University of Minnesota


# The Impacts of Transportation Investment on Economic Growth in the Twin Cities

Final Report

Jason Cao

Humphrey School of Public Affairs
University of Minnesota

CTS 16-11

CENTER FOR
TRANSPORTATION STUDIES

University of Minnesota

## Technical Report Documentation Page

| 1. Report No. | 2. | 3. Recipients Accession No. |
|---|---|---|
| CTS 16-11 | | |

| 4. Title and Subtitle | 5. Report Date |
|---|---|
| The Impacts of Transportation Investment on Economic Growth in the Twin Cities | June 2016 |
| | 6. |
| 7. Author(s) | 8. Performing Organization Report No. |
| Jason Cao, Michael Iacono, David Levinson, Mengying Cui | |
| 9. Performing Organization Name and Address | 10. Project/Task/Work Unit No. |
| Humphrey School of Public Affairs<br>University of Minnesota<br>301 19th Avenue S<br>Minneapolis, MN 55455<br><br>Department of Civil, Environmental, and Geo- Engineering<br>University of Minnesota<br>500 Pillsbury Drive SE<br>Minneapolis, MN 55455 | CTS #2015061<br><br>11. Contract (C) or Grant (G) No. |
| 12. Sponsoring Organization Name and Address | 13. Type of Report and Period Covered |
| Center for Transportation Studies<br>University of Minnesota<br>200 Transportation and Safety Building<br>511 Washington Ave. SE<br>Minneapolis, MN 55455 | Final Report<br><br>14. Sponsoring Agency Code |

15. Supplementary Notes

http://cts.umn.edu/publications/researchreports

16. Abstract (Limit: 250 words)

The transportation system plays a critical role in fostering economic growth. Although previous studies have shed light on the impacts of transportation investments, their results are not readily adapted to predicting economic impacts of individual transportation projects. This study aimed to (1) investigate the impacts of transportation investments on economic growth (wages and employment) in the Twin Cities and (2) develop a method that practitioners can apply to predict economic growth resulting from investments in individual projects (as well as disinvestments). The capacity of such predictions is critical for the economy of the Twin Cities because transportation infrastructure lasts for decades once built. The method is expected to be used by practitioners of planning, programming, and finance at MnDOT and DEED, as well as at the Metropolitan Council.

This study contributes to the base of knowledge by offering new empirical evidence on intra-urban patterns of agglomeration based on small-scale geographic data on job density from the Twin Cities. Our findings indicate that in general urbanization effects tend to dominate localization effects across a range of industries.

| 17. Document Analysis/Descriptors | 18. Availability Statement |
|---|---|
| investments, economic growth, economic impacts, economic development, long range planning, transportation planning | No restrictions. Document available from: National Technical Information Services, Alexandria, Virginia 22312 |

| 19. Security Class (this report) | 20. Security Class (this page) | 21. No. of Pages | 22. Price |
|---|---|---|---|
| Unclassified | Unclassified | 48 | |

# The Impacts of Transportation Investments on Economic Growth in the Twin Cities

Jason Cao

Humphrey School of Public Affairs

Michael Iacono
David Levinson
Mengying Cui

Department of Civil, Environmental, and Geo-Engineering

June 2016

## Table of Contents

## 1 Introduction

Over the past century or more, urban areas have emerged as the loci of production for an increasing share of the economy. This has been the case in the Twin Cities region, but has also been repeated in many other regions throughout the United States and abroad. 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 (Overman and Puga 2010; Rosenthal and Strange 2008; Eberts and McMillen 1999). 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. Furthermore, we develop measures of accessibility both by car and by public transit in order to test for separate contributions to agglomeration across modes (and perhaps also by sector). The use of these 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 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 results and their implications for transportation planning.

## 2 Literature Review

Agglomeration economies can take many forms within urban areas. There are often multiple sources from which they might emerge. Efforts to categorize these sources and develop methods of measuring their impact on productivity have evolved over the course of several decades. In this section, we review some of the important theoretical concepts relating to agglomeration, describe some of the methods employed to measure the impacts of agglomeration, and review some of the available evidence on the size of agglomeration effects. Some additional attention is given to the relationship between transportation and agglomeration, as this will provide the context for the empirical analysis of accessibility and agglomeration in this study.

### 2.1 Agglomeration concepts

Agglomeration economies are, at their base, types of external scale economies that are common to urban locations. A useful way to distinguish agglomeration economies is to place them within a broader classification framework for economies of scale. As shown in Table 1, firms located in urban areas might exploit 12 different types of scale economies.

The most basic distinction is between internal and external sources of scale economies. "Internal" scale economies are those which arise within the context of the firm's internal operations. These include pecuniary, as well as static and dynamic technological economies. Pecuniary scale economies, as their name implies, emerge through changes in relative prices. Table 1 cites an example that a firm is able to purchase intermediate inputs at volume discounts, thus lower the price it faces for these inputs. Technological economies arise from changes in a firm's production technology over time. For example, static technological scale economies might arise from falling average costs at a plant as output increases. Plants with higher fixed costs may be able to reap more of this type of economy, as they can spread the fixed costs over a higher level of output. An example of dynamic, as opposed to static, technological economies is the emergence of lower costs due to "learning by doing" or "learning curve" effects in a firm's operation. In other words, a firm can fine-tune its production technology over time, resulting in greater output from a given level of inputs or, conversely, lower costs for a given level of output.

The scale economies that are associated with agglomeration processes are often referred to as "external" economies, since they mostly arise from sources outside of a given firm's operations. Agglomeration economies can be further classified as either *localization* or *urbanization* economies. Table 1 lists four examples of each, classifying them again according to whether they are static or dynamic in nature. In addition to urbanization and localization effects, there are also "pure" agglomeration effects, which can arise from the spreading of fixed costs for shared inputs such as urban infrastructure.

Table 1 lists four types of localization economies. The first example relates to "shopping" economies in urban areas. Put simply, shoppers are attracted to places featuring many sellers. In principle, this concept could apply to both households and firms. At a small geographic scale, households may frequently visit shopping malls which feature many sellers and a variety of goods. At a larger scale, firms in a given industry may wish to locate in larger urban areas where they can have greater access to upstream suppliers of certain inputs. A related source of localization economies is the returns from economic specialization. These are commonly associated with the work of the early economist Adam Smith in his seminal work *The Wealth of Nations* (Smith 1776). They are characterized in terms of the outsourcing of some activities within the production process which allows both upstream suppliers of inputs and downstream firms to exploit the productivity gains from economic specialization.

Another type of localization effect is the economies that arise from labor pooling. These economies are sometimes referred to as "Marshallian" labor pooling, because of their reference in an early text by Alfred Marshall (Marshall 1890) which is considered to be foundational in the literature on agglomeration economies. The localization type of economy from labor pooling relates to the phenomenon of workers with industry-specific skills being attracted to a location where there is a greater concentration of that industry. A more formalized treatment of this process is detailed in Krugman (1991).

**Table 1. Agglomeration economies and other types of scale economies (Source: Kilkenny (1998); World Bank (2009))**

| | | | | |
|---|---|---|---|---|
| **Internal** | 1. Pecuniary | | | Being able to purchase intermediate inputs at volume discounts |
| | Technological | | 2. Static Technological | Falling average costs because of fixed costs of operating a plant |
| | | | 3. Dynamic Technological | Learning to operate a plant more efficiently over time |
| **External or Agglomeration** | ***Localization*** | Static | 4. "Shopping" | Shoppers are attracted to places where there are many sellers |
| | | | 5. "Adam Smith" specialization | Outsourcing allows both the upstream input suppliers and downstream firms to profit from productivity gains because of specialization |
| | | | 6. "Marshall" labor pooling | Workers with industry-specific skills are attracted to a location where there is a greater concentration |
| | | Dynamic | 7. "Marshall-Arrow-Romer" learning by doing | Reductions in costs that arise from repeated and continuous production activity over time and which spill over between firms in the same place |
| | ***Urbanization*** | Static | 8. "Jane Jacobs" innovation | The more that different things are done locally, the more opportunity there is for observing and adapting ideas from others |
| | | | 9. "Marshall" labor pooling | Workers in an industry bring innovations to firms in other industries; similar to no. 6 above, but the benefit arises from the diversity of industries in one location. |
| | | | 10. "Adam Smith" division of labor | Similar to no. 5 above, the main difference being that the division of labor is made possible by the existence of many different buying industries in the same place |
| | | Dynamic | 11. "Romer" endo-genous growth | The larger the market, the higher the profit; the more attractive the location to firms, the more jobs there are; the more labor pools there, the larger the market—and so on |
| | 12. "Pure" agglomeration | | | Spreading fixed costs of infrastructure over more taxpayers; diseconomies arise from congestion and pollution |

While the previous three types of localization economies are static in nature, the fourth is more dynamic in that it emerges from continuous and repeated production activity over time. Drawing on the work of Marshall as well as separate contributions from Arrow (1962) and Romer (1990), these "learning by doing" economies are analogous to the internal dynamic technological scale economies discussed previously, though they differ in that they tend to operate at the level of an entire industry and to manifest themselves through knowledge spillovers between competing firms.

Urbanization economies are distinct in that they tend to be external to both firms and industries but occur because industries concentrate in an urban area (Eberts and McMillen 1999). Some of the agglomeration economies associated with urbanization arise from the same sources as the localization economies just discussed, such as labor pooling and specialization, yet apply more broadly to all industries within an urban area. Several of the agglomeration economies arising from urbanization relate to the process of innovation within urban areas.

One such source of innovation is a diversity of economic activity within urban areas. Table 1 refers to this type of urbanization economy as "Jane Jacobs" innovation in reference to Jacobs' descriptive work on urban economies (Jacobs 1969). A main tenet of this innovation hypothesis is that a greater diversity of activities taking place locally leads to more opportunities for observing and adapting ideas from others. Others note, however, that although this hypothesis is popularly attributed to Jacobs the main ideas regarding economic diversity and innovation were recognized in earlier work by Chinitz (1961), who used them in a comparison of the post-World War II economies of New York and Pittsburgh (Rosenthal and Strange 2004). The concept was later formalized and tested empirically in work by Glaeser et al. (1992).

The Marshallian labor pooling described earlier in relation to localization economies can also be a source of urbanization economies through their effects on innovation. Specifically, innovation is fostered by workers in an industry bringing innovation to firms in other industries. These "cross-fertilization" effects are assumed to occur because of the diversity of industries in an urban area. This differs somewhat from the localization effects of labor pooling, which are assumed to be confined to a specific industry.

Likewise, the economies due to specialization ("Adam Smith" specialization) which were described as a source of localization economies, also can contribute to agglomeration through urbanization effects. The source of the urbanization effect is presumed to be due to a division of labor made possible by the existence of many different buying industries within the same urban area. This is slightly different from the localization effect of specialization, which is assumed to operate through upstream and downstream supply chain linkages among firms in the same industry, rather than applying to the entire local economy in an urban area.

The urbanization economies arising from labor pooling, the division of labor and specialization, and economic diversity are presumed to be static forms of agglomeration. A fourth type of urbanization economy is more dynamic in nature. Commonly referred to as "endogenous growth" theory (Romer 1986), it describes a virtuous cycle-type process in which urban areas with larger markets generate higher profits. These higher profits make the area more attractive to prospective firms. As more firms locate in the area the employment base grows, resulting in more and larger pools of labor. These larger pools of labor in turn create larger markets which form a positive feedback loop through the process just described. This feedback process, which develops over long periods of time, is what leads it to be characterized as a dynamic form of urbanization economies.

The twelfth type of scale economy listed in Table 1 is a form of external or agglomeration economy, but is not neatly characterized as either an urbanization or localization type of economy. These "pure" agglomeration effects emerge from the ability of urban areas to spread fixed costs for certain types of infrastructure, including transportation networks, over a large base of users. While these agglomeration effects may lead to declining average costs for infrastructure over a range of sizes of urban areas, there are levels at which they can become subject to diseconomies due to the presence of externalities, such as traffic congestion and air pollution (Eberts and McMillen 1999). Unless effective public policies or private actions can control these externalities, which generally increase with city size, there are limits to their contribution as sources of increasing returns.

This discussion of economies of scale and agglomeration economies has presented one type of classification for the different types of scale economies associated with agglomeration. Several other reviews of the literature on agglomeration adopt a similar approach, though some present the concepts slightly differently. Some emphasize the microfoundations described in Table 1, like labor pooling and knowledge spillovers, while also suggesting additional ones like home market effects, consumption, and rent-seeking behavior (Rosenthal and Strange 2004). Others, like Duraton and Puga (2004), offer a slightly different classification of agglomeration economies based on the types of behavior they represent (e.g. "sharing", "matching" and "learning").

**2.2 Measurement of agglomeration**

A variety of methods have been employed to measure the magnitude and scope of agglomeration economies from the sources we have just described. Since the effects of the various types of agglomeration economies are primarily to enhance productivity, the empirical methods employed have sought to measure productivity effects either directly or indirectly through other sources. The three primary methods are production function approaches designed to measure agglomeration effects on output or output per worker, wage rates, and land rents (Eberts and McMillen 1999; Rosenthal and Strange 2004; Puga 2010).

The use of production functions to measure variations in agglomeration across urban areas has been the most common approach in the empirical literature, partly among earlier studies. The approach typically requires specification of a production function with two or three factors (land, labor, and capital, though measures of public infrastructure may be included as well) which are related to a measure of output, either for a particular industry or for a metropolitan area as a whole (Rosenthal and Strange 2004; Melo et al. 2009). The production function also employs a Hicks-neutral shift parameter measuring technical change. This measure of technical change is often systematically related to a measure of urban size, such as population size or total employment in an urban area, in order to provide an estimate of scale economies due to agglomeration (Eberts and McMillen 1999).

While production functions are ideally suited to firm-level data, since this is the level at which most production takes place, in practice many studies have been limited to using more aggregate data at the level of entire urban areas, due to the proprietary nature of most firm-level data and barriers to accessing such data through public sources such as the Census Bureau (Rosenthal and Strange 2004). This often limits the level of detail that can be specified in terms of probing different sources of agglomeration. Consequently, most such studies examine either broader urbanization economies, proxied by population size or total employment, or a general measure of localization proxied by industry-level employment or employment density. One exception to this practice is a paper by Henderson (2003) which uses a panel of plant-level data from U.S. firms to develop more detailed measures of localization and urbanization. These measures are then incorporated into a firm-level production function for machinery and high-tech industries which allows for estimates of scale economies from both types of agglomeration.

Another method for estimating the productivity impacts of agglomeration is to measure the behavior of wage rates in large urban areas. This method provides an indirect measure of productivity effects since, in a competitive market environment, wage rates should approximate the marginal product of labor. The appeal of using this method lies in the fact that micro-level data on wages tend to be more readily available from public sources, and that wages represent a useful way to measure the scope of certain sources of agglomeration economies such as human capital spillovers (Rosenthal and Strange 2008) and labor pooling. However, one complicating factor in the use of wages to infer agglomeration economies is the possibility that the ability or skill level of workers may vary systematically across cities of different sizes. Moreover, this may reflect a process wherein more skilled or productive workers sort themselves into larger urban areas. In the event of such a sorting process, it would be difficult to distinguish the urban wage premium due to skill level from any residual effect of agglomeration on wages (Puga 2010).

While productivity differences due to agglomeration economies can, in principle, be captured by wages, they may also be capitalized into land rents within urban areas. Some firms' willingness to locate in denser environments in spite of the higher land costs such locations entail likely reflects the ability to take advantage of greater productivity in those locations. To the extent that these differences in productivity are capitalized into commercial land rents, data on land rents can be a source of information about the extent of agglomeration economies. However, data on commercial land prices are often difficult to obtain, and so other related sources of data such as residential land prices are sometimes used as a substitute (Dekle and Eaton 1999).

One other method of inferring the extent of agglomeration economies is to simply measure the geographic concentration of industry. Measures of geographic concentration for various industries serve a valuable descriptive function in addition to providing an important input for further studies of agglomeration. One of the more popular measures of concentration is a measure first proposed by Ellison and Glaeser (1997). Its popularity derives in part from the fact that it controls for both plant size within an industry and the size of the geographic areas from which the data used to construct the index are collected. This measure has been used in other studies of agglomeration, such as a recent study of labor pooling by Overman and Puga (2010) in which the Ellison-Glaeser index was used as a proxy for localization economies and was regressed on a measure of labor pooling potential in several different sectors.

### 2.3 The magnitude of agglomeration economies

Through the emergence of an extensive empirical literature on agglomeration economies, a clearer picture is emerging regarding the likely size of their effect on productivity. Several reviews of the literature have suggested a range of effects varying mostly between 2 percent and 8 percent (Rosenthal and Strange 2004; World Bank 2009; Puga 2010). The general interpretation of these findings is that doubling the size of an urban will increase its productivity by between 2 and 8 percent, all else equal.

Of course, these general summaries tend to mask a great deal of variation among different studies in terms their data sets, measurement techniques, geographic scope, and focus on specific industries or sectors. However, a recent meta-analysis of the empirical literature by Melo et al. (2009) has compiled elasticity estimates from a large number of studies and pooled them to examine some possible sources of variation among the estimates. Their data set consists of a sample of 729 elasticity estimates derived from 34 separate papers covering a 35-year period from 1973 to 2008. Explanatory variables were constructed to account for the time period covered by the study, the type of data set employed, the geographic nature of the observation units, whether a measure of localization economies are included, sector-specific versus economy-wide focus, the type of response variable used (total output, labor productivity or wages), and the country or continent where the study was conducted.

The mean elasticity reported for the entire sample was just under 0.06, indicating a 6 percent increase in productivity in response to a doubling in the size of an urban area, well within the range reported elsewhere. The median elasticity reported from the sample was lower (around 0.04) indicating that the distribution of reported elasticities was skewed to the right. Also, the fairly high standard deviation for the sample (0.115) indicates that not only does a significant amount of variation exist among the many estimates, but that many of the reported elasticities had negative values.

Melo et al. estimated a set of eight different meta-regressions, each representing a different combination of variables and estimation techniques (ordinary least squares and generalized least squares with random effects were applied to each model specification). Only a handful of variables proved to be robustly significant across a range of specifications. An indicator variable representing estimates drawn from studies of service industries showed strong and significant effects across a range of specifications. The authors noted that the average elasticity of urban agglomeration of service industries is about 8 percentage points higher than the elasticity for the aggregate economy. Further, studies that controlled for differences in human capital reported elasticities that were about 5 or 6 percentage points lower than those that did not. The inclusion of measures of localization economies in addition to urbanization also appear to have consistent effects on the magnitude of elasticities, with these studies reporting elasticties of about 2 to 3 percentage points below those which consider only urbanization economies. The type of data set and econometric specification employed also appear to affect the estimates of the size of agglomeration economies, as studies using panel data and controlling for cross-sectional unobserved heterogeneity report elasticites a couple of percentage points below those using cross-section data and which do not control for fixed effects.

## 2.4 Incorporating transportation into the measurement of agglomeration economies

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.

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 (2003) 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 (Venables 2007). Graham (2007a) 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 (Graham 2007b). 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 (Graham and Kim 2008), the inclusion of measures of localization (Graham 2009), and for nonlinearities in the relationship between accessibility and productivity (Graham and van Dender 2011).

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. (2013b) 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.

Accessibility as a measure of distance and transport costs has also played an important role in the recent development of theory and empirical evidence on the so-called New Economic Geography, a branch of regional economics concerned with the evolution of trade and spatial economies more broadly (Fujita et al. 1999; Henderson et al. 2001). A key concept in this theory is notion of market potential (Harris 1954; Fujita et al. 1999), which relates the demand for goods in a given location to the sum of purchasing power in other locations, weighted by transport costs (Hanson 2005). The market potential concept is essentially a measure of access to purchasing power in other jurisdictions, yet has proven an important factor in explaining several spatial economic phenomena. Its function is similar to that of measures of urban size in studies of urban agglomeration in that it is theoretically linked to regional productivity (Rice et al. 2006; Holl 2012) and wages (Head and Mayer 2006), along with other outcomes such as foreign investment (Head and Mayer 2004).

While most of the studies relating transportation to agglomeration economies and productivity more broadly tend to focus on road networks (Melo et al. 2013a), there have been some efforts to examine the relationship between alternative modes, most notably public transit, and the potential for agglomeration. Drennan and Brecher (2012) 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 distrct (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 (2014) 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 (2012) and Chatman and Noland (2014) 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.

## 3 Methodology

This study is primarily concerned with the relationship between accessibility and urban agglomeration at an intra-urban 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.

### 3.1 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 for auto and public transit modes.

There are three 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. (2013b) 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. 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.

Third, the effects of separate transportation modes (auto and public transit) ought to be considered. As just discussed, the available evidence on public transit and agglomeration is limited due to the failure to account for the structure of transit networks and the accessibility levels they generate. This study overcomes this limitation by directly calculating accessibility measures for the Twin Cities region, which is then incorporated into the employment density equations.

### 3.2 Data and variables

#### 3.2.1 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 2 illustrates the categories of jobs measured in both RAC and WAC (US Census Bureau 2016). 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.

#### 3.2.2 Speed and network data

Acquired by the Metropolitan Council in the Twin Cities, both road network and auto speed data came from TomTom. The network was displayed as a shapefile that can be directly used in GIS software, such as ArcGIS. 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.

**Table 2 Two-Digit NAICS Sectors**

| Variable | Explanations |
|---|---|
| **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) |

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 (TomTom International BV 2013). The accessibility measurement in this study used the median speed of morning peak hours during 7AM-9AM.

### 3.2.2 Speed and network data

Acquired by the Metropolitan Council in the Twin Cities, both road network and auto speed data came from TomTom. The network was displayed as a shapefile that can be directly used in GIS software, such as ArcGIS. 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 (TomTom International BV 2013). The accessibility measurement in this study used the median speed of morning peak hours during 7AM-9AM.

### 3.2.3 Travel time and accessibility matrix data

Accessibility matrix by transit in 2010 was acquired from Accessibility Observatory of the University of Minnesota. This matrix includes the accessibility to workers and accessibility to jobs by sector using the cumulative opportunity measure. Travel times used to compute the matrix were evaluated based on a detailed pedestrian network and published transit schedule data and calculated for every departure second between 7AM and 9 AM. The travel time thresholds for accessibility measurements were set as 10, 20, 30, 40, 50 and 60 minutes, respectively (Owen and Levinson 2014).

The travel time matrix by auto in 2000 was also obtained from the Accessibility Observatory. It measures travel times between all the OD pairs at the level of transportation analysis zone (TAZ) based on the network in the Twin Cities in 2000.

The travel time matrix by transit in 2000 was acquired from the Minnesota Traffic Observatory of the University of Minnesota. The data measure the travel time by bus based on the 2000 road network for both peak hours (morning and evening) and off-peak hours at the block level. Only blocks with transit access were included in this matrix.

3.2.4 Other data

Census 2010 Geography (US Census Bureau and Metropolitan Council 2010) is a group of polygon shapefiles that contain geographic information of the Twin Cities, including shapefiles of blocks, block groups, collar blocks, counties, and so on. This study used the shapefile of blocks to compute accessibility measurement, which can be joined with the LODES data.

2000 TAZ system of the Twin Cities (Metropolitan Council 2014) was used to visualize the accessibility matrix and to compare the accessibility changes between different years. The data were developed by the Metropolitan Council and displayed as a polygon shapefiles. The area of each TAZ can be measured based on its geometry properties.

The Census 2010 Geography and 2000 TAZ system could be linked together based on the connections of 2010 census blocks and 2000 TAZs, which are contained in the Census 2010 Geography.

### 3.3 Accessibility measure

The cumulative opportunity measure was used for accessibility measurements, which count the number of opportunities within given travel time thresholds. For accessibility to jobs, the opportunity stands for 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 could be expressed as,

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

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

where:

$O_j$ stands for the opportunities (number of jobs or workers) in 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 donut accessibility. It is measured based on the difference between two cumulative opportunity measures,

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

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

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 transit in 2010

  The accessibility matrix by transit in 2010 from the Accessibility Observatory covers the accessibility at every second in the morning peak hours (from 7AM to 9AM) by sector. We aggregated the accessibility matrix using the average accessibility during the two hours.

- 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.

- Accessibility by transit in 2000

  The travel time matrix in 2000 covers only the blocks with transit access and does not consider the blocks 400 meters away from bus stops. To complete the travel time matrix for all the OD pairs, we also measured the walking time matrix. For the blocks without transit access, the walking time was used to measure accessibility. For the blocks with transit access, we took the minimum between transit travel time and walking time between a pair of OD to measure accessibility because transit travel time is sometimes larger than walking time.

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.

### 3.4 Modeling approach

A negative binomial regression with robust error was employed to estimate the influences of accessibility on employment density. Previous studies often model employment density in a logarithmic function (McMillen and McDonald 1997; Small and Song 1994). 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 (King 1988; Silva and Tenreyro 2006). 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 function:

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

where b is a friction factor and $O_i, i = 1, \dots, 6$ , 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 auto accessibility. Similarly, we sum job accessibility by transit and worker accessibility by transit to create transit accessibility. The choice of b is based on grid searches. In particular, we assume that employment density is a function of auto accessibility and then seek the b that maximizes the pseudo R-square of NBREG for all jobs. We find that in 2010, the R-square is maximized when b=0.2 and in 2000, the R-square is maximized when b=0.25 (Table 3). To facilitate the comparison between 2000 and 2010, we choose b = 0.2 for further analyses unless indicated.

**Table 3 Grid searches for *b* values**

| 2010 | Auto | 2000 | Auto |
|---|---|---|---|
| **b** | **R2** | **b** | **R2** |
| 0.10 | 0.0412 | 0.10 | 0.0456 |
| 0.15 | 0.0417 | 0.15 | 0.0470 |
| 0.20 | 0.0418 | 0.20 | 0.0477 |
| 0.25 | 0.0417 | 0.25 | 0.0478 |
| 0.30 | 0.0415 | 0.30 | 0.0477 |

It is worth noting that we also tested choosing different bs and concluded that for most industries, the quotient between the elasticities of different industries are relatively stable (See Appendix A). Since our discussion in the next section focuses on the relative difference, the choice of bs does not have a substantial impact on the results.

### 3.5 Hypotheses

The specification of the employment density equation gives rise to a number of hypotheses regarding the effects of accessibility variables on employment density at the TAZ level. Three specific hypotheses are proposed 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 elasticites for each sector are equal to those of the aggregate economy.
2. *Cross-sectoral hypothesis*: Individual sectors are reliant only on own-sector accessibility (localization) for agglomeration. There is no contribution to agglomeration from access to other sectors (urbanization).
3. *Modal hypothesis*: There are separate contributions to localization and urbanization effects from accessibility via both auto and public transit modes. The effect of auto accessibility is expected to be larger, though some residual effect of public transit accessibility is expected.

The next section presents results from the employment density equations for each two-digit sector. The discussion of these results will refer back to the hypotheses presented here and evaluate the evidence supporting or refuting them.

# 4 Results

For employment density of all industries and each of the industries, we develop three models: the first model includes only auto accessibility as the independent variable, the second model contains only transit accessibility, and the third model includes both transit accessibility and auto accessibility. Then for each of the industries, we develop a model with employment density being the dependent variable and indicators of both urbanization economy and localization economy as the independent variables.

## 4.1 Auto accessibility

Table 4 presents the results for models including only auto accessibility. We report the elasticities for all industries and specific industries in 2000 and 2010. The correlation between the 2000 and 2010 elasticities is 0.83 and their rank correlation (Spearman) is 0.79. Therefore, the 2000 and 2010 elasticities are highly correlated and the results are relatively robust. In general, the elasticities increase from 2000 to 2010. A caveat is that travel time is measured differently in 2000 and 2010. However, we do not think the difference will explain all increase.

As shown in the last two columns, real estate, arts, and management experienced a large increase in relative elasticity from 2000 to 2010 while agriculture, utilities, and manufacturing experienced a large decrease in relative elasticity during the same period. The increase in the elasticity for the Arts, Entertainment, and Recreation sector can be interpreted as an illustration of the trend toward entertainment and recreation activities clustering in more dense, central city-type locations and providing the location amenities that are typical of cities promoting themselves as centers of consumption (Glaeser et al. 2001; Glaeser and Gottlieb 2006; Lee 2010). Increases in the elasticities of the real estate and management sectors are likely more broadly reflective of trends in industries that have traditionally benefitted from the kinds of human capital and information spillovers that occur in dense, highly accessible locations and derive from face-to-face contact (Rosenthal 2003).

**Table 4 Elasticities of auto accessibility for different industries**

| Industry Category | 2010 | | 2000 | | E/Mean(E) | |
|---|---|---|---|---|---|---|
| | Elasticity | Rank | Elasticity | Rank | 2010 | 2000 |
| All Industries | 2.312 | | 1.883 | | | |
| Industry Average | 2.260 | | 1.842 | | | |
| Agriculture, Forestry, Fishing and Hunting | 1.189 | 20 | 1.297 | 19 | 0.53 | 0.70 |
| Mining, Quarrying, and Oil and Gas Extraction | 1.731 | 18 | 1.231 | 20 | 0.77 | 0.67 |
| Utilities | 2.026 | 14 | 2.171 | 4 | 0.90 | 1.18 |
| Construction | 2.142 | 10 | 1.803 | 12 | 0.95 | 0.98 |
| Manufacturing | 1.894 | 16 | 1.914 | 9 | 0.84 | 1.04 |
| Wholesale Trade | 2.662 | 6 | 2.193 | 3 | 1.18 | 1.19 |
| Retail Trade | 2.187 | 9 | 2.075 | 6 | 0.97 | 1.13 |
| Transportation and Warehousing | 1.884 | 17 | 1.428 | 16 | 0.83 | 0.78 |
| Information | 2.842 | 3 | 2.135 | 5 | 1.26 | 1.16 |
| Finance and Insurance | 2.957 | 2 | 2.336 | 2 | 1.31 | 1.27 |
| Real Estate and Rental and Leasing | 2.718 | 5 | 1.876 | 11 | 1.20 | 1.02 |
| Professional, Scientific, and Technical Services | 2.474 | 7 | 2.010 | 8 | 1.09 | 1.09 |
| Management of Companies and Enterprises | 3.395 | 1 | 2.447 | 1 | 1.50 | 1.33 |
| Administrative and Support and Waste Management and Remediation Services | 2.463 | 8 | 2.062 | 7 | 1.09 | 1.12 |
| Educational Services | 1.607 | 19 | 1.344 | 18 | 0.71 | 0.73 |
| Health Care and Social Assistance | 2.142 | 11 | 1.774 | 14 | 0.95 | 0.96 |
| Arts, Entertainment, and Recreation | 2.751 | 4 | 1.907 | 10 | 1.22 | 1.04 |
| Accommodation and Food Services | 2.106 | 12 | 1.777 | 13 | 0.93 | 0.96 |
| Other Services [except Public Administration] | 2.061 | 13 | 1.639 | 15 | 0.91 | 0.89 |
| Public Administration | 1.967 | 15 | 1.412 | 17 | 0.87 | 0.77 |

The decreases in elasticities for agriculture, utilities, and manufacturing were small in absolute terms, but led to lower relative rankings due to the broad increase in elasticities among most sectors over the study period. The lower elasticity for the agriculture, forestry, fishing and hunting sector simply reflects the fact that these activities were being replaced within the region by other urban uses as the region continued to expand, leaving most of the remaining activity in less accessible, peripheral locations. The declining elasticity in the utilities sector probably reflects the expansion of local utility systems, including municipal water and wastewater treatment systems, in response to growth. Since the expansion of these services is more likely to follow new housing development, rather than employment, it is less likely to be responsive to high-accessibility locations. A declining elasticity for the manufacturing sector is indicative of long-term trends toward decentralization of manufacturing in response to falling transport costs, which may weaken agglomeration economies, and the migration toward lower-cost locations within urban areas, which may be of particular benefit to land-intensive manufacturing operations (Carlino and Chatterjee 2001; Desmet nad Fafchamps 2005).

In 2010, the top five industries with the largest elasticities are management, finance, information, arts, and real estate, and the elasticities are 1.50, 1.31, 1.26, 1.26, and 1.20 times as large as the average elasticity for all industries, respectively. The average elasticity is similar to the estimated elasticity for all industries in size. The bottom five industries include manufacturing, warehousing, mining, educational services, and agriculture, and the elasticities are 0.84, 0.83, 0.77, 0.71, and 0.53 times as large as the average elasticity for all industries, respectively. These rankings are consistent with the results of other studies of employment location and centralization (Glaser and Kahn 2001), as well as results from studies of sectoral employment growth and productivity effects of agglomeration which suggest stronger productivity effects for service industries, weaker effects for manufacturing, and often negative effects for basic industries like agriculture and mining (Desmet and Fafchamps 2005; Graham 2007a,b; Graham 2008).

In 2000, the top five industries with the largest elasticities are management, finance, wholesale, utilities, and information, and the elasticities are 1.33, 1.27, 1.19, 1.18, and 1.16 times as large as the average elasticity for all industries, respectively. The bottom five industries include warehousing, public administration, educational services, agriculture, and mining, and the elasticities are 0.78, 0.77, 0.73, 0.70, and 0.67 times as large as the average elasticity for all industries, respectively. Because the travel time matrix in 2010 comes from real data provided by TomTom and is more accurate than that in 2000, the results for 2000 are less reliable than those for 2010.

**4.2 Transit accessibility**

Table 5 presents the results for models including only transit accessibility. The correlation between the 2000 and 2010 elasticities is 0.60 and their rank correlation is 0.58. The correlations are lower than those for auto accessibility.

Unlike auto accessibility, the changes in elasticities of transit accessibility from 2000 to 2010 do not show a clear pattern. Most industries do not show a substantial change; several industries experience an increase in the elasticity; and a few industries show a decrease in the elasticity. In particular, wholesale, public administration, and information show the largest increase among all industries while agriculture and mining experience the largest decrease.

In 2010, the top five industries with the largest elasticities are wholesale, manufacturing, retail, health care, and transportation. None of them appear in the list of the top five industries computed based on auto accessibility. The five industries with the smallest elasticities are professional services, arts, construction, agriculture, and mining. Two of them, agriculture and mining, appear in the list of the bottom five industries based on auto accessibility. In 2000, the top five industries with the largest elasticities are management, manufacturing, health care, retail, and accommodation. Three industries are consistent with those in 2010: manufacturing, health care, and retail. Only management appears in the list of the top five industries based on auto accessibility. The bottom five industries with the largest elasticities are construction, information, professional, mining and public administration. Among them, construction, professional, and mining appear in the list of 2010. Mining and public administration appear in the list of the bottom five industries based on auto accessibility.

**Table 5 Elasticities of transit accessibility for different industries**

| Industry Category | 2010 | | 2000 | | E/Mean (E) | |
|---|---|---|---|---|---|---|
| | Elasticity | Rank | Elasticity | Rank | 2010 | 2000 |
| All Industries | 0.584 | | 0.534 | | | |
| Industry Average | 0.653 | | 0.602 | | | |
| Agriculture, Forestry, Fishing and Hunting | 0.310 | 19 | 0.577 | 13 | 0.47 | 0.96 |
| Mining, Quarrying, and Oil and Gas Extraction | 0.122 | 20 | 0.445 | 19 | 0.19 | 0.74 |
| Utilities | 0.595 | 15 | 0.608 | 10 | 0.91 | 1.01 |
| Construction | 0.438 | 18 | 0.476 | 16 | 0.67 | 0.79 |
| Manufacturing | 0.974 | 2 | 0.813 | 2 | 1.49 | 1.35 |
| Wholesale Trade | 1.081 | 1 | 0.654 | 6 | 1.66 | 1.09 |
| Retail Trade | 0.880 | 3 | 0.737 | 4 | 1.35 | 1.22 |
| Transportation and Warehousing | 0.785 | 5 | 0.603 | 11 | 1.20 | 1.00 |
| Information | 0.679 | 8 | 0.471 | 17 | 1.04 | 0.78 |
| Finance and Insurance | 0.644 | 13 | 0.641 | 8 | 0.99 | 1.06 |
| Real Estate and Rental and Leasing | 0.646 | 12 | 0.643 | 7 | 0.99 | 1.07 |
| Professional, Scientific, and Technical Services | 0.530 | 16 | 0.449 | 18 | 0.81 | 0.75 |
| Management of Companies and Enterprises | 0.780 | 6 | 0.821 | 1 | 1.20 | 1.36 |
| Administrative and Support and Waste Management and Remediation Services | 0.605 | 14 | 0.626 | 9 | 0.93 | 1.04 |
| Educational Services | 0.665 | 9 | 0.522 | 14 | 1.02 | 0.87 |
| Health Care and Social Assistance | 0.800 | 4 | 0.805 | 3 | 1.23 | 1.34 |
| Arts, Entertainment, and Recreation | 0.505 | 17 | 0.511 | 15 | 0.77 | 0.85 |
| Accommodation and Food Services | 0.656 | 11 | 0.656 | 5 | 1.01 | 1.09 |
| Other Services [except Public Administration] | 0.657 | 10 | 0.600 | 12 | 1.01 | 1.00 |
| Public Administration | 0.702 | 7 | 0.386 | 20 | 1.08 | 0.64 |

Overall, the elasticities of transit accessibility show different patterns from those of auto accessibility, particularly on the industries with the largest elasticity. The correlation between the 2000 and 2010 elasticities of transit accessibility is smaller than that between the 2000 and 2010 elasticities of auto accessibility. This pattern is not surprising because transit accessibility depends on not only road network, but also the coverage area and route schedule of transit service. Within the same travel time, driving can reach much more jobs or workers than taking transit. Therefore, transit accessibility is more sensitive to the distribution of jobs and workers than auto accessibility.

### 4.3 Transit accessibility and auto accessibility

Table 6 presents the elasticities for models including both auto accessibility and transit accessibility. Their correlation is -0.46 and their rank correlation (Spearman) is -0.47. That is, auto accessibility and transit accessibility show somewhat opposite patterns. Further, the ranking pattern of transit accessibility in Table 6 is largely consistent with that in Table 5, with a correlation coefficient of 0.87. In contrast, the ranking pattern of auto accessibility in Table 6 varies a lot from that in Table 4, with a correlation coefficient of 0.49. Overall, the results suggest that it is not recommended to model auto accessibility and transit accessibility jointly.

### 4.4 Urbanization and localization economies

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

Table 7 shows the elasticities of urbanization economy and localization economy and their rankings. For 2010, the top eight industries with the strongest urbanization economy include real estate, finance and insurance, professional services, information, management, administrative services, other services, and accommodation and food services. Except for management, the industries tend to have very weak localization economy. On the other hand, the top five industries with the strongest localization economy include utilities, wholesale trade, construction, retail trade, and manufacturing and all of them have very weak urbanization economy. These results mostly align with basic versus non-basic industries (except manufacturing and wholesale trade). The top eight industries with the strongest urbanization economy for 2000 are similar to those for 2010. Real estate ranks the first in 2010 but ranks the tenth in 2000. The specific rankings for other industries vary slightly between 2000 and 2010. For localization economy, the industry with the largest change is utilities, which ranks the first in 2010 but ranks the $10^{th}$ in 2000. Arts, entertainment, and recreation joins the top five strongest localization economy. We also compute correlation coefficients. The correlation between the elasticities of the 2000 and 2010 urbanization economy is 0.79 and the correlation between the elasticities of the 2000 and 2010 localization economy is 0.72. Therefore, the outcomes for the two years are highly correlated.

**Table 6 Elasticities of auto accessibility and transit accessibility for different industries**

| Industry Category | Auto | Rank | Transit | Rank |
|---|---|---|---|---|
| Agriculture, Forestry, Fishing and Hunting | 0.101 | 18 | 0.302 | 17 |
| Mining, Quarrying, and Oil and Gas Extraction | 1.811 | 1 | 0.205 | 19 |
| Utilities | 0.038 | 19 | 0.585 | 8 |
| Construction | 1.753 | 3 | 0.131 | 20 |
| Manufacturing | 0.752 | 15 | 0.849 | 1 |
| Wholesale Trade | 1.521 | 6 | 0.651 | 4 |
| Retail Trade | 0.951 | 12 | 0.681 | 3 |
| Transportation and Warehousing | 1.082 | 10 | 0.540 | 9 |
| Information | 1.406 | 9 | 0.526 | 10 |
| Finance and Insurance | 1.459 | 7 | 0.403 | 13 |
| Real Estate and Rental and Leasing | 1.593 | 5 | 0.374 | 15 |
| Professional, Scientific, and Technical Services | 1.653 | 4 | 0.215 | 18 |
| Management of Companies and Enterprises | 1.784 | 2 | 0.607 | 6 |
| Administrative and Support and Waste Management and Remediation Services | 1.418 | 8 | 0.332 | 16 |
| Educational Services | 0.220 | 17 | 0.605 | 7 |
| Health Care and Social Assistance | 0.777 | 13 | 0.614 | 5 |
| Arts, Entertainment, and Recreation | 0.597 | 16 | 0.413 | 12 |
| Accommodation and Food Services | 0.761 | 14 | 0.498 | 11 |
| Other Services [except Public Administration] | 1.078 | 11 | 0.398 | 14 |
| Public Administration | -0.070 | 20 | 0.720 | 2 |

Table 8 presents the results when the number of jobs for the tested zone are excluded from localization economy. The elasticities for urbanization economy are similar. In particular, for the year 2010, the correlation coefficient between the elasticities in Tables 7 and 8 is 0.85. By contrast, the correlation coefficient between the elasticities of localization economy in Tables 7 and 8 is 0.61. In Table 8, the correlation coefficient between the elasticities of urbanization economy between 2000 and 2010 is 0.86 and the correlation coefficient between the elasticities of localization economy is 0.67. Therefore, urbanization economy is more robust than localization economy.

It is worth noting that the correlation between urbanization economy and localization economy is very high. In 2010, for all but three industries, the correlation coefficients are larger than 0.7. The three industries are agriculture, mining, and public administration. This is true no matter whether the number of industry-specific jobs for the tested zone is included in the indicators of localization economy.

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 elastiecties with respect to total employment, our measure of urbanization, tends to dominate the elasticities with respect to own-sector employment.

The third hypothesis, regarding effects of accessibility via different modes of passenger travel (auto versus public transit) was difficult to substantiate. While positive and statistically significant elasticities were found for most industries with respect to public transit accessibility when the transit accessibility variable was entered by itself, we were unable to obtain clear, independent estimates of its effect apart from auto accessibility when both variables were introduced together. This is likely the result of the substantial amount of overlap between auto and public transit networks which leads to collinearity issues in estimation where both variables are used as regressors.

**Table 7 Elasticities of urbanization economy and localization economy (including the jobs in the tested zone)**

| | 2010 | | | | 2000 | | | |
|---|---|---|---|---|---|---|---|---|
| | Urbanization | Rank | Localization | Rank | Urbanization | Rank | Localization | 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 tested zones. The numbers in the shaded cells are insignificant at the $p < 0.05$ level.

**Table 8 Elasticities of urbanization economy and localization economy (excluding the jobs in the tested zone)**

| | 2010 | | | | 2000 | | | |
|---|---|---|---|---|---|---|---|---|
| | Urbanization | Rank | Localization | Rank | 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 tested zones. The numbers in the shaded cells are insignificant at the $p < 0.05$ level.

## 5 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 intra-urban 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 industries. This result tends to corroborate the findings of other recent studies which have found few or no positive results 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 tended to vary significantly across economic sectors. In general, service sector employment densities tended 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 elasticties. 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. One issue was the use of multimodal networks to generate measures of accessibility. The use of public transit accessibility in our employment density regressions was limited in terms of its inclusion with auto accessibility as a separate variable due to the substantial overlap in the two networks and the resulting collinearity issues. While one would expect to see the effects of auto accessibility dominate due to the much larger overall mode share of trips in the region, there may be some sectors (or perhaps smaller industries) where transit accessibility may have a residual effect, and better methods to isolate this effect (assuming they exist) would be valuable. Similarly, 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 scales, but that the degree of localization is highly skewed across industries (Duranton and Overman 2005). Thirdly, 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.

## Acknowledgements

We would like to recognize the assistance of Andrew Owen at the University of Minnesota Accessibility Observatory and Chen-Fu Liao at the University of Minnesota Traffic Observatory in providing the network accessibility data by mode for use in this study. We would also like to recognize the University of Minnesota's University Metropolitan Consortium and Center for Transportation Studies for their financial support of this research.

## References


Arrow, K.J. (1962) "Economic welfare and the allocation of resources for invention" in R.R. Nelson, ed. *The Rate and Direction of Inventive Activity*, 609-626, Princeton, NJ: Princeton University Press.

Carlino, G. and Chatterjee, S. (2001) Aggregate metropolitan growth and the deconcentration of metropolitan employment. *Journal of Monetary Economics*, 48, 549-583.

Chatman, D.G. and Noland, R.B. (2014) Transit service, physical agglomeration and productivity in US metropolitan areas. *Urban Studies*, 51(5), 917-937.

Chinitz, B.J. (1961) Contrasts in agglomeration: New York and Pittsburgh. *American Economic Review*, 51, 279-289.

Dekle, R. and Eaton, J. (1999) Agglomeration and land rents: evidence from the prefectures. *Journal of Urban Economics*, 46(2), 200-214.

Desmet, K. and Fafchamps, M. (2005) Changes in the spatial concentration of employment across US counties: a sectoral analysis, 1972-2000. *Journal of Economic Geography*, 5(3), 261-284.

Drennan, M.P. and Brecher, C. (2012) Does public transit use enhance the economic efficiency of urban areas? *Journal of Transport and Land Use*, 5(3), 53-67.

Duranton, G. and Puga, D. (2004) "Micro-foundations of urban agglomeration economies" in J.V. Henderson and J.-F. Thisse, eds. *Handbook of Regional and Urban Economics, Vol. 4: Cities and Geography*, 2063-2117, Amsterdam: Elsevier.

Eberts, R.W. and McMillen, D.P. (1999) "Agglomeration economies and urban public infrastructure" in E.S. Mills and P. Cheshire, eds. *Handbook of Regional and Urban Economics*, Vol. 3, 1455-1495, New York: North-Holland.

Ellison, G. and Glaeser, E.L. (1997) Geographic concentration in US manufacturing industries: a dartboard approach. *Journal of Political Economy*, 105(5), 889-927.

Fallah, B., Partridge, M.D., and Rickman, D.S. (2014) Geography and high-tech employment growth in US counties. *Journal of Economic Geography*, 14(4): 683-720.

Fujita, M., Krugman, P., and Venables, A.J. (1999) *The Spatial Economy: Cities, Regions and International Trade*. Cambridge, MA: MIT Press.

Glaeser, E.L. and Kahn, M.E. (2001) Decentralized employment and the transformation of the American city. *Brookings-Wharton Papers on Urban Affairs*, 1-63.

Glaeser, E.L., Kolko, J., and Saiz, A. (2001) Consumer city. *Journal of Economic Geography*, 1(1), 27-50.

Glaeser, E.L. and Gottlieb, J.D. (2006) Urban resurgence and the consumer city. *Urban Studies, 43(8), 1275-1299.*

Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., and Shleifer, A. (1992) Growth in cities. *Journal of Political Economy*, 100, 1126-1152.

Graham, D.J. (2007a) Agglomeration, productivity and transport investment. *Journal of Transport Economics and Policy*, 41(3), 317-343.

_____. (2007b) Variable returns to agglomeration and the effect of road traffic congestion. *Journal of Urban Economics*, 62(1), 102-120.

_____. (2009) Identifying urbanisation and localisation externalities in manufacturing and service industries. *Papers in Regional Science*, 88(1), 63-84.

Graham, D.J. and Kim, H.Y. (2008) An empirical analytical framework for agglomeration economies. *Annals of Regional Science*, 42, 267-289.

Graham, D.J. and Van Dender, K. (2011) Estimating the agglomeration benefits of transport investment: some tests for stability. *Transportation*, 38(3), 409-426.

Hanson, G.H. (2005) Market potential, increasing returns, and geographic concentration. *Journal of International Economics*, 67(1), 1-24.

Harris, C.D. (1954) The market as a factor in the localization of industry. *Annals of the Association of American Geographers*, 64, 315-348.

Head, K. and Mayer, T. (2004) Market potential and the location of Japanese investment in the European Union. *Review of Economics and Statistics*, 86(4), 959-972.

_____. (2006) Regional wage and employment responses to market potential in the EU. *Regional Science and Urban Economics*, 36(5), 573-594.

Henderson, J.V. (2003) Marshall’s scale economies. *Journal of Urban Economics*, 53(1), 1-28.

Henderson, J.V., Shalizi, Z., and Venables, A.J. (2001) Geography and development. *Journal of Economic Geography*, 1, 81-105.

Holl, A. (2012) Market potential and firm-level productivity in Spain. *Journal of Economic Geography*, 12, 1191-1215.

Jacobs, J. (1969) *The Economy of Cities*. New York: Vintage Books.

Kilkenny, M. (1998) "Economies of scale." Lecture for Economics 376: Rural, Urban, and Regional Economics. Iowa State University. Ames, IA.

King, G., 1988. Statistical models for political science event counts: bias in conventional procedures and evidence for the exponential Poisson regression model. *American Journal of Political Science*, 838-863.

Krugman, P. (1991) *Geography and Trade*. Cambridge, MA: MIT Press.

Lee, S. (2010) Ability sorting and consumer city. *Journal of Urban Economics*, 68(1), 20-33.

Marshall, A. (1890) *Principles of Economics: An Introductory Volume*. London: Macmillan & Co.

McMillen, D.P., McDonald, J.F., 1997. A nonparametric analysis of employment density in a polycentric city. *Journal of Regional Science* 37, 591-612.

Melo, P.C., Graham, D.J., and Noland, R.B. (2009) A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39, 332-342.

Melo, P.C., Graham, D.J., and Brage-Ardao, R. (2013a) The productivity of transport infrastructure investment: a meta-analysis of empirical evidence. *Regional Science and Urban Economics*, 43(5), 695-706.

Melo, P.C., Graham, D.J., Levinson, D.M. and Aarabi, S. (2013b) Agglomeration, accessibility, and productivity: evidence for urbanized areas in the US. *Proceedings of the 92nd Annual Meeting of the Transportation Research Board*. Washington, D.C.

Metropolitan Council (2014) Transportation Analysis Zones (TAZ) 2000. (available at https://gisdata.mn.gov/dataset/us-mn-state-metc-trans-anlys-zones2000)

Overman, H. and Puga, D. (2010) "Labor pooling as a source of agglomeration: an empirical investigation" in E.L. Glaeser, ed. *Agglomeration Economics*, 133-150, Chicago: University of Chicago Press.

Owen, A. and Levinson, D. (2014) *Access Across America: Transit 2014*. Technical report, Accessibility Observatory, University of Minnesota.

Puga, D. (2010) The magnitude and causes of agglomeration economies. *Journal of Regional Science*, 50(1), 203-219.

Rice, P., Venables, A.J., and Patacchini, E. (2006) Spatial determinants of productivity: analysis for the regions of Great Britain. *Regional Science and Urban Economics*, 36(6), 727-752.

Romer, P. (1986) Increasing returns and long run growth. *Journal of Political Economy*, 94(5), 1002-1037.

____. (1990) Endogenous technological change. *Journal of Political Economy*, 98(5), 71-102.

Rosenthal, S. and Strange, W. (2003) Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, 85(2), 377-393.

_____. (2004) "Evidence on the nature and sources of agglomeration economies" in J.V. Henderson and J.-F. Thisse, eds. *Handbook of Regional and Urban Economics, Vol. 4: Cities and Geography*, 2119-2171, Amsterdam: Elsevier.

_____. (2008) The attenuation of human capital spillovers. *Journal of Urban Economics*, 64(2), 373-389.

Silva, J.M.C.S., Tenreyro, S., 2006. The log of gravity. *The Review of Economics and statistics* 88, 641-658.

Small, K.A., Song, S., 1994. Population and employment densities: structure and change. *Journal of Urban Economics*, 36, 292-313.

Smith, A. (1776) *The Wealth of Nations* (1976 reprint). Chicago: University of Chicago Press.

TomTom International BV (2013) *Speed profiles*. Technical report.

US Census Bureau (2016) *LEHD Origin-Destination employment statistics dataset structure format version 7.2*. Technical report. (available at http://lehd.ces.census.gov/data/lodes/LODES7/LODESTechDoc7.2.pdf)

U.S. Census Bureau and Metropolitan Council (2010) Census 2010 Geography. (available at https://gisdata.mn.gov/dataset/us-mn-state-metc-society-census2010tiger)

Venables, A.J. (2007) Evaluating urban transport improvements: cost-benefit analysis in the presence of agglomeration and income taxation. *Journal of Transport Economics and Policy*, 41(2), 173-188.

World Bank. (2009) *World Development Report: Reshaping Economic Geography*. Report No. 43738. Washington, D.C.: The World Bank.

## Appendix A: Elasticities of auto accessibility

We computed elasticities of auto accessibility for all industries in 2010 when b=0.1, 0.15, 0.2 and 0.25 (Table A-1). For all industries, as b increases, elasticities decrease. The correlations between the elasticities are very large, particularly when b =0.2 and b=0.25 (Table A-2). Therefore, the relationships between the elasticities in 2000 and 2010 are almost linear. For all jobs in 2000, the correlations are also very large. Overall, the size of estimated elasticities is sensitive to the choice of b. Thus, the face value of these elasticities offer limited information. However, for most industries, the quotient between the elasticities of different industries are relatively stable. That is, the relative magnitude of elasticities are robust.

Table A-1 2010 Elasticities with different b values

| **Industry Category** | **b=0.1** | **b=0.15** | **b=0.2** | **b=0.25** |
|---|---|---|---|---|
| Agriculture, Forestry, Fishing and Hunting | 1.63 | 1.34 | 1.19 | 1.10 |
| Mining, Quarrying, and Oil and Gas Extraction | 3.24 | 2.27 | 1.73 | 1.40 |
| Utilities | 3.47 | 2.54 | 2.03 | 1.72 |
| Construction | 2.95 | 2.40 | 2.14 | 2.01 |
| Manufacturing | 2.59 | 2.11 | 1.89 | 1.78 |
| Wholesale Trade | 3.71 | 2.99 | 2.66 | 2.49 |
| Retail Trade | 2.97 | 2.43 | 2.19 | 2.06 |
| Transportation and Warehousing | 2.71 | 2.15 | 1.88 | 1.74 |
| Information | 4.30 | 3.33 | 2.84 | 2.56 |
| Finance and Insurance | 4.29 | 3.41 | 2.96 | 2.69 |
| Real Estate and Rental and Leasing | 4.13 | 3.18 | 2.72 | 2.46 |
| Professional, Scientific, and Technical Services | 3.88 | 2.94 | 2.47 | 2.21 |
| Management of Companies and Enterprises | 5.11 | 3.96 | 3.40 | 3.07 |
| Administrative and Support and Waste Management and Remediation Services | 3.67 | 2.85 | 2.46 | 2.26 |
| Educational Services | 2.52 | 1.91 | 1.61 | 1.44 |
| Health Care and Social Assistance | 3.14 | 2.47 | 2.14 | 1.97 |
| Arts, Entertainment, and Recreation | 4.02 | 3.17 | 2.75 | 2.51 |
| Accommodation and Food Services | 2.99 | 2.39 | 2.11 | 1.95 |
| Other Services [except Public Administration] | 3.04 | 2.38 | 2.06 | 1.89 |
| Public Administration | 2.89 | 2.26 | 1.97 | 1.81 |

Table A-2 Pearson correlation between elasticities with different b values

| | **b=0.1** | **b=0.15** | **b=0.2** | **b=0.25** |
|---|---|---|---|---|
| **b=0.1** | 1 | | | |
| **b=0.15** | 0.989 | 1 | | |
| **b=0.20** | 0.956 | 0.989 | 1 | |
| **b=0.25** | 0.912 | 0.962 | 0.992 | 1 |

## Appendix B: Elasticities of transit accessibility

We computed elasticities of auto accessibility for all industries in 2010 when b=0.1 and 0.2 (Table B-1). For most industries, as b increases, elasticities decrease. The correlation between the two sets of elasticities is 0.767. Therefore, they are highly correlated. However, the correlation is much smaller than that for auto accessibility (0.956). The size of estimated elasticities is sensitive to the choice of b. The quotient between the elasticities of different industries varies somewhat.

Table B-1 2010 Elasticities with different b values

| **Industry Category** | **b=0.2** | | **b=0.1** | |
|---|---|---|---|---|
| | **Elasticity** | **Rank** | **Elasticity** | **Rank** |
| Agriculture, Forestry, Fishing and Hunting | 0.310 | 19 | 0.480 | 19 |
| Mining, Quarrying, and Oil and Gas Extraction | 0.122 | 20 | 0.257 | 20 |
| Utilities | 0.595 | 15 | 0.678 | 13 |
| Construction | 0.438 | 18 | 0.537 | 18 |
| Manufacturing | 0.974 | 2 | 0.562 | 17 |
| Wholesale Trade | 1.081 | 1 | 1.092 | 1 |
| Retail Trade | 0.880 | 3 | 0.856 | 5 |
| Transportation and Warehousing | 0.785 | 5 | 0.888 | 4 |
| Information | 0.679 | 8 | 0.816 | 8 |
| Finance and Insurance | 0.644 | 13 | 0.902 | 3 |
| Real Estate and Rental and Leasing | 0.646 | 12 | 0.845 | 7 |
| Professional, Scientific, and Technical Services | 0.530 | 16 | 0.647 | 14 |
| Management of Companies and Enterprises | 0.780 | 6 | 0.943 | 2 |
| Administrative and Support and Waste Management and Remediation Services | 0.605 | 14 | 0.782 | 9 |
| Educational Services | 0.665 | 9 | 0.573 | 16 |
| Health Care and Social Assistance | 0.800 | 4 | 0.849 | 6 |
| Arts, Entertainment, and Recreation | 0.505 | 17 | 0.605 | 15 |
| Accommodation and Food Services | 0.656 | 11 | 0.726 | 10 |
| Other Services [except Public Administration] | 0.657 | 10 | 0.713 | 11 |
| Public Administration | 0.702 | 7 | 0.681 | 12 |

Overall, although the elasticities when b =0.1 and 0.2 are highly correlated, the elasticity matrix for auto accessibility has a clearer pattern than that for transit accessibility. This pattern is not surprising because transit accessibility depends on not only road network, but also the coverage area and route schedule of transit service. Within the same travel time, driving can reach much more jobs than taking transit.