, bankers and artists are both categorized under "management, business, science, and arts occupations," but earnings vary dramatically between these jobs: the term "starving artist" is more familiar than "starving hedge fund manager" for a reason. Being in the same category may cause their different earnings to cancel each other out, thereby reflecting the patterns that exist in the real world less accurately. ACS data does include several levels of subcategories within these occupational categories, but in less-populated rural counties, the large margins of error for certain subcategories may affect data reliability. In this case, the goal was merely to start by examining how wage premiums vary in metro, micro, and noncore areas across these general categories.

A related problem lies in the fact that the ACS occupational categories are not explicitly grouped according to the amount of education, training, or other measures of human capital required, which makes it impossible to determine with confidence how much human capital is involved in each category. It is not hard to imagine that someone might need more training to work as a healthcare practitioner or an architect (both listed under management, business, science, and arts occupations) than he or she would to work as a truck driver (a manufacturing, transport, or material moving occupation) or a secretary (a sales occupation)—but what about artists, who fall into the same category? Similarly, within the service occupations category, healthcare support workers and law enforcement officials can reasonably be expected to have specialized skills, but workers in food preparation and serving occupations or building and grounds cleaning might not. To account for this issue, some researchers have developed their own human capital-based occupational clustering schemes by incorporating O*NET skill data (including Feser, 2003; Scott & Mantegna, 2009; Abel, Gabe, & Stolarick, 2014).

Specialization within occupations is a further complication. Burns and Healy (1978) write that "increasing city size should produce specialization in production, even for the same final product mix" (382). Typically, big cities offer greater opportunities for specialization compared to smaller places, where practitioners in various fields (e.g., law, medicine) may be expected to work more as generalists. Specialization is associated with higher earnings, which would unavoidably push urban specialists' wages up compared to their generalist rural counterparts. The most specific occupational subcategories found in ACS data, though, do not even distinguish between doctors and dentists or between farmers, fishermen, and loggers, making it impossible to further subdivide occupations by specialty. This means that within the ACS data, the earnings of a general practitioner treating everything from sprained ankles to heart disease at a rural clinic and an ultra-specialized pediatric neurosurgeon whose big-city practice handles only patients with the rarest diseases would be counted equally, since both doctors would be classified as "health diagnosing and treating practitioners."

Lastly, the informal economy poses another challenge, since its very existence is predicated on a degree of secrecy. Unsurprisingly, informal work is not included in ACS occupational data—or at least not explicitly—and underreporting is an issue even in data which does include it. Individuals whose "day jobs" offer meager pay have a stronger incentive to turn to the informal sector to supplement their earnings, and people whose regular work is off-the-books may count themselves as unemployed. In the context of this study, reported median earnings in areas where the informal sector plays a larger role in the local economy may be lower than actual median earnings, thus skewing the computed wage premiums.

6. Conclusion

Although the results of this paper represent only an initial attempt to understand wage premiums across occupations and within size classes, they are still useful in that they are broadly consistent with the literature to date, and they also provide some basic insights to lay the groundwork for future research. For example, the finding that management, business, science, and arts occupations tend to have high wage premiums relative to other occupational categories, especially in metro areas, is consistent with earlier research showing that knowledge-intensive service work tends to be associated with higher wages in urban vs. rural areas (Gould, 2007). Similarly, occupations in natural resources, construction, and maintenance and in production, transportation, and material moving tend to pay relatively more in micropolitan and noncore areas than in metro areas, which suggests that these sorts of jobs are "better" in small places compared to larger places. Less is known, though, about how gender interacts with these patterns. To illustrate the necessity of this point, one might safely assume that doctors and lawyers in both rural and urban areas earn relatively more than do their neighbors in other types of occupations, such as service or sales jobs, regardless of their sex. However, because many low-paying service jobs are disproportionately held by women (including housekeepers, cooks, customer service representatives), women working in higher-paying, knowledge-intensive occupations might be expected to have higher wage premiums relative to other women across all occupations in a given geographic area, simply because a larger share of women are in lower-paying jobs. Wage premiums for women in knowledge-intensive work may also be higher than those of men, even if men earn more in absolute terms. Similarly, even as white-collar men can expect higher wage premiums compared to blue-collar men in both rural and urban areas, the premiums in rural areas may be smaller than in urban areas because blue-collar work tends to pay better in rural areas. Some research has found that that agglomerations are beneficial to social and cognitive skills for both women and men, but physical skills are not improved by agglomerations for either sex (Bacolod 2017); however, this accounts for differences across size classes rather than within them. Because gender can strongly impact career choices, it would be wise to include occupations and earnings by sex in future research on jobs and earnings in rural and urban areas.

Additionally, including US regional variation among wage premiums, as demonstrated by Arraes, Menezes, and Simonassi (2014) in a Brazilian context, could prove to be a fruitful avenue for future study, perhaps providing detailed insights about which jobs are "better" than others in different parts of the country and why. The fact that so many of the maximum and minimum premiums occurred in western and Midwestern counties might, for example, indicate that more centralized parts of the country experience greater variability among wage premiums even after controlling for occupations and city size. Alternatively, factors such as education and population size might predict wage premiums more accurately in some parts of the country than in others.

A third option for future examination could include looking at change over time: since county boundaries are relatively stable, it might be possible to learn whether wage premiums in metro, micro, and noncore counties have changed in various occupational groupings, and if so, what trends have occurred in the extent and direction of change. For instance, since rural manufacturing in the US peaked in the 1960s and 1970s and has waned ever since (Bloomquist, 1987; Falk & Lobao, 2003), it might be reasonable to expect that rural wage premiums for manufacturing jobs also reached their apex around the same time. On the other hand, even though the number of jobs in natural resource extraction has fallen over time due to increased mechanization, high demand for oil and other commodities may have kept salaries relatively high, especially compared to other kinds of work in rural areas, which could explain why wage premiums for these occupations are higher in micro and rural counties than in metro counties. In any case, it is difficult to argue that changes in metro, micro, and noncore labor markets would not lead to changes in wage premiums.

Consequently, there are many potential opportunities for future inquiry to build on the findings presented here. It is not surprising that so many studies have examined trends in occupations and wages across urban and rural areas, since common knowledge and experience point to the fact that urban workers earn more than their rural counterparts across a variety of occupations. Fewer people, it seems, have wondered how various occupations compare within urban and rural communities. Certain occupations, such as those in teaching or manufacturing, may not pay well compared to the rest of the jobs available in cities, but it should be recognized that they are sometimes among the best jobs on offer in rural areas. Therefore, it is important to recognize that "good" jobs, or those that pay relatively well compared to other jobs in the area, vary according to a place's degree of rurality. Because so little is known at present about how wage premiums vary within urban and rural areas, any future research on the subject will likely yield valuable insights.

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