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Location of health professionals: The supply side

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ABSTRACT

Urban/regional economic analyses help explain several features of health service providers including output determination. Spatial agglomerations increase factor productivity, and therefore rents paid and wages earned. Larger agglomerations imply higher rents and wages, justifying the clustering of health professionals in large cities and medical centers.

We show for 372 US Metropolitan Statistical Areas (2013) that health professionals' wages increase significantly with increased total employment, but fall as the proportion of the total labor force comprised by the sectors within the regional economy increases. Rents respond similarly, although with smaller elasticities.

The wage-rental ratio (W/R) decreases with total regional employment, but increases with jobs per thousand in the health sector. Exogenous factors like heating and cooling degree days are consistent with slight positive increases in the W/R. Inclusion of W/R in a model that accounts for the covariance of wages and rents yields supply elasticities from + 3.47 to + 7.20 for all medical providers, and from + 0.22 to + 0.43 for registered nurses. These interregional elasticities (particularly for nurses) are consistent with estimates in other contexts.

1. . Introduction

Urban/regional analysis has provided many key insights into the allocation of resources both within and among cities. The "open city" model allows analysts to look at the simultaneous determination of wages and rents across a system of cities explaining how:

- The increased productivity of large cities (or metropolitan areas) is capitalized into higher land rents and higher labor wages, which leads to a system of cities in which long-run equilibrium rents, wages, and their ratios will vary in cross-section;
- 2. Econometric analysis can examine predicted rents and wages, as well as their residuals, to provide quality of life measures;
- 3. Given the set of equilibrium wages and rents, cities' sizes and densities will vary in predictable ways both within and among cities.

Even a casual look at equilibrium wages and rents in locations like New York and San Francisco indicates how the desirable features of these locations have been capitalized into high wages and very high rents, particularly in the most desirable city neighborhoods.¹

A largely unrelated "spatial" health economics literature has focused on:

- Distribution of skilled health professionals, with clustering in large metropolitan areas – and corresponding "shortages" in small cities and rural areas.
- Significant and persistent wage differentials for health professionals among geographic areas.
- 3. The need for the Medicare System, the largest health care services payer in the United States, to adjust fee-for-service payments to Medicare providers for geographic differences, largely related to factor prices, in the costs of providing care (IOM, 2012).

Specific features of the health economy extend this analysis beyond applying the "system of cities" model to yet another industry. First, the health care sector is heavily regulated. In many states, health facility (including hospital) construction is heavily constrained by "certificate of need" (CON) legislation, stemming from a debatable policy framework aimed at limiting big ticket construction and hence costs. CON requires costly and time-consuming planning, application, and sometimes litigation.

Aside from CON, new hospital construction costs can exceed one billion dollars, with renovations in the tens of millions of dollars, leading to an industry with "lumpy" and very long-lived capital. The health services labor force also faces substantive regulation. Physicians,

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¹ Subsequent discussions use "cities" and "metropolitan areas" interchangeably. While health-related agglomerations can occur in smaller areas such as the Mayo complex at Rochester, MN, they are much more concentrated in large metropolitan areas. We use the metropolitan statistical area (MSA) level.

as well as registered (RN) and licensed practical (LPN) nurses undergo costly and time-consuming training and licensure. These features slow marginal adjustments to long-run equilibrium.

To address the issues discussed above, the health literature has most often addressed economies of scale or scope at the office, clinic, or hospital level. As a result, health economists have failed to recognize that the agglomeration of such activities, most often at the metropolitan level, may have impacts on overall sectoral wages and/or rents. Additionally, health economists have measured persistent wage differentials across various cities, states and/or regions. However, timeconsuming and costly health provider training and licensure, coupled with costly migration can create drag on responses to differential wages, and long term wage levels fail to converge. Finally, large government programs such as Medicare direct hundreds of billions of geographically-indexed dollars to care for the (largely) over-65 US population. Health expenditures account for close to one in five dollars of US GDP, and Medicare pays for about one-fifth of that, so it is important to understand how these payments are linked to factor costs. This paper concentrates on these supply-related issues.

Urban economic analysts (Glaeser and Resseger, 2010) have recognized that more populous areas (generally cities) tend to be more productive than smaller ones, leading to higher wages and land rents. Agglomeration gains come from economies of scale and network effects. When related activities cluster, production costs may decline significantly as multiple suppliers and concentrations of skilled labor gather. The differential impacts stemming from agglomeration imply

higher factor payments (wages and rents) that explain varying patterns of land, capital, and labor usage across all sectors, including the health sector.

This article continues by connecting the health and urban literatures. It then reiterates the joint determination of land rents and labor wages in a system of open cities. Next, it lays out a model that shows how both wages and rents are predictably higher (and positively correlated) in larger areas, and go hand in hand with increased concentrations of health care professionals. It concludes by using urban economic theory to examine variations in health labor supply.

2. Geographic differences

Wages for health professionals vary widely across U.S. MSAs. Table 1 shows that the Medicare Wage Index for large MSAs ranges from 0.8862 (Louisville KY-IN) to 1.7396 (San Jose CA). Among all MSAs (excluding Puerto Rico), the range is from 0.6768 (Morristown TN) to 1.8062 (Santa Cruz CA), a factor of 2.67. While some of these differences relate to cost-of-living variations, they also reflect differences in capital endowments and factor productivity.

Health care professionals are also distributed unevenly across geographic areas. Maps of the United States show vast areas with personnel shortages. Although it is unsurprising that areas with low residential densities have low medical personnel densities, with the exception of family physicians, most primary care physicians are more centralized than the population. Fig. 1 shows that while 80% of U.S.

Table 1 Medicare Wage Indices – 2013.

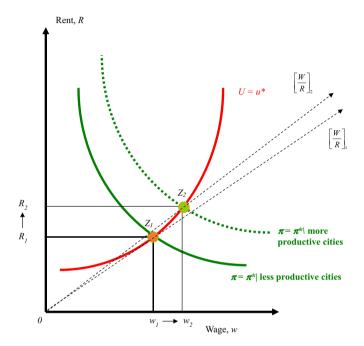
	Metropolitan statistical area	Index
	San Jose-Sunnyvale-Santa Clara, CA	1.7396
	San Francisco-San Mateo-Redwood City, C	1.6327
	Sacramento-Arden-Arcade-Roseville, CA	1.4752
	New York-White Plains-Wayne, NY-NJ	1.2914
	Boston-Quincy, MA	1.2378
	Los Angeles-Long Beach-Glendale, CA	1.2293
	Las Vegas-Paradise, NV	1.2076
	San Diego-Carlsbad-San Marcos, CA	1.1922
	Seattle-Bellevue-Everett, WA	1.1771
	Portland-Vancouver-Hillsboro, OR-WA	1.1673
	Minneapolis-St. Paul-Bloomington, MN-WI	1.1336
	Philadelphia, PA	1.0806
	Washington-Arlington-Alexandria, DC-VA	1.0659
	Chicago-Joliet-Naperville, IL	1.0600
	Phoenix-Mesa-Glendale, AZ	1.0477
	Denver-Aurora-Broomfield, CO	1.0469
	Baltimore-Towson, MD	1.0147
	Miami-Miami Beach-Kendall, FL	1.0130
	Houston-Sugar Land-Baytown, TX	0.9933
	Milwaukee-Waukesha-West Allis, WI	0.9931
	Indianapolis-Carmel, IN	0.9870
	Dallas-Plano-Irving, TX	0.9835
	Columbus, OH	0.9763
	Kansas City, MO-KS	0.9614
	Atlanta-Sandy Springs-Marietta, GA	0.9517
	St. Louis, MO-IL	0.9420
	Detroit-Livonia-Dearborn, MI	0.9361
	Cleveland-Elyria-Mentor, OH	0.9082
	Tampa-St. Petersburg-Clearwater, FL	0.9032
	San Antonio-New Braunfels, TX	0.8936
	New Orleans-Metairie-Kenner, LA	0.8932
	Jacksonville, FL	0.8883
	Louisville-Jefferson County, KY-IN	0.8862
Min	Louisville-Jefferson County, KY-IN	0.8862
Max	San Jose-Sunnyvale-Santa Clara, CA	1.7396
Mean	[Philadelphia, PA - 1.0806]	1.0882
Median	Baltimore-Towson, MD	1.0147

Table 1 shows that the Medicare Wage Index for Urban Areas based on discharges occurring between October 1, 2012 and September 30, 2013. For large MSAs ranges from 0.8862 (Louisville KY-IN) to 1.7396 (San Jose CA). Among all MSAs (excluding Puerto Rico), the range is from 0.6768 (Morristown TN) to 1.8062 (Santa Cruz CA).

EVIDENCE OF GEOGRAPHIC VARIATION



Fig. 1. Distribution of primary care physicians among urban and nonurban areas. Source: AHRO (2010).



This graph illustrates the role that agglomeration has on productivity in a system of cities and the intersections of wages and rents along a utility curve

Fig. 2. Equilibrium rents and wages in a system of cities.

population is located in urban areas, 86% of primary care physicians and 91% of general pediatricians are in urban areas.

How can the urban economics literature address the uneven nature of wage and factor distributions of health services personnel? Increasing returns to scale in production at a given location makes

Table 2 Summary data at MSA level.

Definition Std Dev Mean Min Max Fmr2 Fair market rent for 2 bedroom 887 43 234.56 584 1833 **Population** MSA population in 1000s 1533.58 2412.72 13.32 13.381.42 FL (percent) 1 if in Florida; else 0 6.63 24.91 0 100 CA (percent) 1 if in California; else 0 10.04 30.09 0 100 NE (percent) 1 if in the Northeast; else 0 10.36 30.51 0 100 Mean MSA wage in medical sector 35.45 4 45 25.46 51.53 Mean wage Median wage Median MSA wage in medical sector 29.45 5.10 19.98 50.43 Sector Emp Medical employment by sector by MSA in 1000s 43.45 73.83 0.960 459.93 Sec Jobs_1000 Medical employment per 1000 of total by MSA 62.28 13.38 33.40 159.57 **Total Hospitals** Total hospitals in MSA 23.57 34.34 183 Total Beds Total Beds in MSA 5158.10 9476.89 99 64,648 Cooldd Cooling degree days 1633.21 1096.67 27 5030 Heatdd Heating degree days 4298.17 2418.47 12,436 WR Ratio of median wage in medical sector to FMR2 rent 6.47 1.04 3.72 9.65

Degree days 2013-2014 - selected cities.

	Cooling	Heating
Atlanta	1752	2941
Boston	911	5878
Cleveland	881	6339
Detroit	884	7039
Miami	4836	61
Minneapolis	984	8594
New York City	1388	5033
Phoenix	5030	542
San Diego	776	537
San Francisco	172	1995
Washington DC	1710	4144

This table presents the cooling and heating days for a representative subset of the MSAs observed. Heating degree days indicate household energy consumption for space heating. For an average outdoor temperature of 65 °F, most buildings require heat to maintain a 70-degree temperature inside.

agglomeration of activities desirable. Until constrained by lack of land, or congestion, increasing populations and agglomerations of single and/or groups of industries provide increased productivity leading to increased profits or (nonprofit) residuals (Brueckner 1987, 2011). Internal scale economies occur when firms integrate vertically or merge. This urban explanation parallels a health literature advocating hospital merger and acquisition activity as a means of reducing healthcare costs (e.g. Dranove and Lindrooth, 2003).

With agglomeration, activity concentration enhances productivity. The micro-foundations of these productivity gains include knowledge spillovers (Glaeser and Mare, 2001), labor market pooling, input sharing (Rosenthal and Strange, 2001) and supplier pricing competition (Johansson and Quigley, 2004). In an open economy, where activities and people can migrate without major difficulty, increased productivity will be capitalized over time into higher land rents, and higher worker wages (Wheaton, 1974; Rosen, 1979).

Gabriel and Rosenthal (2004) discuss the static equilibria through Fig. 2, which examines households and entrepreneurs. In this model:

- Households earn wages and pay land (and by inference housing)
- Entrepreneurs use land (with land rents) and labor (paying wages) to produce output.

Consider wages and rents at an arbitrary distance z_0 (say $z_0 = 1$) from the center of the city. City-specific income and transportation factors will cause rents and wages to adjust at different distances z such that no member of a given occupation or income group, competing with others for land or jobs, is better off at one city location than another. A similar relationship occurs across cities. To maintain equilibrium

Table 4a
Principal components analysis for health capital.

MSA Hospital Characteristics	Factor1	Factor2	Factor3
# Hospitals W/C.T. Scanner	0.89790	0.41796	0.08171
# Hospitals W/Mag Resonance Imaging	0.90695	0.39749	0.08442
# Hospitals W/Positron Emission Tom	0.87840	0.34464	0.15694
#Hospitals W/Multi-slice Special Com Tom < 64	0.90790	0.39706	0.08981
#Hospitals W/Multi-slice Special Com Tom 64 +	0.91023	0.36491	0.11610
# Hospitals W/Ultrasound	0.90300	0.40754	0.08863
# Hospitals W/Image-guided Radiation Therapy	0.93390	0.23616	0.15348
# Hospitals W/Robotic Surgery	0.89244	0.38763	0.12875
# Short Term General Hospitals	0.88949	0.41959	0.08717
# Long Term Hospitals	0.94481	0.02093	0.10725
# Hospital Beds	0.94750	0.23497	0.14925
# Psychiatric Short Term Hospitals	0.78540	0.49318	- 0.03286
# Rehabilitation ST Hospitals	0.42174	0.68765	- 0.17721
# Children's Gen Med/Surgery ST Hospitals	0.22565	0.89914	0.10546
# Beds/Hospital	0.19133	- 0.01486	0.96336
Variance Explained by Each Factor	10.00105	2.87086	1.12101

This table presents the results from the principal components models. Factor1 measures MSA care sophistication with both numbers of hospitals in general and various specialty measures. Factor2 focuses more on specialty hospitals as exhibited by the loading for rehabilitation and children's hospitals. Factor3 focuses on average hospital size (beds/hospital), and tracks MSAs with small numbers of hospitals.

among a *system* of cities, increased wages must accompany increased rents— otherwise consumers will leave the city for another in the system. Hence the consumer equilibrium is upward sloping in land rents and wages.

For (profit- or surplus-seeking) entrepreneurial activities in com-

petitive economies, increased wage levels must be compensated with decreased rents, again as noted in Fig. 2. If not, firms will move among cities. Start at initial equilibrium Z_I , at (w_I, R_I) . If firms in large cities enjoy agglomeration economies, they will have excess profits. Competition among firms in those cities will raise equilibrium rents,

Table 4b
Metro areas with highest factor scores.

MSA Factor1 New York-Northern New Jersey-Long Island, NY-NJ-PA 6.47 Chicago-Joliet-Naperville, IL-IN-WI 3.20 Los Angeles-Long Beach-Santa Ana, CA 1.61 Houston-Sugar Land-Baytown, TX 1.29 Boston-Cambridge-Quincy, MA-NH 1.24 Philadelphia-Camden-Wilmington, PA-NJ-DE-MD 1.04 Atlanta-Sandy Springs-Marietta, GA 0.99 Detroit-Warren-Livonia, MI 0.913 Washington-Arlington-Alexandria, DC-VA-MD-WV 0.909 Baltimore-Towson, MD 0.71 Highest Factor2 MSA Factor2 Dallas-Fort Worth-Arlington, TX 6.87 Los Angeles-Long Beach-Santa Ana, CA 7.68 Philadelphia-Camden-Wilmington, PA-NJ-DE-MD 2.43 Houston-Sugar Land-Baytown, TX 2.14 Kansas City, MO-KS 1.50 Austin-Round Rock-San Marcos, TX 1.44 Pittsburgh, PA 1.40 Omaha-Council Bluffs, NE-IA 1.37 MSA Factor3 Lynchburg, VA 7.60 Gainesville, GA 4.25 </th <th>Highest Factor1</th> <th></th>	Highest Factor1	
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Lynchburg, VA 7.60 Gainesville, GA 4.25 Napa, CA 4.13 Greenville, NC 3.78 Orlando-Kissimmee-Sanford, FL 3.51 Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Highest Factor3	
Gainesville, GA 4.25 Napa, CA 4.13 Greenville, NC 3.78 Orlando-Kissimmee-Sanford, FL 3.51 Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	MSA	Factor3
Napa, CA 4.13 Greenville, NC 3.78 Orlando-Kissimmee-Sanford, FL 3.51 Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Lynchburg, VA	7.60
Greenville, NC 3.78 Orlando-Kissimmee-Sanford, FL 3.51 Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Gainesville, GA	4.25
Orlando-Kissimmee-Sanford, FL 3.51 Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Napa, CA	4.13
Gainesville, FL 3.15 Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Greenville, NC	3.78
Cape Coral-Fort Myers, FL 2.64 Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Orlando-Kissimmee-Sanford, FL	3.51
Pascagoula, MS 2.51 Auburn-Opelika, AL 2.38	Gainesville, FL	3.15
Auburn-Opelika, AL 2.38	Cape Coral-Fort Myers, FL	2.64
1 ,	Pascagoula, MS	2.51
Pueblo, CO 2.24	Auburn-Opelika, AL	2.38
	Pueblo, CO	2.24

This table illustrates the 10 MSAs with the highest factor scores for each of the 3 factors identified.

Table 5aMSA level wage estimates – linear.

Dep variable	Wage			
	(a)	(b)	(c)	(d)
Intercept	41.3060***	38.0430***	40.9142***	42.9018***
-	1.05992	0.87702	1.43677	1.77038
Sector Emp	0.00013***	0.00012***	0.00010***	0.00009***
•	0.00002	0.00002	0.00002	0.00002
ajobs_1000	- 0.10461***	- 0.06868***	- 0.06718***	- 0.06976**
•••	0.01598	0.01309	0.01318	0.01328
Total Hospitals	- 0.09147 ***	- 0.06226***	- 0.17820***	- 0.15812**
	0.02178	0.01781	0.04357	0.04567
Total Beds	- 0.00055***	- 0.00060***	- 0.00050***	- 0.00046**
	0.00014	0.00011	0.00013	0.00014
FL		- 0.26813	- 0.17490	0.26607
		0.63636	0.67406	0.75993
CA		7.34045***	7.52710***	6.53019***
		0.54045	0.56209	0.73016
NE		3.68771***	3.87057***	3.79664***
112		0.55904	0.55755	0.57421
Factor1		0.00501	3.74797**	3.27064*
1 401011			1.66224	1.73389
Factor2			2.30312**	2.05618**
ractor2			0.79659	0.81994
Factor3			0.28933	0.21587
ractors			0.25050	0.25222
Cooldd1			0.23030	- 0.00067 **
Cooluu1				0.00028
Heatdd1				- 0.00024 *
Heatuui				0.00024
MSE	3.7627	2.9953	2.9688	2.9531
R ²	0.2961	0.5576	0.5690	0.5760
Adj R ²	0.2884	0.5491	0.5570	0.5617
Elasticities	0.2004	0.3431	0.3370	0.301/
Employment	0.1599	0.1448	0.1233	0.1144
Job/1000	- 0.1837	- 0.1206	- 0.1180	- 0.1225
Job/1000 Factor1	- 0.103/	- 0.1200	- 0.1180 0.1057	- 0.1225 0.0922
Factor1			0.105/	0.0922
Factor2			0.0649	0.0580
			0.0082	
Cooling				- 0.0310
Heating				- 0.0289

and workers will be attracted to higher wages, at point Z_2 (w_2 , R_2). The inter-relationship of consumers and producers jointly determines wage and rent levels within a system of cities, but without wages, rents, or their ratios being equal everywhere. Gabriel and Rosenthal (2004) verify this hypothesis in a set of empirical tests.

Health economics features the considerable agglomeration economies of large medical centers, specialized providers, and the scale and scope economies of medical complexes, lab-oratories, large universities and teaching hospitals. Under these circumstances, health care providers pay higher wages to their workers, and higher building rents (or implicitly higher opportunity costs for hospital space) for this improved productivity. Although a substantial portion of the health care community operates under not-for-profit status, the optimization economies are essentially the same (see Lakdawalla and Philipson, 2006) as in for-profit settings. Whereas the health literature views differing staffing levels, provider mixtures, and treatment levels, as economically inefficient (Folland et al., 2018), the urban model accepts these differences as gains to agglomeration, and shows how to measure them.

3. The empirical content

This section specifies regressions to estimate equilibrium wages, rents, and wage-rental ratios. It then develops a two-stage model to estimate labor supply across metropolitan areas.

One would expect wages of health-related workers, and rents paid

for both production and living facilities to be higher in larger metropolitan areas. This correlation relates to potentially higher capital-labor ratios, and to increasing returns to scale until congestion or logistical control problems offset the scale benefits.

Although urban theory suggests higher real wages and land rents in areas with larger capital-labor ratios and agglomeration economies, additional factors will dictate which of the two (wages and rents) is higher. Higher rents may deflate wage differentials, but rents do not comprise the entire price index deflator (which also includes consumer and non-traded goods). Therefore, large rent differentials may constitute small portions of Metropolitan Statistical Area (MSA) level price indices

Most of the factors leading to wage differentials relate to demand for labor, so it is possible to identify a labor supply function. We attempt such estimation and identification for two groups; (1) all health professionals; (2) registered nurses (RNs), a relatively more homogeneous occupation. We find supply elasticities greater than +1 for all health-related personnel, and between 0 and +1.0 for registered nurses. We derive two estimation procedures from these models. The first provides reduced form estimates for Wages, Rents, and for Wage/Rental ratios, following from the urban model. The second attempts potential identification of a labor supply equation across MSAs.

The reduced form specification leads to estimation equations for MSA i, Sector j and location-specific factors k:

Wages:

^{*** 1%; ** 5%; * 10%} significance.

Table 5bMSA level wage estimates – semi-log.

Dep variable	Ln Wage					
	(e)	(f)	(g)	(h)		
Intercept	3.71807***	3.63449***	3.70909***	3.74780***		
•	0.02860	0.02417	0.03966	0.04900		
Sector Emp	0.0000356***	0.0000324***	0.00000277***	2.58E-06***		
•	5.95E-07	4.84E-07	5.68E-07	5.77E-07		
Sec Jobs 1000	- 0.00283***	- 0.00193***	- 0.00189***	- 0.00197***		
_	0.00043117	0.00036061	0.0003637	0.0003674		
Total Hospitals	- 0.00235***	- 0.00154***	- 0.00451***	- 0.00396**		
•	0.00058757	0.00049079	0.00120	0.00126		
Total Beds	- 0.0000155***	- 0.0000169***	- 1.448E-05***	- 1.325E-05**		
	0.0000377	0.00000311	0.000036	3.75E-06		
FL		- 0.00422	- 0.00218	0.01023		
		0.01754	0.0186	0.02103		
CA		0.18787***	0.19248***	0.17223***		
		0.01489	0.01551	0.02021		
NE		0.10371***	0.10839***	0.10551***		
		0.01541	0.01539	0.01589		
Factor1		******	0.09702**	0.08231*		
1 401011			0.04588	0.04799		
Factor2			0.05943**	0.05237**		
1 40001 =			0.02199	0.02269		
Factor3			0.00797	0.00613		
1 401010			0.00691	0.00698		
Cooldd1			0.00071	- 1.496E-05*		
Coolda				7.71E-06		
Heatdd1				- 4.53E-06		
11cutuu1				0.0000037		
MSE	0.1015	0.0825	0.0819	0.08173		
R ²	0.3003	0.5413	0.5517	0.5565		
Adj R ²	0.2926	0.5324	0.5392	0.5416		
Elasticities	0.2720	0.0021	0.0072	0.5 110		
Employment	0.1547	0.1408	0.1203	0.1121		
Job/1000	- 0.1762	- 0.1202	- 0.1177	- 0.1227		
Factor1	0.1/02	0.1202	0.0970	0.0823		
Factor 1 Factor 2			0.0594	0.0524		
Factor3			0.0080	0.0061		
Cooling			0.0000	- 0.0244		
Heating				- 0.0195		

$$W_{ij} = a_0 + a_1 Capital_{ij} + a_2 Employ_{ij} + a_3 JFraction_{ij} + \sum_{k=1}^{M_W} \alpha_k G_k + \varepsilon_{ij}^W$$
(1)

Rents

$$R_{ij} = b_0 + b_1 Employ_{ij} + b_2 JFraction_{ij} + \sum_{k=1}^{M_R} \beta_k G_k + \varepsilon_{ij}^R$$
(2)

Wage-rental ratio WR:

$$\left[\frac{W}{R}\right]_{ij} = c_0 + c_1 Capital_{ij} + c_2 Employ_{ij} + c_3 JFraction_{ij} + \sum_{k=1}^{M \left(\frac{W}{R}\right)} \gamma_k G_k + \varepsilon_{ij}^{\left(\frac{W}{R}\right)}$$
(3)

It is assumed that more, and higher quality, health production capital increases laborers' marginal productivity, and hence wages. The following section will create a measure to account for the multiple dimensionality of health care capital. One can view sectoral employment as a scale term. The larger the Labor Force (Employ), the better the scale economies. A corresponding decrease in marginal improvement at some inflexion point, leads to positive signs for coefficients a_2 , b_1 , and c_2 . In Eqs. (1)–(3), JFraction controls for the importance of health care in the total economy. Its impact may be positive or negative depending on relative supply of and demand for the factor.

The G terms are exogenous shifters. Due to regulations or price

disparities, state or regional factors matter. Climate is also a natural and exogenous amenity with heating and cooling degree days measuring how the climate varies from 65 °F. To the extent that significant departures from the baseline require significant heating or cooling costs to increase comfort, the wage sign is uncertain, but either would make land in a particular MSA less desirable than in other MSAs, so the impact on rents would be negative (Roback, 1982).

Eq. (1) through (3) represent well-understood relationships that link health economics with urban economics, but it may also be possible to identify labor supply, related to the wage rate, in a simultaneous system. Consider equation system:

Supply

$$\ln N_{S} = s_{0} + s_{1} \ln \frac{W}{R} s_{1} + \Sigma \sigma_{k} G_{k} \quad s_{0}, \quad s_{1}, \quad \sigma_{k} > 0,$$
(4)

where G_k are exogenous supply shifters such as climate. Demand:

$$ln N_D = r_0 + r_1 ln \frac{W}{R} D, + r_2 Capital (K) + r_3 Technology(T)$$

$$+ r_4 Population (Pop) + r_5 JFraction (Mix), r_0, r_2, r_3$$

$$, r_4 > 0; r_1, r_5 < 0$$
(5)

In regional labor market equilibrium, setting (4) and (5) equal leads to:

^{*** 1%; ** 5%; * 10%} significance.

Table 6 MSA level rent estimates.

Rent reduced form (N = 370)								
	Linear	Linear			Ln Rent			
Dep variable	(a) Rent	(b) Rent	(c) Rent	(d) Ln Rent	(e) Ln Rent	(f) Ln Rent		
Dep variable	Kent	Kent	Keiit	Lii Keiit	Lii Keiit	Lii Keiit		
Intercept	813.0863 *** 11.9557	974.8135 *** 42.5791	1241.1079 *** 65.2952	6.6847 **** 0.0121	6.8665 *** 0.0433	7.1185 **** 0.0667		
Sector Emp	0.0017 *** 0.0001	0.0013 *** 0.0001	0.0012 *** 0.0001	0.0000017 *** 1.42E-07	1.23E-06*** 1.19E-07	1.19E-06*** 1.15E-07		
Sec Jobs_1000		- 3.3126 *** 0.6420	- 3.2386 *** 0.6238		- 0.00365 *** 0.00065	- 0.00355 *** 0.00064		
Cooldd			- 0.0614 *** 0.0136			- 0.00005 7*** 0.000014		
Heatdd			- 0.0362 *** 0.0067			- 0.000035 *** 0.000007		
Florida		133.9665 *** 32.9793	112.1556** 36.9307		0.1629*** 0.0335	0.1366*** 0.0377		
California		319.0603 *** 28.1493	184.7349 *** 36.6433		0.3064*** 0.0286	0.1 777*** 0.0374		
Northeast		225.2490 *** 28.0089	239.9194 *** 27.8954		0.2336*** 0.0285	0.2496*** 0.0285		
MSE	198.3224	156.4687	150.8064	0.2012	0.1591	0.1540		
\mathbb{R}^2	0.2900	0.5628	0.5961	0.2808	0.5553	0.5857		
Adj R ² Elasticities	0.2880	0.5568	0.5883	0.2789	0.5492	0.5777		
Employment	0.0837	0.0617	0.0597	0.0739	0.0534	0.0517		
Job/1000		- 0.2324	- 0.2272		- 0.2273	- 0.2211		
Cooling			- 0.1131			- 0.0929		
Heating			- 0.1751			- 0.1502		

Eauilibrium:

$$\ln \frac{W}{R} = \frac{r_0 - s_0}{s_1 - r_1} + \frac{r_2}{s_1 - r_1} K + \frac{r_3}{s_1 - r_1} T + \frac{r_4}{s_1 - r_1} Pop + \frac{r_5}{s_1 - r_1} Mix$$

$$- \sum_k \frac{\sigma_k G_k}{s_1 - r_1}$$
 (6a)

Equilibrium:
$$ln\frac{W}{R} = t_0 + t_1K + t_2T + t_3Pop + t_4Mix - \Sigma t_kG_k$$
 (6b)

where $t_0 = \frac{r_0 - s_0}{s_1 - r_1}$, $t_1 = \frac{r_2}{s_1 - r_1}$, and so on. The fitted value from (6b) will identify parameter s_1 from Eq. (4). Structural parameters r_1 , r_2 , r_3 , r_4 , and r_5 , and σ_k are not identified, but their signs can be determined, because the denominators of terms in (6a) are unambiguously positive.

4. Data

The analysis uses four separate databases for the year 2013.

- a) Occupational Employment Statistics Survey, by the Bureau of Labor Statistics, 2013. This database aggregates employment data at multiple geographic levels for numbers of participants, mean and median wages.
- b) Fair Market Rent measures, distributed by the Department of Housing and Urban Development. Although most formal economic theory refers to land rents, the FMR measures the market dwelling unit rents that will presumably equalize utility in housing across metropolitan areas.
- c) Area Resources Files (AHRF) from the US Department of Health and Human Services. These files provide data on hospital and technology facilities in metropolitan areas.
- d) Degree Days measures of heating and cooling, from National Centers for Environmental Prediction (NCEP) – NOAA. These climate measures provide useful shift terms, that are exogenous both to wages and rents.

The accompanying footnote gives web sites for items a-d²

The analysis uses MSA level data for the United States. The Census defines MSAs by commuting patterns, so they better represent individual labor or housing markets than do counties or states. Table 2 shows summary statistics and includes *Healthcare Practitioners and Technical Occupations*, a category containing occupations as diverse as licensed practical nurses, podiatrists, dental hygienists and brain surgeons. Although heterogeneous, it describes the health care economy as a whole relative to other sectors. We will also stratify by looking at registered nurses (RNs), a more homogeneous occupation segment in health care. Finer occupational gradations reduce the number of MSAs because the relatively small numbers in many categories trigger the suppression of Census-based data.

The measures in Table 2 show a mean wage of \$35.45 per hour, about 20% higher than median wage, and indicative of a long right hand tail. Fair Market Rent represents a two-bedroom unit (HUD has measures for various size units, but with rents highly correlated with number of bedrooms, results are largely invariant to the explicit rental unit size). Total sectoral employment means are skewed by very large values of the metropolitan New York and Los Angeles areas. The degree days (sample in Table 3) provide plausible climate descriptions.

An MSA health services capital stock measure must incorporate the multidimensional nature of underlying resources. Capital measures indicating numbers of beds, or beds per hospital, must differ from access to higher-tech facilities such as CT or MRI devices, or robotic surgery. Initial investigations show severe multicollinearity among quality and quantity measures. We choose principal components analysis (Vari-max method; SAS Version 9.3) to see which factors correlate together. Table 4a provides information on the three compo-

^{*** 1%; ** 5%; * 10%} significance.

² At this time (October 2017), the wage database (a) is at http://www.bls.gov/oes/; rent database (b) is at https://www.huduser.gov/portal/datasets/fmr.html; Area Resource database (c) is at http://ahrf.hrsa.gov/. The heating/cooling database (d) is at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/.

Table 7a
Wage-rental estimates and amenity residuals.

Wage rental ratios (N = 30	59)	
	(a)	(b)
	Linear	Log
Intercept	4.8503***	1.6073***
	0.4800	0.0754
Sector Emp	- 0.000018***	- 0.000003***
	0.000006	0.000001
Sec Jobs_1000	0.008340**	0.001330^{**}
	0.003600	0.000565
Cooldd	0.000166**	0.000026**
	0.000076	0.000012
Heatdd	0.000205***	0.000033***
	0.000036	0.000006
Total Hospitals	0.0143	0.0029
-	0.0124	0.0019
Total Beds	0.0001***	0.0000***
	0.0000	0.0000
Factor1	- 0.4599	- 0.0532
	0.4701	0.0738
Factor2	- 0.2598	- 0.0381
	0.2223	0.0349
Factor3	- 0.0073	0.0044
	0.0684	0.0107
Florida	- 0.6857 ***	- 0.1057 ***
	0.2061	0.0324
California	- 0.0010	- 0.0072
	0.1980	0.0311
Northeast	- 1.1515***	- 0.1857 ***
	0.1557	0.0245
MSE	0.8007	0.1257
\mathbb{R}^2	0.4341	0.4565
Adj R ²	0.4150	0.4381
Elasticities		
Sector Employment	- 0.1224	- 0.1468
Sector Jobs 100	0.0803	0.0828
Cooling	0.0419	0.0432
Heating	0.1360	0.1397

nents with values of the Eigenvectors exceeding 1.0.

Factor1 may be interpreted as MSA care sophistication with both numbers of hospitals in general and various specialty measures including CT, MRI, PET scans, and robotics. Actual number of MSA hospitals also factors in strongly. Table 4b sorts factor scores by MSA size, and suggests that Factor1 relates to the size of the MSA. Factor2 focuses more on specialty hospitals including rehabilitation and children's hospitals. It excludes larger MSAs (New York and Chicago) and concentrates more on smaller MSAs such as Austin, Pittsburgh, and St. Louis. Factor3 focuses on average hospital size (beds/hospital), and tracks MSAs with small numbers of hospitals. The highest scores (Table 4b) are Lynchburg VA, Gainesville GA, and Napa CA.

4.1. Analytical results for wages and rents – reduced form

Tables 5a and 5b presentwage regressions in both linear (Table 5a) and semi-log (Table 5b) form. The (parsimonious) regressions (a) and (e) use total MSA employment, and number of jobs per thousand in the medical sector. Regressions (b), (c), (f), and (g) also examine numbers of hospitals, beds, and the quality factors discussed above. Following Oi (1996) and others, regressions (d) and (h) show the degree day variables.³ Binary variables show Florida, California and the Northeast;

other geographic gradations were tested, but reduced degrees of freedom without additional insight. We weight all regressions by the square root of the Census-estimated standard error of the population from the data base. Column (d) presents the most complete linear regression.

For regression (d), two important effects emerge. A one percent increase in total sectoral employment increases the wage rate by \pm 0.114% (similar among all regressions). The second variable measures the impact of increased sectoral employment as a fraction of all regional employment. A one percent increase in medical jobs per 1000 people employed relates to a \pm 0.122 decline in wages (again, broadly similar among regressions).

Quality factors 1, 2, and 3 all have expected positive impacts, speaking to the positive impact on wage levels of increased quality- and capital-intensiveness. Factor1 (care sophistication) has a wage elasticity of about + 0.09. Factor2 (specialty and children's hospitals) has a wage elasticity of + 0.06. Factor3 (beds per hospital) has an elasticity of about + 0.01 and is not statistically significant.

The cooling and heating terms have qualitative impacts like those found by Oi. Hot weather (more cooling degree days) has an elasticity of – 0.031; cold weather (more heating degree days) has an elasticity of – 0.029. Florida workers earn about 0.27 (0.8%) more than other states (not significant). Workers in California and in the Northeast earn 0.53 (18.4%) and 0.80 (10.7%) respectively. These relationships are all consistent with the Fig. 2 analysis. Semi-log regressions (e)–(h) have similar interpretations.

Table 6 presents the rent estimate model and the sign patterns are the same as for wages. Increased total sectoral employment implies higher rents with an elasticity of approximately + 0.060 for the linear form (column c) and + 0.052 for the semi-log form (column f). This is consistent with increased marginal productivity of the land. Increased sectoral employment per 1000 has a negative impact on the rent, with elasticities of -0.227 and -0.221 for the linear and semi-log rent regressions respectively. The rent market evaluates both heating and cooling days as undesirable, with heating days (cold weather) more undesirable. In the linear (semi-log) regression the heating elasticity is about -0.175 (-0.150), whereas the cooling elasticity is -0.113 (-0.093). These relationships are also consistent with the Fig. 2 analysis.

The analyses thus far have indicated how wages and rents would adjust to mobility within a system of cities or metropolitan areas. Although theory predicts both higher wages and rents in larger areas, it does not indicate the absolute, or relative, magnitude of the differences. This is where the wage-rent ratio (W/R) is incorporated. In addition to the theoretical basis for the use of both wages and rents in regional models, the rental index provides a partial deflator for the costs of living around the country. The elasticities presented in Tables 4 and 5 indicate the total employment effect on wages is a little over twice as large as that on rents.

The dependent variable for Table 7a is the wage-rental ratio from Eq. 3 above, where $W/R = (1875 \times \text{hourly wage})/(12 \times \text{monthly rent})$. A one percent increase in total employment is related to a -0.122 (linear) or a -0.147 (semi-log) decrease in the wage-rental ratio, thus driving up rents relatively more than wages. This is consistent with our separate analyses from the wage and the rent regressions because it constitutes a rightward shift in the constant profit curve, as shown in Fig. 2 (movement from ray $[\frac{W}{R}]_1$ to ray $[\frac{W}{R}]_2$). The sectoral impact on the wage-rental ratio is between + 0.080 (linear) and + 0.083 (semi-log). Wage-rental ratios are higher in locations with large heating and/or cooling needs.

The ratios are also higher (but not significant) in metropolitan areas with more hospitals and more hospital beds (significantly so). Irrespective of these adjustments the wage-rental ratio is -0.686 (10.0%) lower in Florida than elsewhere, and -1.151 (16.9%) lower in the Northeast. Moreover, differential levels of health services capital

^{*** 1%; ** 5%; * 10%} significance.

³ Oi (1996) (referring to workplace air conditioning) finds, at the state level, significantly lower wages in states with higher temperatures and more cooling degree days. There is also a literature on the short-term impacts of weather on labor supply (e.g., taxi drivers may more work more if it rains because there will be more customers).

Table 7bTwenty-Five Largest Cities by Amenity Residuals.

Sorted by Regionally adjus	sted				
	Residual	Regionally Adjusted	Texas v. <u>Austin</u>	N'East v. <u>Wash DC</u>	California v. <u>San Jose</u>
Washington, DC	-0.16042	-0.34609		0.0000	
Philadelphia, PA	-0.09814	-0.28381		0.0604	
Boston, MA	-0.05140	-0.23707		0.1033	
New York, NY	0.03786	-0.14781		0.1799	
Austin, TX	-0.14681	-0.14681	0.0000		
San Jose, CA	-0.11058	-0.11780			0.0000
San Diego, CA	-0.10977	-0.11699			0.0008
Nashville-Davidson, TN	-0.08397	-0.08397			
San Antonio, TX	-0.05687	-0.05687	0.0860		
Jacksonville, FL.	0.07292	-0.03277			
San Francisco, CA	-0.02228	-0.02950			0.0845
Denver, CO	-0.01215	-0.01215			
Chicago, IL	0.00449	0.00449			
Memphis, TN	0.01594	0.01594			
Los Angeles, CA	0.02691	0.01969			0.1285
Houston, TX	0.02897	0.02897	0.1612		
Indianapolis, IN	0.03518	0.03518			
Phoenix, AZ	0.04398	0.04398			
Seattle, WA	0.04767	0.04767			
Detroit, MI	0.08358	0.08358			
Columbus, OH	0.10024	0.10024			
Dallas, TX	0.12204	0.12204	0.2357		
Fort Worth, TX	0.12204	0.12204			
El Paso, TX	0.12235	0.12235	0.2360		
Charlotte, NC	0.13406	0.13406			

(the Factor components), as well as the total number of hospitals, are insignificant with respect to W/R (although the effects were important for the wage indices).

Gabriel and Rosenthal (2004) use wage-rental indices for quality of life measures. A city with relatively desirable amenities would show a negative residual with workers willing to accept lower wages and/or pay higher rents than otherwise. Both would serve to lower the wage-rental ratio. Table 7b ranks the 25 largest (2013) cities in terms of raw residuals (semi-log regression b in Table 7a), and adjusted residuals (adjusted for the regional effects). For example, Washington DC has a raw residual of -0.1604. However, since Washington is estimated (here) as part of the Northeast, its adjusted residual is -0.3461.

Because an algebraically negative residual indicates higher amenity value, one can compare cities within the same state. Looking at the 25 largest cities, holding Texas constant, for example, Austin has the highest amenities. The San Antonio value is about 8.6% worse than Austin (in log terms), Houston about 16.1% worse, Dallas/Ft. Worth about 23.57% worse, and El Paso about 23.60% worse. In short, the reduced form analyses explain large portions of variation in wages earned and rents paid. They are consistent with higher productivity due to agglomeration and due to deeper capital stocks.

4.2. Analytical results - Structural labor supply model

We have shown how wages and rents adjust across metropolitan areas for health professionals. Eqs. (4)–(6) showed how to structure a regional labor supply function that indicates the mobility of health-services-related professionals across metropolitan areas.

Table 8a estimates the first stage regression in both linear and semilog form using determinants of health-services capital quantity and quality, as well as geographical indicators. Notably all three of the health services capital factors enter positively and significantly. Although the major purpose of the first-stage estimator is to identify the supply elasticity, we note that capital quality has a positive impact on the wage instrument, whereas quantity has a negative impact.

Table 8b estimates the impacts of fitted wages on the size of the

health care labor force, with and without geographic indicators (a further analysis including heating and cooling in the second stage shows essentially no impact). Calculating the elasticity must recognize the cor-relation of wages and rents within the system. Starting from the following simplified equations:

$$\ln L = s_1 \ln \frac{W}{R}$$

$$\frac{dL}{L} = s_1 \left(\frac{dW}{W} - \frac{dR}{R} \right)$$

$$\frac{dL/L}{dW/W} = Elas_{LW} = s_1 \left(1 - \frac{dR/R}{dW/W} \right) = s_1 (1 - Elas_{RW})$$

where s_1 is the coefficient of W/R.

Rents R and wages W are correlated through the system of cities, and we estimate $Elas_{RW}$ directly below (coefficient of 1.4652) for all health workers.

 $\ln R = 1.5412 + 1.4652 \ln W$, SEE = 0.1579, $R^2 = 0.5566$; N = 371 (S. E.) (0.2425) (0.0681)

Therefore, the calculated supply elasticity varies from 3.470 in the simplest estimator (Table 8b - col a) to +7.203 (Table 8b - col c). We discuss the size of these elasticities, as well as those in the nursing sector, in Section 7.

5. The RN sectors

The preceding analyses examine a health services population ranging from licensed practical nurses, pharmacists, and physical therapists, to surgeons. The heterogeneity internalizes substitution, sorting, and selection among the occupations. However, the underlying urban models imply homogeneity among land renters (for consumers) and among laborers (for firms). The rent conditions imply *similar* consumers competing with each other for dwelling units or land parcels; likewise, the equal-profit conditions among firms imply *similar* firms competing. The income range from support staff to specialized surgeons is expansive. It is reasonable to expect that laborers in different wage strata may face different rental markets.

Table 8a Structural Wage-Rental Equations – First Stage.

	All Professions	RNs Only
	(N = 369)	(N = 347)
Dep. Var	Log W/R	Log W/R
Intercept	1.57570***	1.43602***
	0.07535	0.07263
Population	-0.00004066***	-0.00004922***
	0.00001445	0.00001457
Ajobs_1000	0.00113°	0.00401***
,	0.00059735	0.00135
Tothsp	0.00365*	0.00740***
Tomsp	0.00201	0.00205
Hospbeds	0.00000595	-0.00000242
Trospoeds	0.00000487	0.00000487
Factor1	-0.12216 [*]	-0.12786*
ractorr	0.07038	0.06992
Factor2	-0.07118**	-0.09697***
1 40012	0.03379	0.03369
Factor3	-0.00356	0.00889
1 40.010	0.01037	0.01111
FL	-0.10870**	-0.14078***
T.L.	0.03268	0.03267
CA	0.00346	0.14273***
CA	0.03181	0.03320
NE	-0.19888	-0.17091***
NE	0.02517	0.02616
G 1114	0.000001***	0.0000060**
Cooldd1	0.0000291 *** 0.0000119	0.0000260** 0.0000125
	***	00.00.00
Heatdd1	0.0000313***	0.0000261***
	0.0000058	0.0000060
MSE	0.1269	0.1239
R ²	0.4466	0.3941
Adj-R ²	0.4280	0.3723

The next analysis concentrates on registered nurses (RNs). RNs represent a more homogeneous group of medical workers, although a cursory examination indicates that there is considerable heterogeneity in their job descriptions as well. RNs have lower mean (\$31.19 per hour) wages than the average health employee (\$35.45). Mean MSA sectoral employment for RNs is 8954, a little over 20% of the "all professions" category (43,445). Even with these relatively large counts, confidentiality constraints reduce sample size from 371 to 353 MSAs.⁴

The Table 8 RN regressions validate the two-stage supply parameter estimates from the larger sample. Table 8a shows that the hospital quality factors had similar impacts on RNs as they did on all healthcare personnel. For example, Factor1 (care sophistication) decreases all healthcare W/R by 12.2% and the RN ratio by 12.8%. Factor2 (specialty hospitals) reduce the all healthcare W/R by 7.1%, compared to 9.7% for registered nurses. Factor3 has little impact on

either, but a slightly higher impact for RNs compared to all wages.

The last line of Table 8b compares the All Health and RN wage elasticities., calculated from the coefficient of W/R, and the elasticity of rent to wage. For RNs, as for the all health category, rents R and wages W are correlated through the system of cities, and we estimate the elasticity directly (coefficient of 1.0338) below for all health workers.

$$\ln R = 3.18724 + 1.03383 \ln W$$
, $SEE = 0.1578$, $R^2 = 0.5631$, $N = 354$ (S. E.) (0.1680) (0.0485)

Here the calculated supply elasticity varies from 0.221 in the simplest estimator (Table 8b - col d) to + 0.431 (Table 8b - col f).

6. Interpreting the supply elasticities

The cross-MSA wage elasticities for the all health category (estimated in Section 4.2) varied from 3.47 to 7.20. For RNs (estimated in Section 6) they varied from 0.22 to 0.43. How good are these estimates? There has been a substantial literature on nursing supply, often related to perceived shortages. The nursing supply wage elasticities here are consistent with estimates by Antonazzo et al. (2003) and Shields (2004).

The "all health" supply elasticity estimates are higher, and it is difficult to relate them well to a comparison literature. The values are consistent with increasing returns to agglomeration, which lead to higher densities and to higher real wages. This suggests that some considerable portion of the observed variation in the geographic density of health-related personnel results from scale-related efficiencies in the health care sector. Logically, one would expect labor to concentrate in areas with the best opportunities and/or greatest wages, or in the case of this analysis, in areas offering a comparative advantage in the health care sector.

Moretti's (2011) theoretical framework looks at the joint determination of wages and rents in terms of labor supply and housing supply elasticity. He notes that the high mobility of educated workers across states implies that investments in human capital made by one state may benefit other states. He cites work by Bound et al. (2004) which finds the elasticity of *labor stocks* to *labor flows* to be approximately 0.3 for those with the BA degree, and even lower for students with medical degree. This implies a relatively high labor supply elasticity.

In the health literature Polsky et al. (2000) find that expected income (which is positively related to wage rate) appears to be important in the decisions of new physicians. Rizzo and Blumenthal (1994) find that a 1% increase in wages leads to a 0.49% increase in physician labor supply, controlling for income effects.

Finally, Monte et al. (2015) estimate elasticities of local employment to productivity shocks ranging from 0.5 to 2.5, with substantial heterogeneity across both counties and commuting zones. Productivity shocks are presumably reflected in wages and increased labor supply.

In short, evidence points to potentially higher wage elasticities for health care workers than for RNs, but much of the comparison literature is dated and does not relate explicitly to the health labor force. We will continue to research the issue.

7. Final observations and conclusions

The study has addressed an intersection of urban and health economics, the influence of agglomeration on productivity and therefore rents paid and wages earned by health services professionals. It validates the urban perspective that agglomerations imply higher wages and higher rents, and hence justifies the gathering of healthcare professionals in large cities and medical centers. It explains how, from a health economics perspective, differing factor costs cause health care provision to vary geographically.

Analytically, we provide a theoretical basis for using rents to deflate wages, particularly across metropolitan areas among which health

^{*** 1%; ** 5%; * 10%} significance

⁴ We sought, for example, a sample of general practitioners (GPs), but values in some MSAs were implausibly low, suggesting errors in Census or self-classification. The number of GPs per capita in St. Louis, for example, was almost 10 times larger than Dallas-Fort Worth. Attempts to identify outliers proved arbitrary and unsatisfactory.

Structural Supply Equations - Second Stage.

Second Stage	All Medical			RNs Only		
	N = 369 (a)	(b)	(c)	N = 347 (d)	(e)	(f)
Dep Var: Intercept	<u>Log Workers</u> 23.5596*** 0.9312	<u>Log Workers</u> 31.2960*** 1.1653	<u>Log Workers</u> 36.1137 *** 1.1384	<u>Log Workers</u> 20.1122 *** 1.1413	<u>Log Workers</u> 26.7494 *** 1.4416	Log Workers 29.3634*** 1.5200
Fitted log WR	-7 .4591 *** 0.5014	-11.4197*** 0.6126	- 15.4845 *** 0.6572	- 6.5293 *** 0.6512	- 10.2162 *** 0.8095	- 12.7279 *** 0.9297
FL		- 1.6094 *** 0.2295	- 1.4428 *** 0.2149		- 1.5940 *** 0.2849	- 1.6092 *** 0.2935
CA		- 1.2360 *** 0.1940	- 0.2581 0.2042		0.4607 ** 0.1940	1.4899 0.2952
NE		- 1.5799 *** 0.2015	-2.6822 *** 0.2067		- 1.2884 *** 0.2402	- 1.8959 *** 0.2659
Cooldd1			0.00048 *** 0.00008			0.000330 *** 0.00010813
Heatdd1			0.00045 *** 0.00004			0.000280 *** 0.00005785
MSE dR/dW E*	1.0782 1.4652 3.470	0.9677 1.4652 5.312	0.8455 1.4652 7.203	1.1923 1.0338 0.221	1.1144 1.0338 0.346	1.1079 1.0338 0.431

services professionals frequently migrate. Since wages and rents are intertwined with urban characteristics, the rent index serves as a partial deflator for the wages. Because both contribute to the costs of providing care, they could offer substantive explanations for the geographical differences in factor proportions.

In particular, wages increase significantly (Table 5a) with increased sectoral employment (Elasticity = +0.114), but fall as the proportion of the labor force comprised by the sector within the regional economy increases (Elasticity = -0.122). Rents respond similarly (Table 6) though with slightly higher magnitudes. The sectoral employment elasticity of rents is + 0.060; the elasticity related to employment proportion is -0.227.

We then combine the two to create a wage-rental ratio W/R which reflects the influence that agglomeration has on the relative wage rate in an environment of differential land rents. W/R tends to decrease with total employment (semi-log elasticity of -0.147), but increase with jobs per thousand in the sector (semi-log elasticity of + 0.083). Exogenous amenity factors such as heating and cooling degree days are consistent with slight increases in the W/R.

Finally, we estimate a health services labor supply function across metropolitan areas. We find health labor supply to be elastic, varying from +3.5 to +7.2 for all health sector providers and from +0.2 to +0.4for registered nurses. While economy-wide the supply elasticities are almost certainly much lower, our estimates validate the theory that new supply and migration among metropolitan areas may be responsive to differential wages among them.

Further work on this topic should:

- a. Investigate more thoroughly the estimates of agglomeration effects, which suggest decreasing average costs on wages (about + 0.12) and rents (about + 0.05) leading to decreasing average costs in larger
- b. Seek improved specifications for cross-MSA local labor supplies. Moretti (2011) notes the difficulties in creating credible empirical estimates of local labor supply elasticity, arguing that one needs both

- to isolate labor market shocks that are both localized and demand driven, and to identify the effects both on wages and land prices.
- c. Evaluate the impact of systematically varying factor costs (wages and rents) on geographic variation in health production through production functions that allow substitution among inputs.

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^{*** 1%: ** 5%: * 10%} significant

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