Intraurban Accessibility and Employment Density

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ABSTRACT

This study investigates the relationship between urban accessibility and firm agglomeration, as reflected in patterns of urban employment densities. We use measures of accessibility derived from the regional highway network, combined with small-scale (Census block-level) data on employment from the Longitudinal Employer-Household Dynamics (LEHD) data set to generate proxies for different sources of agglomeration, specifically urbanization and localization economies. These variables are employed in a set of employment density regressions for 20 two-digit NAICS code sectors to identify the propensity of each sector to agglomerate in response to varying levels of accessibility. The density regressions are applied to sample data from the Minneapolis-St. Paul, Minnesota (Twin Cities) metropolitan region for the years 2000 and 2010.

We find that in general urbanization effects tend to overshadow those of localization effects. Moreover, these effects tend to vary by sector, with many service-based sectors showing a stronger propensity to agglomerate than manufacturing and several "basic" sectors like agriculture, mining and utilities.

Keywords: Agglomeration; Accessibility; Employment; Localization; Count data models

INTRODUCTION

For more than a century urban areas have served as the loci of production for an increasing share of the economy. One important reason for this transformation has been the ability of firms to take advantage of productivity gains unique to larger urban settings. These productivity advantages stem from several sources, such as the ability to take advantage of a larger, more skilled labor pool, the spillover of knowledge among workers in a particular industry, and the shared use of certain inputs like public infrastructure (*1*, *2*, *3*). These types of advantages are often described collectively under the concept of *agglomeration economies*.

The role transportation networks play in fostering agglomeration is still the source of considerable debate. In principle, improved transportation networks might enhance agglomerative forces by lowering transport costs for firms and expanding the spatial reach of markets for labor and other goods. If true, this could have implications for the types of investments in network improvements that generate greater economic development outcomes. In this study we incorporate direct measures of the service provided by regional transportation networks in the form of measures of accessibility, which measure the ease of accessing various destinations, and assess their influence on the propensity for firms to agglomerate across several sectors. Variations in accessibility are hypothesized to affect the propensity for agglomeration, as measured by employment densities.

Our approach to studying agglomeration differs somewhat from many prior empirical studies in that we examine intraurban variations in agglomeration across industries, rather than using entire urban areas as sample units. We also investigate variations across economic sectors in the degree of agglomeration. The use of disaggregate accessibility measures allows us to distinguish between sources of agglomeration, as we develop separate, industry-specific measures to proxy for localization effects in contrast to urbanization effects, which are assumed to arise from greater access to all types of activity in the region.

The next section of this study reviews some of the available literature on agglomeration economies and what has been established to date about their links to transportation. The third section covers the research methodology, including sources of data, empirical specification for the employment density regressions, and hypotheses to be tested. The fourth section provides a summary of the results of the empirical analysis and an examination of the hypotheses. In the concluding section, we discuss the result, their implications for transportation planning, and some considerations for future research.

LITERATURE REVIEW

Recent advances in computation to facilitate geographic analysis, along with the greater availability of disaggregate sources of economic data, have allowed for more detailed analysis of the sources of agglomeration economies. Historically, transportation networks played little role in the analysis of agglomeration economies. To the extent that transportation was included, it often took the form of an infrastructure stock and was approximated by an estimate of its value, rather than the flow of services it provided. This infrastructure was assumed to take the form of a club-type good consumed by all the firms locating a given region. Accordingly, agglomeration economies were implicitly assumed to arise from urbanization effects – the types of external scale economies that arise from access to larger, thicker markets. Other potential sources of agglomeration economies such as localization effects, where firms are able to obtain productivity gains by locating near other firms within the same industry, were sometimes recognized but seldom directly incorporated (*4*).

More recent analyses of agglomeration economies, which have sought to distinguish among competing sources of agglomeration and which have employed more disaggregate sources of data, have noted the tendency for localization economies to attenuate with distance. Rosenthal and Strange (*5*) noted this tendency when examining data on firm births and employment growth at the ZIP code level. In this case, the effect of distance was incorporated in the form of a set of concentric rings of varying distances which captured the proximity of employment in both a given industry (to approximate localization effects) and in other industries (a measure of urbanization effects). One of the notable findings was that localization economies tended to attenuate rapidly over distances of a couple of miles, but much more slowly thereafter. In speculating about the possible sources of these localization effects, they noted that one source, information spillovers from contact between workers, might dissipate over very short distances, while the benefits from other sources such as labor market pooling and input sharing might extend over greater distances because they rely on the ability of agents to drive from one location to another.

Similar developments have resulted from efforts to more explicitly incorporate space and the effects of transportation networks into tradition production functions to measure agglomeration effects, partly motivated by theoretical developments suggesting potentially larger productivity gains from transportation improvements (*6*). Graham (*7*) applied this approach to firm-level data from the UK, using ward-level employment data to construct a measure of urbanization (labeled as "effective density") based on employment density discounted by distance. Production functions were fitted to the firm-level data in a number of two-digit SIC (Standard Industrial Classification) industries. Results indicated that for certain industries, particularly service industries, the urbanization effect was substantial.

This initial framework was later extended to include a more complete measure of access to economic activity as a surrogate for urbanization in the form of a generalized cost variable (*8*). The use of generalized cost more completely captures the effect of the cost of transportation by including the effects of congestion, which Graham cited as an important factor in explaining diminishing returns in the most highly urbanized locations. Further extensions allowed for decomposition of elasticity estimates to distinguish agglomeration effects from returns due to the increased efficiency of factor inputs (*9*), the inclusion of measures of localization (*10*), and for nonlinearities in the relationship between accessibility and productivity (*11*).

In addition to being used as an improved proxy for urbanization effects in production functions, measures of urban accessibility have also been applied to estimate the productivity effects from agglomeration via wages. Melo et al. (*12*) used a panel of 50 large U.S. metropolitan areas ("large" defined as a population greater than one million) to estimate the relationship between agglomeration and real average wages. Two different measures of agglomeration were compared, one using a conventional measure of employment density and the other using a formal measure of employment accessibility to incorporate the more realistic effects of transportation networks. The authors tested both a 60-minute time threshold measure of employment accessibility as well as a series of time threshold variables designed to capture the incremental contributions of additional levels of access at greater distances, and to approximate the decaying effect of agglomeration at greater distances. Results indicated that both measures of urban size produced roughly similar estimates of agglomeration economies, with real average wages rising by between 7 and 10 percent in response to a doubling of employment density or jobs accessible within 60 minutes. Also, the travel time thresholds defined for the accessibility variables seemed to indicate a somewhat limited spatial scope of agglomeration, with most of the effects concentrated within 20-minute travel time bands.

While most of the studies relating transportation to agglomeration economies and productivity more broadly tend to focus on road networks (*13*), there have been some efforts to examine the relationship between alternative modes, most notably public transit, and the potential for agglomeration. Drennan and Brecher (*14*) estimated the relationship between public transit use and office rents, which were considered as a proxy for productivity, in a panel data set of real estate markets in US metropolitan areas. The definition of markets was rather crude, dividing metropolitan areas into central business district (CBD) and suburban markets. Simultaneity between public transit use and office rents was addressed using a two-stage estimation procedure. The authors found positive and statistically significant, though small, relationships between transit use and office rents in urban areas with higher concentrations of office space in the CBD, defined as having greater than 30 percent of regional office space in the CBD. Elasticities of office rents with respect to transit use were on the order of 4 to 5 percent, though no significant effects were found for markets with low concentrations of CBD office space.

Chatman and Noland (*15*) examined the relationship between transit service, in this case measured in terms of various measures of service supply, and productivity as measured alternately by average wages and output (gross metropolitan product per capita) in US metropolitan areas. The authors posited that the relationship between service supply and productivity is mediated by the effect of service on population or employment density, which in turn would have spillover effects on productivity. Perhaps not surprisingly, the authors found the largest effects of transit service supply on wages in larger urban areas. This would be expected due to the presence of more transit service in larger urban areas (the authors attempted to instrument for endogenous service levels using older transit maps) as well as the general tendency for larger agglomeration effects in larger urban areas. The reported net transit-wage elasticities were on the order of 0.02, while the elasticities for gross metropolitan product per capita were larger (0.09 to 0.18).

One important weakness of Drennan and Brecher (*14*) and Chatman and Noland (*15*) is that neither study incorporated actual transit networks into their analysis. The former used a measure of transit demand at the region-wide level, while the latter used a measure of service supply, albeit moderated through its effect on central city population and employment density. However, the real value of public transit networks in contributing to urban agglomeration economies lies in its ability to expand the reach of markets and reduce the friction of distance for firms and households within urban areas. Hence, a measure of the service provided by the network itself, in the form of accessibility, is a more appropriate concept for capturing the ability of public transit systems to contribute to urban agglomeration. This consideration will be a key part of the approach adopted in this study, which is described in more detail in the next section.

METHODS AND DATA

This study is primarily concerned with the relationship between accessibility and urban agglomeration at an intraurban level. As the preceding discussion noted, there is evidence of the spatial attenuation of agglomeration economies within urban areas for localization effects and possibly also for urbanization effects. We therefore need to be able to measure agglomeration at a relatively fine spatial resolution in order to capture these attenuation effects, to the extent that they may exist.

Research Design

The variable that will be employed to measure agglomeration effects is employment density, measured as employment per square kilometer. While employment density does not directly yield productivity benefits from agglomeration, it is a useful proxy for the effects of agglomeration, since employment densities are likely to be highest where agglomeration effects are the strongest. Densities are measured at the level of census blocks and aggregated up to transportation analysis zones (TAZ) for the Twin Cities region. The use of this level of aggregation is designed to correspond with the level at which measures of urban accessibility are available.

There are two main considerations that guide our empirical approach. The first is that there ought to be separate variables to capture urbanization and localization economies. As outlined previously, urbanization economies are external to firms and their industries, and so have a wider geographic scope. For example, Melo et al. (*12*) used a 60-minute employment accessibility measure to approximate the effects from urbanization, in addition to measures representing incremental travel time thresholds throughout the region. We adopt this method as well in order to test for the attenuation of urbanization effects over greater distances. Localization economies are approximated with measures of access to own-sector employment for each of the 20 two-digit NAICS code sectors within 10 minutes. They also should be spatially fairly limited given the evidence discussed previously regarding their rather sharp attenuation.

The second consideration is that estimates of urbanization and localization effects ought to be allowed to vary across sectors. This implies that separate equations ought to be estimated for each of the sectors in the data set. Certain types of industries like agriculture and mining are likely to be less susceptible to agglomeration, while others such as manufacturing and various service industries can be expected to demonstrate higher levels of agglomeration.

Data Sources and Variables

LODES Data

The data regarding the number of jobs and workers came from the LEHD Origin-Destination Employment Statistics (LODES) of the US Census Bureau, in which LEHD stands for Longitudinal Employment Household Dynamics. The LODES contain three groups of information including Origin-Destination (OD) data, Residence Area Characteristic data (RAC), and Workplace Area Characteristic (WAC) data. The OD data specify the origins and destinations of commuters, which are not used in this analysis. The RAC and WAC contain the number of jobs by sectors living or working in each census block, which are used to measure accessibility to workers and accessibility to jobs, respectively. Table 1 illustrates the categories of jobs measured in both RAC and WAC (*16*). Since LEHD was initiated in 2002, we extracted the LODES data of Minnesota in 2002 and 2010 to approximate the job and worker data in 2000 and 2010.

TABLE 1 **Two-Digit NAICS Sectors**

Variable	Definition
C000	Total number of jobs
CNS01	Number of jobs in NAICS sector 11 (Agriculture, Forestry, Fishing and Hunting)
CNS02	Number of jobs in NAICS sector 21 (Mining, Quarrying, and Oil and Gas Extraction)
CNS03	Number of jobs in NAICS sector 22 (Utilities)
CNS04	Number of jobs in NAICS sector 23 (Construction)
CNS05	Number of jobs in NAICS sector 31-33 (Manufacturing)
CNS06	Number of jobs in NAICS sector 42 (Wholesale Trade)
CNS07	Number of jobs in NAICS sector 44-45 (Retail Trade)
CNS08	Number of jobs in NAICS sector 48-49 (Transportation and Warehousing)
CNS09	Number of jobs in NAICS sector 51 (Information)
CNS10	Number of jobs in NAICS sector 52 (Finance and Insurance)
CNS11	Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)
CNS12	Number of jobs in NAICS sector 54 (Professional, Scientific, and Technical Services)
CNS13	Number of jobs in NAICS sector 55 (Management of Companies and Enterprises)
CNS14	Number of jobs in NAICS sector 56 (Administrative and Support and Waste Management and Remediation Services)
CNS15	Number of jobs in NAICS sector 61 (Educational Services)
CNS16	Number of jobs in NAICS sector 62 (Health Care and Social Assistance)
CNS17	Number of jobs in NAICS sector 71 (Arts, Entertainment, and Recreation)

CNS18	Number of jobs in NAICS sector 72 (Accommodation and Food Services)
CNS19	Number of jobs in NAICS sector 81 (Other Services [except Public Administration])
CNS20	Number of jobs in NAICS sector 92 (Public Administration)

Speed and Network Data

Acquired by the Metropolitan Council in the Twin Cities, both road network and auto speed data for use in computing 2010 accessibility measures came from TomTom International BV. The network is displayed as a shapefile that can be directly used in GIS software. The total number of links in the Twin Cities on the TomTom network is 48,009. The road network can be linked with the TomTom speed data. We derived the 2010 auto speed from the 2011 TomTom data, which were collected and aggregated based on millions of GPS logging and navigation devices. The TomTom speed data were organized based on road classifications, time periods and speed percentiles. First, based on the Functional Roadway Classifications (FRC), speed data were categorized into 4 groups, of which FRC0 to FRC4 were combined. For each category of FRC, speed data were separately recorded at different times of a day including overnight (10PM-5AM), morning peak hours (5AM-7AM and 7AM-9AM), mid-day (9AM-2PM), evening peak hours (2PM-4PM and 4PM-6PM), and evening (6PM-10PM). Moreover, the TomTom speed data provided different percentiles of speed measurements. The accessibility measurement in this study used the median speed of morning peak hours during 7AM-9AM.

Zone-to-zone travel time matrices for the year 2000 were obtained from a previous study which derived them via travel time skims from the region's travel forecasting model (*17*). Travel times were measured between all the OD pairs at the level of transportation analysis zones (TAZs) based on the year 2000 regional highway network.

Accessibility Measures

The cumulative opportunity measure is used for accessibility measurement, which counts the number of opportunities within given travel time thresholds. Regional accessibility to jobs, our proxy measure for urbanization economies, is calculated from the number of jobs in the WAC data, while for accessibility to workers, the opportunity stands for the number of workers (number of jobs associated with people who live in the residential blocks) in the RAC data. The cumulative opportunity measure is expressed as:

$$A_i = \sum_j O_j f(C_{ij})$$

$$f(C_{ij}) = \begin{cases} 1, if\ C_{ij} \le T \\ 0, if\ C_{ij} > T \end{cases}$$

O_j stands for the opportunities (number of jobs or workers) at destination j ,

C_{ij} stands for the travel time between origin i and destination j ,

T stands for the travel time threshold.

When developing models, we used a 'donut' accessibility measure. It is calculated based on the difference in accessibility between two adjacent travel time thresholds:

$$A_{i,donut_T} = A_{i,T} - A_{i,T-10}$$

$$A_{i,donut_{10}} = A_{i,10}$$

Where:

T equals to 20, 30, 40, 50 and 60 minutes respectively,

$A_{i,T}$ stands for the accessibility within the time threshold of T .
So $A_{i,donut_{10}}$ measures the number of opportunities with 10 minutes of travel time, $A_{i,donut_{20}}$ measures the number of opportunities between 11 and 20 minutes, and so on.

The procedure to create accessibility measures is described as follows:

- Accessibility by auto in 2010
  For this measurement, ArcGIS was used to search the shortest travel time path between each of the OD pairs at the block level based on the TomTom speed data and the linked road network. The travel time was recorded as the C_{ij} to construct travel time matrix. The 2010 LODES data were then joined with the travel time matrix. Then the accessibility matrix is calculated based on the pre-determined time thresholds (10, 20,.., 60 minutes).
- Accessibility by auto in 2000
  Since the travel time matrix by auto in 2000 was measured at the 2000 TAZ level, it was joined with the 2002 LODES data to compute the 2000 accessibility matrix with the pre-determined time thresholds.

Moreover, all the accessibility matrices are displayed using the 2000 TAZ system, which has 1,201 TAZs in total. The modeling is also based on the data of the 1,201 TAZs.

Modeling Approach

A negative binomial regression with robust error is employed to estimate the influence of accessibility on employment density. Previous studies often model employment density in a logarithmic function (*18*,*19*). However, if the error term is heteroskedastic, the estimates from the log-linear function are biased while a Poisson-family regression with robust error is preferred (*20*,*21*). Because some TAZs may not have any jobs for a particular industry, employment density of the industry in those zones is zero. To handle excessive zeros in industry-specific employment density, we adopted negative binomial regression (NBREG).

With a negative binomial link function and robust error, employment density can be expressed as a function of accessibility measures. Here, the accessibility measures include job accessibility by auto, job accessibility by transit, worker accessibility by auto, and worker accessibility by transit. Each of the accessibility measures is expressed as the following weighted cumulative opportunity, or gravity, function:

$$Accessibility = \sum_{i=1}^{6} O_i e^{-b \times i \times 10} ,$$

$O_i, i = 1, \dots, 6$ ction factor and $O_i, i = 1,2, \dots, 6$ measures the opportunity between 0-10, 11-20, 21-30, 31-40, 41-50, 51-60 minutes of travel time by a particular mode (transit or auto), respectively. The opportunity indicates the number of jobs or workers. Here we assume that jobs and workers outside of the one-hour travel time buffer do not impact employment density. Because job accessibility by auto and worker accessibility by auto are highly correlated in this study, with a correlation coefficient larger than 0.95, we sum the two accessibility measures to construct a composite measure for auto accessibility. Similarly, we sum job accessibility by transit and worker accessibility by transit to create a composite measure for transit accessibility, as shown below.

$$Auto_{accessibility} = \sum_{i=1}^{6} Job_{Auto_i} e^{-b \times i \times 10} + \sum_{i=1}^{6} Worker_{auto_i} e^{-b \times i \times 10}$$

The choice of b is based on a grid search technique. In particular, we assume that employment density is a function of auto accessibility and then seek the value of b that maximizes the pseudo-R^2 of NBREG for all jobs. We find that in 2010, the R^2 is maximized when $b = 0.2$ and in 2000, the R-square is maximized when $b = 0.25$. To facilitate the comparison between 2000 and 2010, we choose $b = 0.2$ for further analyses.

Hypotheses

The specification of the employment density equation gives rise to a pair of hypotheses regarding the effects of the accessibility variables on employment density at the TAZ level. Two specific hypotheses are examined here:

1. *Sectoral hypothesis*: Different industrial sectors are likely to have different agglomeration responses to accessibility. Service-related sectors are anticipated to have the strongest agglomeration effects (especially localization), along with manufacturing. Agricultural, extractive (e.g. mining), and utilities are less likely to agglomerate. The null hypothesis is that there is no statistically significant difference across sectors; that is, the elasticities for each sector are equal to those of the aggregate economy.
2. *Cross-sectoral hypothesis*: Individual sectors rely only on own-sector accessibility (localization) for agglomeration. There is no contribution to agglomeration from access to other sectors (urbanization).

RESULTS

In this section, we estimate models for employment density in of each of the 20 sectors. For urbanization economies, we choose the accessibility measure in which the opportunity includes jobs and workers in all sectors and the friction factor is set at 0.2. For localization economies, we use the number of sector-specific jobs within a 10-minute driving distance. We test two versions of the localization economy variable. In the first version, the number of sector-specific jobs includes jobs within the observed zone, whereas in the second version, these jobs are excluded.

Table 2 shows the estimated elasticities of the urbanization and localization economy variables and their rankings (model coefficients are not reported here, but are available from the authors upon request). For 2010, top eight sectors with the strongest urbanization effects include real estate, finance and insurance, professional services, information, management, administrative services, other services, and accommodation and food services. Except for management, the sectors tend to have very weak localization effects. On the other hand, the top five sectors with the strongest localization effects include utilities, wholesale trade, construction, retail trade, and manufacturing, all of which show weak urbanization effects. These results mostly align with basic (exporting) versus non-basic (local-serving) sectcoral classifications (except manufacturing and wholesale trade).

The top eight sectors with the strongest urbanization effects in 2000 are similar to those for 2010. Real estate ranks highest in 2010 but ranks the tenth in 2000. The specific rankings for other sectors vary slightly between 2000 and 2010. For localization effects, the sector with the largest change is utilities, which ranks the first in 2010 but ranks the 10^{th} in 2000. Arts, entertainment, and recreation join the top five sectors with the strongest localization effects. We also compute correlation coefficients between the elasticities by sector in 2000 and 2010. The correlation between the elasticities of the 2000 and 2010 urbanization variables is 0.79 and the correlation between the elasticities of the 2000 and 2010 localization economy variables is 0.72.

TABLE 2 Elasticities of Urbanization and Localization Economy Variables (including jobs in the observed zone)

	2010 Urbanization	2010 Rank	2010 Localization	2010 Rank	2000 Urbanization	2000 Rank	2000 Localization	2000 Rank
Agriculture, Forestry, Fishing and Hunting	-0.064	20	0.704	11	-0.228	19	0.759	8
Mining, Quarrying, and Oil and Gas Extraction	0.399	16	0.571	12	0.611	14	0.420	14
Utilities	0.592	14	1.863	1	1.156	8	0.691	10
Construction	0.029	19	1.449	3	-0.252	20	1.525	1
Manufacturing	0.137	17	1.227	5	0.286	18	1.165	2
Wholesale Trade	0.062	18	1.822	2	0.803	11	0.920	5
Retail Trade	0.419	15	1.292	4	0.515	15	1.108	3
Transportation and Warehousing	0.742	13	0.772	8	0.676	12	0.528	13
Information	3.006	4	0.045	16	2.023	3	0.281	16
Finance and Insurance	3.644	2	-0.157	18	3.188	1	-0.266	20
Real Estate and Rental and Leasing	4.019	1	-0.549	20	0.808	10	0.767	7
Professional, Scientific, and Technical Services	3.339	3	-0.230	19	2.561	2	-0.114	19
Management of Companies and Enterprises	2.223	5	1.010	6	1.452	7	0.814	6
Administrative and Support and Waste Management and Remediation Services	2.159	6	0.292	14	1.813	4	0.310	15
Educational Services	0.798	12	0.569	13	0.501	16	0.557	11
Health Care and Social Assistance	1.131	10	0.769	9	0.835	9	0.710	9
Arts, Entertainment, and Recreation	1.419	9	0.960	7	0.468	17	0.934	4
Accommodation and Food Services	1.941	8	0.114	15	1.641	6	0.167	17
Other Services [except Public Administration]	2.143	7	-0.054	17	1.800	5	0.069	18
Public Administration	1.032	11	0.738	10	0.664	13	0.532	12

Notes: The indicator of localization economy includes industry-specific jobs in the observed zones. The numbers in the shaded cells are insignificant at the $p < 0.05$ level.

TABLE 3 Elasticities of Urbanization and Localization Economy Variables (excluding jobs in the observed zone)

	2010 Urbanization	Rank	Localization	Rank	2000 Urbanization	Rank	Localization	Rank
Agriculture, Forestry, Fishing and Hunting	0.083	19	0.152	8	-0.028	20	-0.355	18
Mining, Quarrying, and Oil and Gas Extraction	-0.102	20	0.199	6	0.416	19	0.219	6
Utilities	3.686	8	-0.528	12	1.857	10	0.131	10
Construction	0.916	16	0.699	3	0.946	17	0.365	4
Manufacturing	0.506	17	0.798	2	0.726	18	0.576	3
Wholesale Trade	0.339	18	1.584	1	1.088	13	0.67	1
Retail Trade	1.789	12	0.041	9	1.018	15	0.638	2
Transportation and Warehousing	0.987	15	0.562	4	0.972	16	0.18	9
Information	5.228	1	-1.574	20	3.304	2	-0.554	19
Finance and Insurance	4.142	5	-0.575	13	3.636	1	-0.609	20
Real Estate and Rental and Leasing	5.034	2	-1.282	18	1.689	12	0.203	7
Professional, Scientific, and Technical Services	3.882	6	-0.605	14	2.92	4	-0.337	17
Management of Companies and Enterprises	4.293	3	-0.706	16	2.955	3	-0.148	12
Administrative and Support and Waste Management and Remediation Services	3.747	7	-0.693	15	2.533	5	-0.172	13
Educational Services	1.753	13	0.022	10	1.883	9	-0.238	15
Health Care and Social Assistance	2.103	11	0.17	7	1.722	11	0.191	8
Arts, Entertainment, and Recreation	4.289	4	-1.394	19	2.1	8	-0.078	11
Accommodation and Food Services	2.715	10	-0.496	11	2.244	6	-0.271	16
Other Services [except Public Administration]	3.056	9	-0.71	17	2.137	7	-0.208	14
Public Administration	1.562	14	0.38	5	1.087	14	0.285	5

Notes: The indicator of localization economy excludes industry-specific jobs in the observed zones. The numbers in the shaded cells are insignificant at the $p < 0.05$ level.

Table 3 presents the results when the number of jobs for the observed zone are excluded from the localization economy variable's calculation. The elasticities for the urbanization economy are similar. In particular, for 2010, the correlation coefficient between the elasticities in Tables 2 and 3 is 0.85. By contrast, the correlation coefficient between the elasticities of the localization economy variables in Tables 2 and 3 is 0.61. In Table 3, the correlation coefficient between the elasticities of the urbanization economy variables between 2000 and 2010 is 0.86, while the correlation coefficient between the elasticities of the localization economy variables is 0.67. Therefore, the estimated urbanization effects appear to be more robust than the localization effects across time.

It is worth noting that the correlation between the urbanization economy and localization economy variables is fairly high. In 2010, for all but three sectors (mining, agriculture, and public administration), the correlation coefficients between the variables are larger than 0.7. This finding holds regardless of how the localization variable is specified. While some correlation between the two variables ought to be expected, as the own-sector jobs are a subset of total employment for purposes of accessibility calculation, the level of correlation between them casts some doubt on whether two variables are truly independent.

Returning to our earlier hypotheses about the relationship between accessibility and sector-specific agglomeration, our first hypothesis (sectoral variation) seems to be borne out by the evidence on sector-by-sector density elasticities. Service-oriented sectors seem to show the strongest propensity for agglomeration, with the source of this agglomeration coming from urbanization rather than localization effects. The manufacturing sector shows modest (generally less than unity) positive agglomeration effects from both urbanization and localization economies, while sectors such as agriculture, mining, utilities and construction seem to show less propensity to agglomerate

The second hypothesis (cross-sectoral hypothesis) regarding reliance on own-sector accessibility for agglomeration seems to find little support. Employment density in several of the sectors examined have no statistically significant relationship to our measure of localization, proxied by own-sector employment accessibility within 10 minutes. The magnitude of density elasticities with respect to total employment, our measure of urbanization, tends to dominate the elasticities with respect to own-sector employment.

CONCLUSIONS

Our understanding of the nature of agglomeration economies and the role that transportation networks play in promoting them continues to evolve. This study contributes to the base of knowledge by offering new empirical evidence on intraurban patterns of agglomeration based on small-scale geographic data on job density from the Twin Cities. The employment density elasticities reported here for two-digit NAICS code sectors incorporate realistic travel time estimates for both road and public transit networks in order to approximate the role of transport costs in the urban economy, but also allow for distinction between urbanization and localization effects as sources of agglomeration.

Our findings indicate that in general urbanization effects tend to dominate localization effects across a range of economic sectors. This result tends to corroborate the findings of other recent studies which have found few or no positive agglomerative effects from localization but significant urbanization effects at higher levels of aggregation (Desmet and Fafchamps 2005; Fallah et al. 2014). Also, the magnitude of our estimates of urbanization and localization economies seem to vary significantly across economic sectors. In general, service sector employment densities tend to be most prominently correlated with high levels of accessibility, with sectors traditionally associated with central business district locations like finance, insurance and real estate joined by other sectors such as management of companies and enterprises, information, and arts and entertainment among the largest density elasticities. In contrast, sectors such as agriculture, mining and construction tended to show a lower propensity to agglomerate.

The results generated in this study offer qualified support for the notion that high levels of accessibility may be linked to gains from agglomeration. Though they are limited by the cross-sectional nature of our data, the employment density regressions suggest that certain economic sectors, primarily those involved in finance, insurance, real estate, information, and arts and entertainment, may place a premium on being able to locate in high-accessibility locations. From the perspective of transportation planning, these findings tentatively suggest that there may be a valid rationale for pursuing projects and policies that limit the effects of congestion on the region's roadway networks. To the extent that congestion reduces the accessibility provided by the network, it may affect the ability of firms to benefit from the types of urbanization effects documented in this study, including labor market pooling and the use of shared inputs among firms in unrelated industries. Improvements to the network that lower the cost of travel (including time) thus can expand the scope of markets and improve the matching process between firms and their workers, as well as customers and suppliers. Efforts on the part of planners to directly identify the sources of these benefits and incorporate them into project appraisal practices seem warranted.

Some practical issues arose within the scope of this analysis which may be of interest to future research. For example, the definition of the localization variable may need to be refined. Our analysis settled on a 10-minute measure of own-sector employment accessibility as a proxy for localization effects, but other specifications may be worth investigating. Other recent studies of firm localization tend to suggest that localization takes place at small geographic scales, but that the degree of localization is highly skewed across industries (Duranton and Overman 2005). Additionally, an important consideration for future studies will be developing a time series of accessibility measures using a single source of travel time data. The use of two different sources in the present study, with one representing modeled traveled times, limits the comparability of the results across years and the ability to estimate the results of incremental changes. The increasing availability of observational data from real-time sources should aid in this improvement.

The present study uses zone-level data to investigate the relationship between accessibility and agglomeration at an intra-urban level. While this approach allows for a reasonably small-scale level of geography which more closely approximates the firm-level nature of economic decision-making, the reliance on employment data does not allow for direct estimation of the welfare benefits of agglomeration. While employment density generally represents an outcome of agglomeration processes, it may be seen as a proxy for the effects of agglomeration on productivity. Obtaining more direct estimates of productivity effects through its effects on output levels or land rents would be a useful next step, and such results could be compared with the elasticities derived from the employment density data in the present study. Such an analysis would likely require the identification of a suitable source of firm-level microdata.

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