Transit service, physical agglomeration, and productivity in US metropolitan areas

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Abstract. Public transit improvements could cause more clustered and higher-density employment and enable urban growth, giving rise to agglomeration economies by making labor markets more accessible, increasing information exchange, and facilitating industrial specialization. Using data on almost all metropolitan areas in the United States, we explicitly traced the links between transit service and multiple physical measures of agglomeration, and hence to wages and gross metropolitan product per capita. Doubling transit service levels (using measures such as total seat capacity) is associated with large increases in central city employment density and consequent wage increases ranging from 1.1 to 1.8 percent, or between $7 million and $12 billion yearly per metropolitan area depending on the size of the workforce and the starting average wage. Firms and households likely receive unanticipated benefits from transit-induced agglomeration, and current benefit-cost evaluations may underestimate the benefits of improving transit service.

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1. INTRODUCTION

Along with internal economies of scale in production, and the invention of elevators and structural steel, streetcars and underground rail lines enabled the creation of central business districts and the rapid growth of large cities in the late 1800s (Jackson, 1985; Mills and Hamilton, 1989). Dense downtown districts, clusters near transit stops, and larger cities are all examples of physical changes in the form of the city that could give rise to agglomeration economies, or external economies of scale in production (Marshall, 1997 (1920); Anas, Arnott, and Small, 1998).

Do public transit services continue to enable agglomerations, and the increased productivity that agglomerations bring, even in the face of ubiquitous road networks and auto ownership? There is a relatively well developed set of theoretical possibilities that suggest so. By reducing road congestion enough to let cities grow larger, transit services could create larger labor markets, leading to better sharing of the labor pool among industries whose employment contracts are of short duration, and better matches between the needs of a job and the skills and interests of workers. Transit services could concentrate development near transit stops in employment centers, lowering the transactions costs associated with intermediate inputs (Scott, 1988), and causing information spillovers that happen when workers in innovation-based industries mix and mingle with each other (Arzaghi and Henderson, 2008).

But it is an open question whether and how city size or employment density change in response to transit improvements in modern-day US cities, and it is likely that much depends on the specific context. If transit services provide a significant-enough accessibility advantage, more centralized and higher-density employment clusters and larger cities could develop. But by reducing transportation costs, higher transit accessibility could instead lead to sprawl and de-densification; cheaper land markets; reduced costs of housing and nonresidential space on urban fringes; and reduced proximity of firms, workers and consumers to each other. Which of these things happens is partly contingent upon how firms produce their goods, and how declines in transport costs affect the costs of their production inputs and outputs.

It is also an open question whether firm productivity will increase in response to any such transit-induced agglomeration. Transit services may enable tighter spatial clustering for firms that want access to each other, and thus increase agglomeration economies. But such densification, if it exists, could instead be largely because firms capitalize upon lower transportation costs.

Thus it is helpful to distinguish between two fundamental questions. First, what effect does public transit have on physical agglomeration? Second, what effect do any such physical changes have on productivity? There is also a third important question: what effect does increased public transit accessibility have directly upon productivity, regardless of any physical changes it may cause? Establishing a research design to credibly answer these causal questions is a significant challenge largely because there is no truly exogenous variation in public transit services. This paper addresses the first two questions to the limit of available data at the metropolitan area level in the US, while only indirectly addressing the third question, which has been the subject of most previous relevant studies (Graham, 2007; Venables, 2007).

2. LITERATURE REVIEW

Empirical research on the link between transportation investments, agglomeration, and productivity increases is limited. The lack of empirical research is particularly marked for transit, which is likely to have different effects on agglomeration than road and highway networks, because of its different service characteristics (Chatman and Noland, 2011) and because it may reduce diseconomies of agglomeration due to road congestion (Wheaton, 2004). Those few estimates available suggest that the agglomeration-related productivity benefits of significant rail projects in large urban areas can add as much as a 25 percent increment to a conventional benefit-cost ratio (Graham, 2007; Vickerman, 2008).

Few studies have related transit services to physical agglomeration measures. A study of Seoul, South Korea defined intra-metropolitan industry clusters using spatial hot spot analysis and analyzed whether agglomeration status, measured for spatial units (villages) within the metro area, were correlated with simple measures of subway and road accessibility when controlling for population density and average rent (Song *et al.*, 2012). Own-village subway accessibility and spatially-lagged subway accessibility were both significantly associated with agglomeration status, more so than road accessibility. Because this study uses cross-sectional data and few control variables, it is not clear whether the correlation is causal in the direction of subways influencing agglomeration, or the reverse.

Other studies have made engineering and service based assumptions about the role that transit might play in agglomerations. For example, Shefer and Aviram (2005) assume that the extra capacity enabled by a new light rail line serving the central city of Tel Aviv would enable growth that would otherwise go to an outlying area. They estimate the effect on external economies of production using agglomeration elasticities found in other studies, and estimate an increase in the benefit cost ratio of 1.1 to 1.4.

A number of studies have related physical measures of agglomeration to measures of productivity such as wages, gross metropolitan product, or firm revenues, as well as indirect measures such as rents and property values. Much of the research has focused on agglomeration economies in the manufacturing sectors, but transit services tend to be focused on central business districts often comprised of non-manufacturing industries including information, producer services, and finance/insurance. Drennan and Kelly (2011) studied how office rents were related to the amount of producer services employment. Using an 18-year panel of 120 office markets in 49 US metropolitan areas, they found a positive relationship when controlling for other factors, but only in large "strong core" cities.

Abel, Dey and Gabe (2011) used population-weighted population density as a measure of agglomeration, controlling for endogeneity with instrumental variables and finding elasticities of agglomeration with respect to productivity consistent with but somewhat lower than previous literature, at between 1 and 3 percent. They found that the agglomeration influence was mediated by human capital; for example, population densification in low-education metropolitan areas had little or no relationship with per capita GMP, but did in higher-education metros. In a recent working paper, Melo et al. (2012) modeled wages as a function of both employment accessibility and employment density for a selection of 51 US urbanized areas (UZAs) observed in four years: 1990, 1995, 2001, and 2009, using data from the Nationwide Personal Transportation Survey (NPTS) and its successor, the National Household Travel Survey (NHTS). To calculate average UZA-wide employment accessibility they used estimated network speeds from NPTS/NHTS data, and specified isochronic measures yielding the number of jobs within a given time band.

They found a positive relationship between urbanized area employment density and wages, that increased with higher levels of density.

A meta-analysis of 729 agglomeration-productivity estimates found an average elasticity of about 0.06 for US studies with metro-level agglomeration measures that control for human capital (Melo, Graham, and Noland, 2009). Most of these studies used various physical agglomeration measures, some industry-specific (implying localization/Marshallian economies) and others measured for all industries or the entire population of a metropolitan area (implying urbanization/Jacobsian economies).

A related set of literature has correlated employment accessibility (often called "effective density") with measures of productivity such as firm revenues (e.g., Graham, 2007; Holl, 2011), or demonstrated in mathematical models how better employment accessibility can increase employment search success and reduce vacancies (Venables, 2007; Pilegaard and Fosgerau, 2008). These studies have typically resulted in estimates of agglomeration elasticities that are similar in size to estimates from studies of physical agglomeration measures (Melo, Graham, and Noland, 2009).

3. MODEL SPECIFICATION AND METHODS

We carried out two series of models for almost all US metropolitan areas in the US: one series estimating relationships between different measures of transit service and of physical agglomeration; and a second series between physical agglomeration and productivity. To the extent that Census-defined metropolitan area boundaries correspond to economically self-contained regions, any intra-regional redistribution of economic activity is controlled for.

We expect different kinds of agglomeration to be differentially influenced by transit services, and to have different effects on productivity. We tested the density of employment in the Census-defined principal cities of each metropolitan area, as a measure of centralization in monocentric and polycentric urban areas; the density of employment in the Census-defined Urbanized Area (UZA), as a proxy for dispersion outside the central cities but within the confines of the urbanized area; and metropolitan area population, as a proxy for labor force size. Central city employment density has not been tested in previous research, possibly because only recently have data become available to make it possible to calculate it across the US.

Different kinds of transit services might affect agglomeration in different ways. Connectivity and coverage might affect physical agglomeration more than does total system size. Rail might affect intensity of development more than bus service, and different kinds of rail service might have more or less efficacy because of differences in service characteristics. Thus we tested a number of different transit service measures, as described below.

In specifying the models we had to address two estimation problems. The first is that transportation services can directly affect common productivity measures, independent of agglomeration effects (e.g., Berechman, Ozmen, and Ozbay, 2006), by reducing commuting costs for labor, freight costs for physical inputs and outputs, and travel time for other factors in the production process. Any such capitalization is entirely separate from increasing returns of scale due to the various agglomeration mechanisms made possible by clustering, densification, or growth. We accounted for *direct* effects of transit service on productivity and *indirect* effects via agglomeration by controlling for both in the agglomeration-productivity models.

The second estimation issue is endogeneity. Transit services may cause agglomeration, and agglomeration may increase the productivity of firms and workers. But other possible relationships complicate matters. Higher-productivity areas may stimulate transit agencies to

provide more services as travel demand increases. Productive cities might grow faster. Denser areas may receive better transit services. We addressed endogeneity using instrumental variables, as described later in the paper.

4.1 Transit-agglomeration series

We specified three sets of models in the transit-agglomeration series, corresponding to three agglomeration measures: employment density in the principal or "central" cities (*CCED*); employment density in the urbanized area (*UZED*); and the population of the metropolitan area (*POP*):

$$CCED_i = \beta_1 T_i + \beta_2 H_i + \beta_3 UZED_i + \beta_4 POP_i + \boldsymbol{\Gamma_1 D_i} + \boldsymbol{\Phi_1 E_i} \quad (1)$$

$$UZED_i = \beta_5 T_i + \beta_6 H_i + \beta_7 CCED_i + \beta_8 POP_i + \boldsymbol{\Gamma_2 D_i} + \boldsymbol{\Phi_2 S_i} \quad (2)$$

$$POP_i = \beta_9 T_i + \beta_{10} H_i + \beta_{11} CCED_i + \beta_{12} UZED_i + \boldsymbol{\Gamma_3 D_i} + \boldsymbol{\Phi_3 S_i} \quad (3)$$

For each equation the other two agglomeration measures appear as endogenous right-hand-side variables. The main variable of interest is *T*, a measure of transit service. We test 21 measures, as discussed below. The control variables are *H*, a measure of highway and arterial road capacity; ***D***, a vector of metropolitan area population characteristics that might affect population and employment density; and ***S***, a vector of variables representing employment in different industrial sectors, with different tendencies to higher or lower patterns of density and that might also be correlated with metropolitan area population. Without an *a priori* theoretical basis for model form, we tested log-log, semilog and unlogged, and based on diagnostics chose the latter. The linear coefficients from this series of models are used to estimate average point elasticities in a later stage.

4.2 Agglomeration-productivity series

We define a production function that includes a multiplier to account for additional productivity effects from agglomeration, similar to Graham (2007),

$$Y = g(z)f(X), \quad (4)$$

where *Y* is gross metropolitan product (GMP) or wages; *g(z)* is the Hicks multiplier, representing an external agglomeration benefit if greater than one; and *f*(*X*) is the production function.

Most research on agglomeration and productivity uses a Cobb-Douglas production function, which assumes a nonlinear relationship between inputs, corresponding to firm production theory in microeconomics. Abel, Dey and Gabe (2011) specify their model as follows (we have substituted some symbols):

$$Y_{ij} = M_{ij} K_{ij}^{\alpha} E_{ij}^{\beta} L_{ij}^{1-\alpha-\beta}, \quad (5)$$

where M_{ij} is the Hicks multiplier, K_{ij} is physical capital, E_{ij} is education (a human capital measure) and L_{ij} is labor supply. Subscript *i* denotes the metropolitan area, and *j* represents the larger region within which the metropolitan area is found (e.g. the state). Constant returns to scale are assumed in all inputs. The Hicks multiplier can be specified as a function of agglomeration, denoted *A*, as follows:

$$M_{ij} = \gamma_0 A_{ij}^{\gamma_1}, \tag{6}$$

where γ_1 represents the elasticity of output with respect to agglomeration.

Abel, Dey and Gabe (2011) assume that the rate of return on physical capital is constant and use this to redefine their model to factor out the physical capital input. We use a measure of per-capita highway capital. To control for the role that transit service might play directly in affecting GMP or wages, we also include a separate term for total transit supply:

$$Y_{ij} = \gamma_0 A_{ij}^{\gamma_1} H_{ij}^{\alpha} E_{ij}^{\beta} T_{ij}^{\omega} L_{ij}^{1-\gamma_1-\alpha-\beta-\omega} \tag{7}$$

This model distinguishes three measures of labor's impact on productivity: human capital or education, *E*, accessibility due to transit services, *T*, and total labor supply, *L*. Physical capital is represented by *H*, highway/arterial distance per capita.

Omitting the region-specific subscript, normalizing by labor supply to convert to a per capita productivity function, and taking logs yields

$$ln\left(\frac{Y_i}{L_i}\right) = ln(\gamma) + \frac{1}{1-\alpha-\beta-\omega}\left\{\gamma_1 ln(a_i) + \alpha ln\left(\frac{H_i}{L_i}\right) + \beta ln\left(\frac{E_i}{L_i}\right) + \omega ln\left(\frac{T_i}{L_i}\right)\right\} \tag{8}$$

We assume that labor supply is embodied in the constant, γ, to simplify the model. Our agglomeration measure, a_i, is normalized (and equal to A_i/L_i). We substitute for coefficients to simplify the equation, giving

$$lnP_i = ln\gamma_o + \tau lna_i + \varphi lnE_i + \delta lnT_i + \rho lnH_i, \tag{9}$$

where τ is the elasticity of agglomeration with respect to per worker wages or per capita GMP; φ the elasticity of human capital; ρ the elasticity of physical capital, as measured by highway/arterial road length per capita; and δ the elasticity of transit accessibility. We also controlled for industry mix, as described in more detail in a later section.

4.3 Transit-agglomeration-productivity estimates

We used the two sets of models to construct net transit-productivity elasticities via the three agglomeration channels for various measures of transit service. Because the transit-agglomeration series is linear, we estimated point elasticities, as described below. The relationship between transit service and productivity via the three agglomeration channels is expressed as the following elasticities:[1]

$$\epsilon_{T_i CCED} = \frac{\beta_1 T_i}{CCED_i}\tau, \tag{10}$$

$$\epsilon_{T_i UZED} = \frac{\beta_5 T_i}{UZED_i}\tau, \tag{11}$$

$$\epsilon_{T_i POP} = \frac{\beta_9 T_i}{POP_i}\tau, \tag{12}$$

Note that these are additive estimates, because both series of models control for all three measures of agglomeration.

[1] As shown below, we use mean rather than median values for transit service measures where the median value is zero (that is, for all measures that are limited to rail only).

4.4 Controls for endogeneity

We relied on two methods to control for mutual causality: lagged independent variables, observed four years prior to the year in which the dependent variable was measured, and two-stage least squares with instrumental variables. We predicted levels of transit service and levels of agglomeration as a function of instruments correlated with historical transit investment decisions but not caused by recent levels of agglomeration, or correlated with historical levels of agglomeration but not caused by recent levels of productivity. The instruments are described below. We tested for underidentification with the Kleibergen-Paap Wald statistic; for weak instruments using the Kleibergen-Papp rank F statistic and the Stock-Yogo (2005) critical values; and for overidentification using the Hansen J statistic.

4. DATA

We were able to collect complete data for about ninety percent of the 364 metropolitan areas[2] in the continental United States. The number of metropolitan areas included in the regressions varied between 319 and 354, depending on missing values for some transit service measures, employment density measures, and instruments.

Transit service data were derived from two sources. The American Public Transportation Association made track mileage data available. There were 27 metropolitan areas with some form of rail transit in 2003. Seat capacity and revenue service miles for bus and rail were taken from the National Transit Database. There were 290 metropolitan areas with some form of bus service in 2003. We tested these three transit service variable types in total terms, per land area within the UZA, and per capita in the metropolitan area (see Table 1).

Annual population estimates by county were obtained from the Census, aggregating county-level data to the metropolitan area level using the 2008 Census definitions. Urbanized area employment density and central city employment density were calculated using worker-at-place-of-work data from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) data set, available at the Census block level for the years 2002 to 2008, along with block-level land and water area from the 2009 Census TIGER shapefiles, using geographical information software.[3] Central city employment density was calculated only for those Census blocks falling within the urbanized-area portions of the Census-defined "principal cities" of the metropolitan areas. For example, there are nine principal cities in the Dallas-Fort Worth metropolitan area: Dallas, Fort Worth, Arlington, Plano, Irving, Carrollton, Denton, McKinney, and Richardson, the urbanized portions of which account for 60 percent of employment and 9.5 percent of the urbanized land in the metropolitan area (see Figure 1 for an illustration).

[Figure 1 about here]

Average wages were from the County Business Patterns (CBP) data from the Census Bureau. GMP data were obtained from the Bureau of Economic Analysis.

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[2] The term "metropolitan area" is used throughout to refer to Census-defined Core-Based Statistical Areas.

[3] Data for the ten metropolitan areas in Massachusetts, New Hampshire, and Connecticut were not available.

Table 1 summarizes the main variables of interest that were tested in the model system: 21 transit service measures, three agglomeration measures and two measures of productivity.

[Table 1 about here]

Highway/arterial road network data were drawn from National Highway Planning Network files in the National Transportation Atlas Database. Jaison Abel kindly provided a measure of human capital used in Abel, Dey and Gabe (Abel, Dey, and Gabe, 2011): the share of the working-age population with a college degree.

Seven Census data variables were included as controls: the share of the population aged under 18, aged 65 or over, aged 25+ and holding a high school diploma, aged 25+ holding a bachelor's degree, and the share identified as White, Black/African-American, and Hispanic/Latino. In both model series we controlled for the share of the workforce in the two-digit NAICS industry categories, using the LEHD data.

We used six variables in different combinations as exogenous instruments in the two sets of models. We calculated the sum of the length of passenger rail right-of-way in each city using a 1898 map of US passenger and freight rail, helpfully provided to us by Matthew Turner (see Duranton and Turner (2011)), that we geocoded to match our geography. We calculated the percentage of the metropolitan area covered by water from the Census, as a measure of constrained land availability in the metropolitan area that might cause higher density. Two other instruments—the population in 1900 and the climate index—were kindly provided by Jaison Abel who had used them in the work cited previously (Abel, Dey, and Gabe, 2011). Our other instruments, used as potential measures of urban fragmentation and therefore of lower density and population, were an indicator variable representing whether the metropolitan area has some form of metropolitan-level governance structure, another indicator variable for metropolitan areas is states permitting township forms of governance (both from the Census of Governments).

5. RESULTS

5.1 Transit-agglomeration models

We estimated three sets of transit-agglomeration regressions, one set for each of the agglomeration measures, with each regression in the set varying only by which of 21 transit service measures was included. Only a small handful of these measures were successfully instrumented and we report only the successful models below, though the results are qualitatively and quantitatively similar even for those models that were not successfully instrumented. The transit service coefficients must be interpreted with caution because each when singly entered into the models is a stand-in for all transit service in the metropolitan area. That is, we do not simultaneously test and simultaneously control for the endogeneity of multiple transit measures, though undoubtedly different kinds of transit service could play distinct and simultaneous roles in physical agglomeration.

Each transit service measure was predicted using a first stage instrumental variables regression on all of the endogenous variables in the main model as well as one or more of the following instruments: the population in 1900, the length of rail track in 1898, the percentage of area covered by water, and an index of climate. We present only models that do not include New York City, since it is an outlier on multiple dimensions, and also only present those models that passed underidentification, overidentification, and weak instruments tests. Models were specified

with robust standard errors and limited information maximum likelihood (LIML) estimation to correct for heteroskedasticity. We also estimated ordinary least squares (OLS) models for comparison.

Central city employment density

Our first set of models tested the relationship between transit service and central city employment density. We found strong correlations in most of the OLS models, but just four of 21 instrumental variables models passed all diagnostic tests. Per capita rail track is successfully instrumented only when New York City is excluded and a single instrument, population in 1900, is used, with the coefficient increasing in size in comparison to the OLS result (Table 2, columns 1-2). Models using the per capita seat capacity measures were more robust, with well-instrumented measures for total seat capacity per capita and adequately instrumented measures for bus and rail seats per capita, both with and without New York City. We show the total seat capacity regression only (Table 2, columns 3-4), which again shows a large increase in the coefficient in comparison to the OLS model. The seat density models perform well for total seats per area, but not when looking only at rail or bus seats in isolation, increasing in size and significance when instrumented (Table 2, columns 5-6). Rail service miles per capita was also successfully instrumented (Table 2, columns 7-8). A similar result is obtained for rail service mile density; in this case only the models with one instrument are successful, so the result is less reliable (Table 2, columns 9-10).

Urbanized area employment density

Next up are the urbanized area employment density models. When transit service measures are instrumented they tend to become larger and statistically significant, and change sign from negative to positive. Urbanized area employment density is more highly correlated with population than is central city employment density, so part of the reason for the change in sign is relatively high collinearity. Variance inflation is reduced in the two-stage models, and population becomes highly statistically significant, while transit service becomes negative and sometimes significant.

[Table 3 about here]

Per capita rail length was not significantly associated with urbanized area employment density in the OLS model, but was negatively associated when instrumented (Table 3, columns 1-2). The per capita total seat capacity models show a marginally positive relationship to urbanized area employment density in the OLS model, and become clearly negative when instrumented (Table 3, columns 3-4). Rail revenue miles are insignificant in the OLS model, becoming negative and highly significant when instrumented, though the instruments are not as strong, achieving the 15% level on the Stock-Yogo test (Table 3, columns 5-6). Finally, there are some diagnostically acceptable results for rail service mile density (Table 3, columns 7-8).

Metropolitan area population

For the last of our three agglomeration measures, metropolitan area population, we estimated a slightly different set of models. Taking advantage of data on population in previous

periods, we included 1970 metropolitan area population as an independent control. Population is measured in 100,000s, and coefficients must be interpreted appropriately.

[Table 4 about here]

Only a few metropolitan area population models came close to having proper diagnostics. When New York City was excluded and three instruments were used—population in 1900, a climate index, and the percent of the metro area covered in water—the model of total revenue miles barely missed the underidentification cutoff, had strong instruments, and was not clearly overidentified. This model showed a strong positive relationship between total revenue miles and population (Table 4, columns 3-4). A similar effect occurs when instrumenting bus revenue miles separately (Table 4, columns 6-7). However, these results are sensitive to the choice of instruments. Using rail in 1898 and the percentage of metropolitan area covered in water, we found three well-instrumented models hitting all benchmarks but showing insignificant relationships with population (Table 4, columns 5 and 8). The third diagnostically reliable model finds no significant relationship between total bus seat capacity and population, consistent with the OLS result (Table 4, columns 1-2).

Our measures of transit reflect investments made long before 1970 in many cities with heavy rail and commuter rail. The dataset does not include dates of transit capacity additions over such a long time period. We separately estimated the same lagged-population models with light rail track mileage separated from the other rail types, since the majority of light rail was built after 1970. We found that light rail was positively associated with population growth, and commuter rail and heavy rail negatively associated, but the models suffered from weak instruments and we do not display the results here.

Overall interpretation of the transit-agglomeration models

The central city and urbanized area employment density results indicate that transit services redistribute employment from the urbanized area outside of the central cities to the central cities. Transit service may densify central city employment at the expense of outlying parts of the urbanized area. The population models in which 1970 population was added as a control for persistence imply that transit-agglomeration relationships are possibly very long term. Changes in locational patterns of firms can take time as opposed to other more immediate economic effects. Outside the four-year lags, a period of time that is very short in terms of changes to population or employment density in metropolitan areas, these models are essentially cross-sectional and silent on the period over time during which physical agglomeration will occur. The time potentially needed for physical agglomeration change is in marked contrast to travel-time-based agglomeration changes, which occur quickly when transportation investments reduce travel time.

The changes in agglomeration via CCED (central city employment density), UZED (urbanized-area employment density), and metropolitan area population that are associated with doubling various measures of transit service are summarized in Table 6, below (see column 3). Average point elasticities were calculated for each city having non-zero values of transit service, and averaged. They range in magnitude from -0.32 to 0.57, with negative elasticities for UZED and POP. Although more of the rail-only measures are successfully instrumented, average point elasticities for measures that include both bus and rail, such as total seat capacity and total service miles, are roughly similar in size.

5.2 Agglomeration-productivity models

We next regressed GMP per capita and wages per worker upon the three measures of agglomeration. For the instrumental variable models, the first stage was to estimate up to three logged agglomeration measures as a function of a set of exogenous and endogenous instruments, followed by a model of per-worker wages or per-capita GMP as a function of the instrumented agglomeration measures and controls. Because diagnostics on the models with three simultaneously instrumented agglomeration measures were sometimes poor depending on specification, we tried instrumenting two at a time, and also tried a series of staged models in which each of the agglomeration measures was instrumented separately in turn while controlling in the productivity equation for the other two uninstrumented agglomeration measures. We included state-level fixed effects in the initial models, but those models failed the overidentification test, so were omitted in subsequent models. We lagged the agglomeration measures 4 years behind the productivity measures. Only selected models are shown here.

Including two or three agglomeration measures simultaneously significantly reduces the significance of each of them without causing variance inflation factors that are so large that it implies collinearity is the problem. Each kind of agglomeration may have distinct roles to play. Note that transit service is not instrumented in the productivity models. Along with the other independent variables, it is treated as a control variable here to help isolate the independent effects of agglomeration on productivity.

Starting with the per-worker wage models, population and central city employment density are positively associated with average wages when using OLS and including all three agglomeration measures, with elasticities of 0.02 and 0.03 respectively (Table 5, column 1). Urbanized area employment density is not significant for wages. Urbanized area employment density omitted in the second wage model (column 2) which retains similar-sized coefficients for both population and central city employment density. The omission is necessary because we could not find successfully instrumented models with all three agglomeration measures. In the final wage model (column 3) we simultaneously instrument central city employment density and population, finding larger elasticities for both, increasing to 0.03 and 0.07 respectively.

[Table 5 about here]

In the GMP per capita models (Table 5, columns 4-6), when using OLS urbanized area employment density is positively correlated with an elasticity of 0.13 while the other two measures do not achieve statistical significance (column 4). The sign flips when urbanized area employment density is instrumented (column 5), and the magnitude becomes even larger, increasing to -0.41. Even when urbanized area employment density is omitted altogether, neither population nor central city employment density is correlated with GMP per capita (column 6). We discuss the meaning of this below.

Human capital—as measured by the share of population of working age with a college degree—was insignificant in some of the wage models while staying significant and large in the GMP models. This could be partly because of collinearity of population and central city employment density with wages and human capital. Transit seat capacity in the instrumented wage models shows a negative coefficient, according with theory. But it is also negatively correlated with GMP. We tested multiple other measures of transit service and only seat capacity was statistically significant.

5.3 Linking transit service with productivity via agglomeration

We estimated how transit services are associated with wages and GMP via the three agglomeration channels by calculating elasticities for each of the successfully instrumented regressions in the two model series that could be combined with significant effects. There were ten such combinations—five for central city employment density, four for urbanized area employment density and one for metropolitan area population. Note that these effects are net of each other, because both stages of our models control for all three agglomeration measures simultaneously.

In the central city employment density channel, doubling total seat capacity, seat density, rail track miles per capita, rail service miles per capita, or rail service density is associated with between 1.1 and 1.8 percent net increase in average wages for a doubling of transit service (Table 6, rows 1 to 5).

[Table 6 about here]

The other two channels have larger net correlations. In the urbanized area employment density channel, the combination of a negative effect on urbanized area density outside the central cities—combined with a negative influence of urbanized area density on GMP when controlling for central city employment density and population—means that doubling total seat capacity, rail track per capita, rail service miles, or rail service density is associated with increases in GMP per capita ranging from 13 to 19 percent (Table 6, rows 6-9).

Finally, doubling combined bus and rail service miles is associated with population-based productivity increases of a somewhat more modest 2.5 percent (Table 6, row 10).

The estimates imply that the average wage effects of an absolute change in transit service are smaller for larger metropolitan areas, in percentage terms. The effects are higher in a net sense for larger metropolitan areas because of the larger pool of workers. They are even higher on a percentage change basis when applied to an existing transit system, since percentage changes to larger systems result in substantially larger absolute changes. For example, a percentage increase in transit service will have much larger overall productivity benefits in the Chicago metropolitan area, which has a large pool of workers and an extensive transit system, than it will be in the Tampa-St. Petersburg metro, which has a smaller worker pool and a less developed transit system. In general, larger regions with more population and those regions with more extensive transit systems tend to have higher agglomeration-related productivity increments for larger transit investments in percentage terms, while having smaller per capita increases from absolute changes in transit service.

For illustrative purposes, we can calculate dollar value estimates using 2008 data on average wages and the size of the worker pool by metropolitan area in the US. Looking at the central city employment density wage channel alone, the marginal dollar value associated with doubling transit service varies between $251 and $1,374 in wages per worker yearly, depending on metropolitan area variation in the average wage. Across metropolitan area, net "effects" in this agglomeration channel of doubling transit service range from $7 million to $12 billion per year—a greater range, because larger cities have larger average worker wages and a larger worker pool.

5.4 Tests of robustness

We also tested for nonlinearity, including threshold effects of density levels and interactions—for example, between population and employment density, and between employment density and levels of transit service. One might expect that agglomeration economies would exist only with high-enough levels of density, for example. We added to the transit-productivity models several sets of variables: dummy variables for above-median population and above-median employment density, similar dummy variables for tritiles of those variables, and splines for the same divisions. The coefficients on different ranges were within 10 percent of each other and the differences were not statistically significant. This finding implies that the log-log model form, in which the model predicts percentage increases in productivity per percentage increases in agglomeration, is accurate. We also tested for nonlinearity in transit capacity's effects on population size and employment density, expecting that only sufficiently large transit systems might have significant effects on population growth or employment density. Testing for nonlinearity in some of the agglomeration-transit models was hindered by the relatively small number of metropolitan areas with rail service, but regardless, we found no strong evidence of nonlinearity here either.

6. CONCLUSIONS

Previous research has concluded that higher employment accessibility is associated with higher firm revenues and worker wages. This research is distinct from that body of work because it uses physical agglomeration measures; explicitly traces links from transit to physical agglomeration, and hence to productivity; and controls for the capitalization of transit service as a separate phenomenon from increasing returns to scale enabled by agglomeration. Previous studies relating agglomeration to productivity have typically looked at just one measure of agglomeration at a time. Different correlated agglomeration measures may have slightly different roles to play in productivity. For example, central city employment density can be thought of as being associated with informational spillovers and other firm-to-firm mechanisms (e.g., fashion and finance in Manhattan); urbanized employment density with industrial specialization, vertical disaggregation, and access to upstream and downstream suppliers (e.g., information technology in Silicon Valley, auto manufacturing in Michigan); and population with labor force access and firm-to-worker matching mechanisms (a true urbanization economy applying to any large city, but particularly applying to US cities at the turn of the20th century).

Of the three measures of agglomeration, the most reliable and intuitive results were for the effects of transit service central city employment density, which was significantly correlated with higher wages. Previous research on physical agglomeration and productivity has often used metropolitan-area-wide agglomeration measures, but finer measures such as this one are potentially important. Central cities are particularly important because they include concentrations of employment that are most likely to be served by transit. Total transit services, including buses which are more commonly used outside the core CBD, are about as highly associated with central city employment density as our rail service measures, and the results validate the results because they include many more cities with non-zero values for transit service.

The urbanized area employment density result seems counterintuitive, but it makes sense to the extent that the models control simultaneously for the other agglomeration channels. Transit

services may centralize or retain centralization, and this may be associated with higher GDP per capita.

This analysis is essentially cross-sectional with endogeneity corrections, and so there are the usual reasons for caution in applying our estimates to future increases in transit service. Given the varying transit service measures used in our analysis, and the difficulty of estimating models with suitable diagnostic results, the estimates should be interpreted mostly by sign, statistical significance, and overall magnitude. Impediments to improving this work are significant, but at least partly surmountable as data become more readily available. It would be particularly helpful to have long panels of data, substantially greater than the eight years of data used here; and more finely created measures of agglomeration, such as measures of firm clustering near transit stops.

These results are consistent with a narrative in which increases in transit capacity redistribute development from the outlying parts of urbanized areas to the nuclei of polycentric metropolitan areas, while maintaining good access to the larger labor pool. Large metropolitan areas with dense central cities may benefit more from transit service; and constraints on employment densification in central cities may lower these benefits. These results also have policy implications if they hold up under the scrutiny of further research. They imply that there is an external productivity benefit from transit investment, and that current benefit-cost frameworks in the US undervalue the benefits of transit.

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8. FIGURES AND TABLES

Figure 1: Metro area, UZA, and principal cities - Milwaukee example

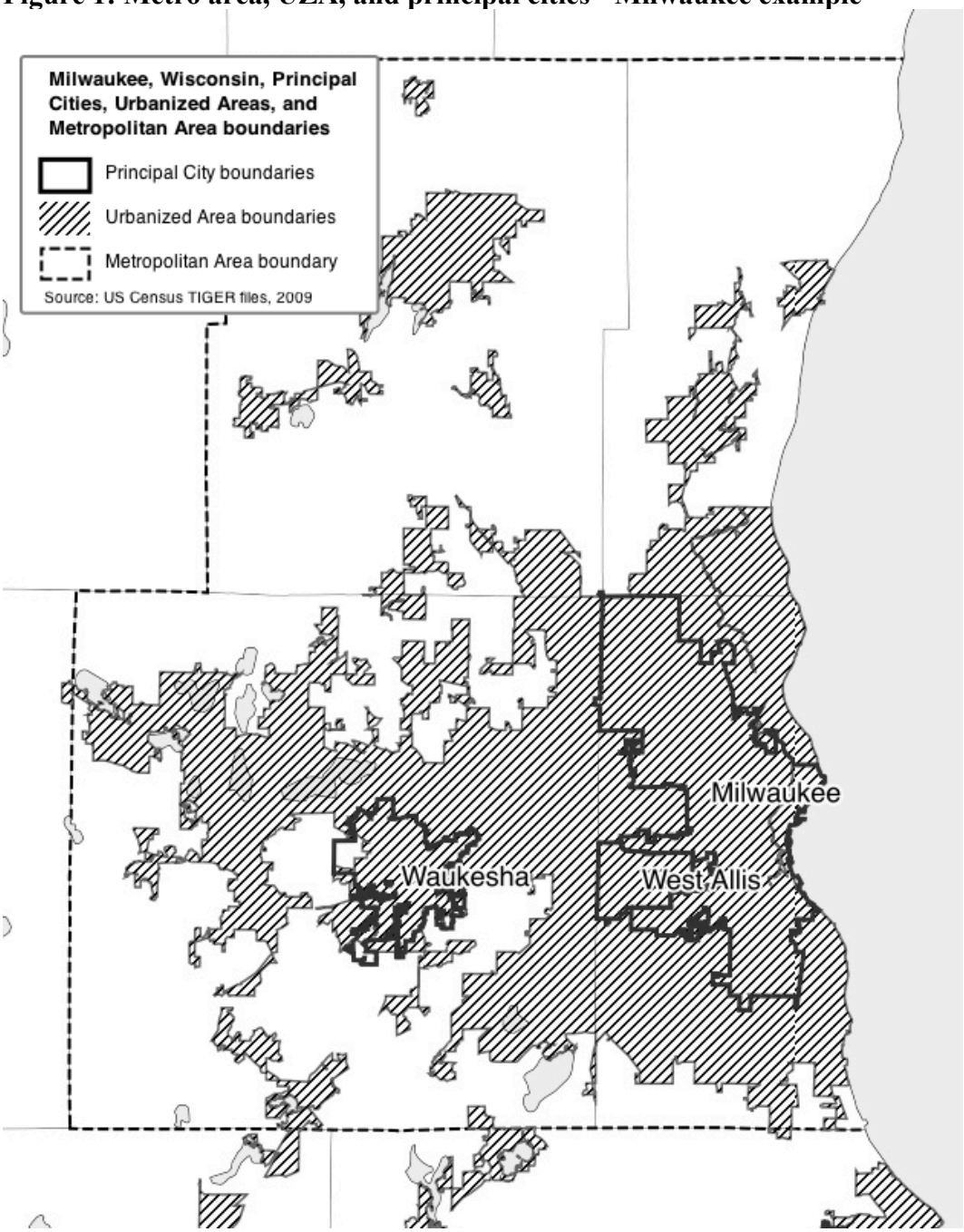

Table 1: Principal variables used in the models

Variable type	Transit service[1] →	Agglomeration →	Productivity
Variables tested	1 Total rail length 2 Rail length per capita 3 Rail length density 4 Total seat capacity 5 Bus seat capacity 6 Rail seat capacity 7 Total seats per capita 8 Bus seats per capita 9 Rail seats per capita 10 Total seat density 11 Bus seat density 12 Rail seat density 13 Total service miles 14 Bus service miles 15 Rail service miles 16 Total service miles per capita 17 Bus service miles per capita 18 Rail service miles per capita 19 Total service mile density 20 Bus service mile density 21 Rail service mile density	1 Metro area population 2 Central city employment density 3 Urbanized area employment density	1 Wages per capita 2 Gross metropolitan product (GMP) per capita
Notes:			
[1]Only 14 of the 21 transit service measures were tested in the transit-population models. Per capita measures were excluded, since, all else equal, increases in population will lower per capita measures.			

Table 2: Central city employment density as a function of transit service, selected models

Model number	1	2	3	4	5	6	7	8	9	10
Transit service variable	Rail track miles per 100,000 capita		Bus+rail seat capacity per 1,000 capita		Bus+rail seat capacity per UZA sq mi		Rail revenue mi per 1,000 capita		Rail revenue miles per UZA sq mi	
Model type	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Rail track miles per 100,000 capita	100.5	610.8*								
	-1.15	-2.44								
Bus+rail seat capacity per 1,000 capita			30.81***	90.80***						
			(3.78)	(3.72)						
Bus+rail seat capacity per UZA sq mi					5.914*	33.44**				
					(2.19)	(3.04)				
Rail revenue mi per 1,000 capita							0.390**	1.348***		
							(2.71)	(3.48)		
Rail revenue miles per UZA sq mi									0.0576	0.458**
									(1.53)	(2.88)
Freeway/arterial miles per 1,000 pop	-83.73	-96.27	-80.17	-85.32	-64.49	-15.88	-83.35	-88.72	-77.29	-80.31
	(-1.59)	(-1.61)	(-1.49)	(-1.28)	(-1.22)	(-0.24)	(-1.58)	(-1.58)	(-1.46)	(-1.38)
Population of metro area (100,000s)	7.643	-11.95	7.158+	-1.338	8.415	-8.043	6.566	-5.688	9.312+	-9.117
	(1.21)	(-1.45)	(1.73)	(-0.30)	(1.63)	(-1.34)	(1.53)	(-0.96)	(1.80)	(-1.15)
Employment density - urbanized area	0.964***	0.715*	0.881***	0.606**	0.838***	0.011	0.962***	0.842***	0.960***	0.614*
	(6.15)	(2.47)	(5.88)	(2.90)	(5.14)	(0.03)	(6.28)	(4.41)	(5.89)	(2.31)
Constant	2044.5+	1588.2	1400.7	114.6	1463	-1187.3	2070.2+	1991.9	1938.4+	1092.9
	(1.82)	(0.95)	(1.26)	(0.08)	(1.29)	(-0.63)	(1.83)	(1.41)	(1.74)	(0.58)
N	353	350	353	350	343	340	353	350	343	340
Adjusted R-squared	0.465	0.284	0.49	0.38	0.47	0.23	0.47	0.37	0.46	0.20
Underidentification test (Kleibergen-Paap)		4.852		12.66		10.57		6.679		5.123
Underidentification probability		0.0276		0.002		0.005		0.036		0.024
Weak identification test (Kleibergen-Paap)		17.14		22.44		15.87		11.88		17.19
Weak identification probability (Stock-Yogo)		<10%		<10%		<10%		<10%		<10%
Overidentification test (Hansen's J)		N/A		0.006		0.13		0.89		N/A
P value for over-ID null hypothesis		N/A		0.94		0.72		0.35		N/A

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; t statistics in parentheses. Robust standard errors on all models. IV models estimated with limited information maximum likelihood (LIML).

Instrument for models 2 and 10: Metro area population in 1900. Instruments for models 4, 6, and 8: Metro area population in 1900, percent metro area covered by water.

Included, not shown: Shares of employment in 2-digit NAICS categories from LEHD 2008 (e.g., agricultural, manufacturing, retail, professional services, education, arts, and 14 others); demographic variables from American Community Survey 2005-07 metropolitan area data (share of metropolitan population under 18, over 65, with high-school degree, college-educated, white, black, Hispanic).

Table 3: Urbanized Area employment density as a function of transit service, selected models

Model number	1	2	3	4	5	6	7	8
	Rail track miles per 100,000 capita		Bus+rail seat capacity per 1,000 capita		Rail revenue miles (100,000s)		Rail revenue miles per UZA sq mi	
Model type	OLS	IV	OLS	IV	OLS	IV	OLS	IV
L4.Rail track miles per 100,000 capita	30.44	-223.7*						
	-1.18	(-2.29)						
L4.Bus+rail seat capacity per 1,000 capita			5.372+	-35.34**				
			-1.68	(-3.19)				
L4.Rail revenue miles (100,000s)					-0.283	-7.770*		
					(-0.23)	(-2.43)		
L4.Rail revenue miles per UZA sq mi							0.0244*	-0.162**
							-2.1	(-2.69)
L4.Freeway/arterial miles per 1,000 population in me	38.41**	48.53**	38.81**	47.77**	40.06***	42.60***	42.37***	49.41***
	-3.24	-3.08	-2.93	-3.08	-3.33	-3.33	-3.41	-3.47
Population of metro area (100,000s), US Census esti	3.173	12.85***	3.621	9.006***	4.597	11.84***	3.009	11.64***
	-1.12	-3.49	-1.38	-4.23	-1.59	-4.17	-1.06	-3.67
Employment density - principal city	0.104***	0.147***	0.0986***	0.179***	0.110***	0.129***	0.101***	0.146***
	-4.54	-3.88	-4.43	-4.02	-4.77	-4.67	-4.57	-4.22
Constant	889.2*	1176.1	802.1+	1715.2**	929.8*	865.1+	987.0*	1496.7+
	-1.98	-1.56	-1.7	-2.7	-2.01	-1.67	-2.09	-1.85
R-squared	0.664	0.4	0.665	0.387	0.66	0.597	0.667	0.331
N	353	350	353	350	353	350	343	340
Weak identification test (Kleibergen-Paap)		5.859		14.38		7.266		7.354
Weak identification probability (Stock-Yogo)		<15%		<10%		<15%		<15%
Overidentification test (Hansen's J)		0.488		0.187		0.206		0.000118
P value for over-ID null hypothesis		0.485		0.665		0.65		0.991

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; t statistics in parentheses. Robust standard errors on all models. IV models estimated with limited information maximum likelihood (LIML).

Instruments: Population in 1900; percentage of metropolitan area covered by water.

Included, not shown: Shares of employment in 2-digit NAICS categories from LEHD 2008 (e.g., agricultural, manufacturing, retail, professional services, education, arts, and 14 others); demographic variables from American Community Survey 2005-07 metropolitan area data (share of metropolitan population under 18, over 65, with high-school degree, college-educated, white, black, Hispanic).

Table 4: Metropolitan area population as a function of transit service, with 1970 population lag, selected models

Model number	1	2	3	4	5	6	7	8
	Bus seat capacity (1,000s)		Revenue vehicle miles, bus + rail (100,000s)			Bus revenue miles (100,000s)		
Model type			OLS	IV	IV	OLS	IV	IV
Instruments		1900 rail, water		1900 pop., water, climate	1900 rail, climate		1900 pop., water, climate	1900 rail, climate
L4.Bus seat capacity (1,000s)	0.217***	-0.0363						
	-3.45	(-0.15)						
L4.Revenue vehicle miles, bus + rail (100,000s)			0.0374***	0.0609***	-0.00128			
			-4.8	-4.75	(-0.05)			
L4.Bus revenue miles (100,000s)						0.0430***	0.0533***	-0.00137
						-5.64	-4.41	(-0.06)
L4.Freeway/arterial miles per 1,000 population in metro area	-0.187	-0.172	-0.254*	-0.318*	-0.168	-0.227+	-0.253*	-0.169
	(-1.41)	(-1.13)	(-1.97)	(-2.14)	(-1.01)	(-1.89)	(-2.00)	(-1.07)
1970 Census Total Population (100,000s)	0.880***	1.30**	0.702***	0.356*	1.26***	0.684***	0.548***	1.26***
	-7.66	-3.15	-6.25	-2.05	-3.37	-7.36	-3.87	-3.71
Employment density - principal city	-0.00042	-0.00026	-0.000339	-0.000367	-0.00029	-0.0003	-0.000305	-0.000291
	(-1.28)	(-0.73)	(-1.05)	(-0.95)	(-0.81)	(-0.94)	(-0.89)	(-0.80)
Employment density - urbanized area	0.000898	0.0025	-0.000174	-0.0018	0.00238	-0.0004	-0.00109	0.00238
	-0.6	-1.36	(-0.12)	(-1.18)	-1.25	(-0.28)	(-0.78)	-1.28
Constant	-1.8	8.578	-0.964	-3.151	8.191	-2.659	-3.547	8.226
	(-0.24)	-0.66	(-0.14)	(-0.43)	-0.78	(-0.42)	(-0.55)	-0.76
N	353	350	353	350	347	353	350	347
Adjusted R-squared	0.913	0.897	0.924	0.915	0.9	0.928	0.927	0.9
Underidentification test (Kleibergen-Paap)		7.646		7.352	8.326		6.458	6.107
Underidentification probability		0.0219		0.0615	0.0156		0.0913	0.0472
Weak identification test (Kleibergen-Paap)		8.728		12.58	9.258		14.79	5.983
Weak identification probability (Stock-Yogo)		<10%		<10%	<10%		<10%	<15%
Overidentification test (Hansen's J)		2.28		5.512	0.187		6.673	0.186
P value for over-ID null hypothesis		0.131		0.0636	0.665		0.0356	0.667

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; t statistics in parentheses. Robust standard errors on all models. IV models estimated with limited information maximum likelihood (LIML).

Included, not shown: Shares of employment in 2-digit NAICS categories from LEHD 2008 (e.g., agricultural, manufacturing, retail, professional services, education, arts, and 14 others); demographic variables from American Community Survey 2005-07 metropolitan area data (share of metropolitan population under 18, over 65, with high-school degree, college-educated, white, black, Hispanic).

Table 5: Per worker wages and per capita gross metropolitan product as a function of agglomeration measures and controls

Model reference number	1	2	3	4	5	6
Dependent variable	Per-worker wages (logged)			Per-capita GMP (logged)		
Model type	OLS	OLS	IV[1]	OLS	IV[2]	IV[3]
L4.Metro area population (logged)	0.0215*	0.0216*	0.0312*	0.00416	-0.018	0.0116
	(2.33)	(2.35)	(2.13)	(0.24)	(-0.76)	(0.55)
L4.Central city employment density (logged)	0.0325*	0.0317*	0.0716*	-0.00799	0.0957	0.0336
	(2.18)	(2.41)	(2.38)	(-0.28)	(1.18)	(0.70)
L4.UZA employment density (logged)	-0.00249			0.130**	-0.409*	
	(-0.11)			(3.17)	(-1.97)	
College-educated share (human capital) (logged)	0.0706**	0.0701**	0.0542*	0.336***	0.468***	0.356***
	(2.62)	(2.64)	(1.97)	(7.50)	(5.89)	(7.57)
L4.Freeways/arterials per capita (logged)	7.69	7.611	12.05	17.99	34.15	24.83*
	(1.22)	(1.22)	(1.85)	(1.51)	(1.88)	(2.19)
Rail transit in metro area	0.0508*	0.0507*	0.00325	0.0891*	0.141**	0.0858*
	(2.29)	(2.29)	(0.13)	(2.13)	(2.84)	(2.20)
L4.Transit seat capacity (logged)	-0.00309	-0.00312	-0.0112**	-0.0141**	-0.00372	-0.0142*
	(-1.10)	(-1.12)	(-2.91)	(-2.66)	(-0.42)	(-2.24)
Constant	10.33***	10.32***	9.866***	-3.043***	0.436	-2.490***
	(53.35)	(65.54)	(28.45)	(-8.06)	(0.32)	(-5.69)
R-squared	0.714	0.714	0.73	0.728	0.569	0.715
N	322	322	348	322	319	319
Kleibergen-Paap test of weak identification			11.17		4.745	24.27
Stock-Yogo probability			<10%		<10%	<10%
Hansen's J			6.194		4.331	3.151
Hansen's J probability			0.185		0.363	0.0759

Notes: t statistics in parentheses. * p<0.05, ** p<0.01, *** p<0.001. "L4" refers to a four-year lag (measured for the year 2004). Control variables included but not shown in wage models: Metropolitan area employment shares in mining, wholesale, retail, transportation/utilities, information, professional services, arts and entertainment, food and accommodation. Control variables included but not shown in GDP models: Metropolitan area employment shares in mining, wholesale, retail, transportation/utilities, finance/insurance, real estate, other services.

[1]Population & central city density instrumented.

[2]Urbanized area and central city employment density instrumented; metropolitan area population uninstrumented. Six instruments: Population of metro area in 1900, passenger and freight rail track mileage in 1898, in state allowing township form of government, climate index, has metropolitan government structure, percent of metropolitan area covered by water.

[3]Population and central city employment density instrumented; urbanized area employment density omitted. Three instruments: Population of metro area in 1900, passenger and freight rail track mileage in 1898, in state allowing township form of government.

Table 6: Net transit-productivity elasticities via three agglomeration channels

Transit service measure	Agglom. measure[1]	Transit-agglom. coefficient	Mean trans-agglom elasticity[2]	Agglom-wage elasticity[3]	Net transit-wage elasticity	Agglom-GMP elasticity[4]	Net transit-GMP elasticity
Bus+rail seats per 1,000 capita	CCED	90.8	0.36	0.0312	0.0111	-	-
Bus+rail seat density (per UZA sq mi)	CCED	33.44	0.38	0.0312	0.0118	-	-
Rail track length per 100,000 capita	CCED	610.8	0.49	0.0312	0.0154	-	-
Rail revenue mi per 1,000 capita	CCED	1.348	0.45	0.0312	0.0139	-	-
Rail revenue miles per UZA sq mi	CCED	0.458	0.57	0.0312	0.0177	-	-
Bus+rail seat capacity per 1,000 capita	UZED	-35.34	-0.32	-	-	-0.409	0.131
Rail track length per 100,000 capita	UZED	-223.7	-0.42	-	-	-0.409	0.173
Rail revenue service miles (100,000s)	UZED	-7.77	-0.32	-	-	-0.409	0.130
Rail service miles density (per UZA sq mi)	UZED	-0.162	-0.47	-	-	-0.409	0.190
Bus+rail service miles (100,000s)	Pop	0.0609	0.34	0.0716	0.0245	-	-

[1]CCED - central city employment density; UZED- urbanized area employment density; Pop - metropolitan area population

[2]Average point elasticities calculated offline by multiplying linear coefficients by the transit measure, dividing incremental change in agglomeration measure by same-year value for agglomeration measure in that metro, and taking the average.

[3]From Table 6, column 3

[4]From Table 6, column 6.