Agglomeration, Accessibility, and Productivity: Evidence for Urbanized Areas in the US

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ABSTRACT

This paper undertakes an empirical analysis with the aim of improving the current understanding of the relationship between labor productivity and urban agglomeration economies across a sample of urbanized areas in the US. Agglomeration economies are represented with driving time measures of employment accessibility to establish a direct account for the link between transport and agglomeration economies. The paper investigates the presence of nonlinearities in the relationship between labor productivity and agglomeration economies, and examines the spatial decay pattern of the effects arising from this relationship. The findings indicate that there is considerable nonlinearity in the relation between productivity and transport induced agglomeration effects, implying that the estimation of country-level aggregate elasticities is likely to misrepresent the actual magnitude of any productivity gains from urban agglomeration. The results also suggest that the magnitude of the productivity-agglomeration effects decays very rapidly with time and is very strong within 20 minutes driving time. This suggests that knowledge spillover externalities are likely to be a very important Marshallian source of agglomeration economies.

KEYWORDS: Agglomeration economies, network accessibility, labor productivity

1. INTRODUCTION

Improvements to transport, by changing relative proximity, affect agglomeration economies. Transport is thought to increase the strength of production-related agglomeration economies because it facilitates the connectivity between and among firms, and workers. The theory is that improved connectivity reinforces the benefits of agglomeration externalities related to knowledge spillovers, labor market pooling, and input-output sharing. This relationship between transport improvements and agglomeration economies has been formally described by Venables [1], who showed that there are productivity gains from urban transport improvements that arise through city size.

Two separate bodies of research have devoted considerable attention to the study of the relationship between transport and productivity, on one hand, and the relationship between agglomeration economies and productivity on the other hand. Surprisingly, and in spite of the abundant research in these two literatures, there is limited research on the relationship between transport-induced agglomeration effects and productivity [2]. To establish a clearer link between transport and agglomeration economies, accessibility type measures of agglomeration economies such as *market potential* or *effective density* have increasingly been used in the agglomeration literature. This type of measures improves on the previously used measures of agglomeration economies (i.e. total population, employment density, etc.) because it provides a better representation of real proximity to economic activities.

However, the majority of studies using accessibility type measures can only offer a limited representation of 'real' accessibility to economic activities because they define accessibility in terms of physical distance [e.g. 3, 4-11]. To improve on this limitation some studies have added an explicit role for transport in their measures of *market potential* [e.g. 12, 13], *effective density* [e.g. 14], and *economic mass* [e.g 15]. Rice et al. [15] develop measures of proximity to economic mass based on driving times for UK regions, Graham [14] uses a measure of effective density based on generalised cost of travel for UK firms, and Lall et al. [12] and Holl [13] use market potential measures based on travel times for Indian districts and Spanish provinces respectively. Of these studies, Holl [13] is the only one using road network travel times that vary over time. All the other studies have used road network travel times that refer to a single time period and hence cannot capture changes in real accessibility to economic activity [12, 14, 15].

Similarly to Holl's paper, our analysis also represents urban agglomeration economies with an accessibility measure based on driving times that vary over time. The key interest is to estimate the productivity gains from urban agglomeration economies represented by travel time accessibility to economic activities across a sample of large US urbanized areas. We ask two main questions: How do differences in productivity result from differences in both physical and time measures of proximity to economic activities, and how does the spatial decay pattern of the productivity-agglomeration affect the linearity of the relationship? We develop an empirical framework based on wage models that allows us to provide answers to these questions and apply it to a balanced panel data set consisting of 4 years of observations for 51 urbanized areas (UZA) in the US.[1] The models estimated control for urbanized area related unobserved heterogeneity, time specific effects, and simultaneity bias between productivity and agglomeration economies. We interpret our results as being specific to this geographic context, that is, a group of large urban areas with already reasonably well developed road networks.

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[1] Urban areas are defined by the US Census Bureau and can be divided into two categories: urbanized areas (population >=50,000) and urban clusters (population <50,000). Urbanized areas consist of the core of Metropolitan Statistical Areas (MSA). MSA are defined as areas that have at least one urbanized area and all the adjacent territory that has a strong social and economic integration with the core as measured by commuting flows. See the link: http://www.census.gov/geo/www/tiger/glossry2.html#UR.

The results obtained from our preferred models suggest that doubling employment density leads to an increase of 4.3% in average wages. In addition, there is also some evidence in favour of a nonlinear relationship between productivity and employment density. The findings also suggest that the geographical scope of the productivity-employment accessibility effects can extend up to 60 minutes, while their magnitude decays very rapidly with travel time. Doubling the number of jobs accessible within 20 minutes of driving time leads to an increase in real average wages of 6.5%, while the impact for a similar increase within 20 to 30 minutes is as small as 0.5%. This result implies that the effects from urban agglomeration externalities are quite localised, a finding that has also been established by previous research on the topic.

The structure of paper is as follows. Section 2 provides an overview of the related literature. Section 3 describes the data and empirical methodology, and provides a discussion of the main estimation issues. Section 4 presents and discusses the key findings, while Section 5 draws together the main conclusions.

2. EMPLOYMENT DENSITY, EMPLOYMENT ACCESSIBILITY, AND PRODUCTIVITY: AN OVERVIEW OF RELATED LITERATURE

Various variables have been used to represent urban agglomeration economies, ranging from simple measures of total population or employment density to more complex measures of market potential and effective density [for a review see 16]. The latter measures are more appropriate because they provide a better description of real accessibility and the potential for opportunities available to a given firm, worker, or city. As a result, accessibility type measures are increasingly being used in the empirical literature estimating the productivity effects of agglomeration economies. The general form of accessibility type measures of agglomeration economies can be described as shown in Equation (1):

$$A_{it} = \sum_{j=i}[O_{jt} * f(d_{ijt})] \tag{1}$$

where O_{jt} denotes the opportunities (e.g. jobs, firms, etc.) available in destination area j and $f(d_{ijt})$ represents the cost (time, distance, etc.) of travelling from origin i to destination j. The vast majority of studies using this type of measure to represent agglomeration economies define d_{ijt} in terms of physical distance, thus not taking into account the role of transport networks. To our knowledge, Lall et al. [12], Rice et al. [15], Graham [14] and Holl [13] are the only studies using accessibility type measures based on travel times derived from actual road networks. Of these studies, only Holl [13] takes account of changes in the road network over time, while Lall et al. [12], Rice et al. [15], and Graham [14] use road network travel times for a single time period. Like Holl [13], we use a measure of accessibility based on road network travel times for different periods. As a result, our measure of accessibility accounts for changes in the road network, particularly those affecting network speeds (e.g. congestion).

Another dimension of the literature we explore in this paper relates to the spatial decay of agglomeration effects. One of the main points emerging from the empirical literature is the insufficient understanding of the pattern of spatial decay of the productivity-agglomeration effects. There have been some recent investigation efforts attempting to provide evidence on this topic. Overall, the existing evidence suggests a steep decay pattern of agglomeration effects, although the geographic range over which the effects are relevant can vary and extend beyond the borders of urban labor markets [e.g. 7, 8, 15, 17, 18]. The following paragraphs provide an overview of existing evidence on the spatial decay of agglomeration effects obtained from studies using wage models [e.g. 7, 8, 15, 18]. With the exception of Rice et al. [15], the evidence summarised refers to measures of market access based on physical distance.

Rice et al. [15] investigate the spatial scope of agglomeration forces for Great Britain by estimating how earnings increase with proximity to economic mass, where economic mass is measured by population of working wage within a certain driving time band. They find that the impact of economic mass reduces rapidly with driving time, but is statistically significant up to 80 minutes driving time. The elasticity of earnings with respect to population of working age within 40 minutes travel time is 5.12% and declines to 1.49% for the 40-80 minutes travel time band.

Rosenthal and Strange [7] investigate the spatial reach of agglomeration externalities by regressing US worker wages on the total employment contained within concentric distance rings from workers' place of work. They find that wages increase by 1.5% to 2.14% for an additional 100,000 full-time workers within 5 miles (about 8 kilometres) from the workers' place of work and fall sharply thereafter: 0.52% (5-25 miles), 0.84% (25-50 miles), and 0.20% (50-100 miles). The elasticity of wages with respect to urban agglomeration economies is between 0.031 and 0.047: doubling total employment within 5 miles increases wages by 3.1 to 4.7%.

Di Addario and Patacchini [8] estimate that an increase of 100,000 inhabitants within 4 kilometres raises wages by 0.1-0.2% but the increase falls sharply thereafter. The impact of urban size on wages is found to be significant only up to 12 kilometres, which is less than the average radii of Italian local labor markets (14.7 kilometres), and thus suggests that agglomeration economies occur within local labor markets. Evidence produced by Melo and Graham [19] and Melo [18] based on measures of physical accessibility to employment also suggests that the effects from agglomeration externalities are quite localised and can decay sharply, similar to what was found for the US and Italy. The findings also suggest that agglomeration externalities occur mainly within labor markets, although there is some evidence of effects related to inter-labor market interactions.

The following section describes the data and empirical methodology used in this paper, as well as the main estimation issues.

3. DATA AND METHODOLOGY

3.1. Data

The dataset consists of a balanced panel of 51 Urbanized Areas (UZA) and 4 years (1990, 1995, 2001, and 2009). A list of the 51 UZA considered in this study is given in Table A.1 of Appendix A. To estimate wage models we matched the employment accessibility data available for the sample of UZA to economic data as available from different sources. We describe the data sources and variables used in this study in the paragraphs below. Table 1 provides a summary of some key descriptive statistics for the related variables.

The measure of employment accessibility ($A_{E,it}$) used in this analysis consists of the number of jobs that can be reached by car in a certain amount of time (20, ... , 60 minutes). Equation (1) below describes how the measure of employment accessibility was estimated using information for the urbanized area employment density, average circuity, and network speed. The measure was also constrained not to exceed the total urbanized area employment [see 20 for more details on the methodology].

$$A_{E,it} = \pi * [V_{n,t} * t/C] * \rho_{E,it} \qquad (2)$$

where,
$\rho_{E,it}$= urban area employment density;
t = time threshold;

$V_{n,t}$ = average network speed in km/h (VKT divided by VHT, obtained from the National Household Travel Survey (NHTS));
C = average circuity (network distance divided by airline distance for a sample of OD points).

Compared to the measures of accessibility based solely on physical distance, this measure provides a better representation of real accessibility and road network performance. In order to compare the results obtained with employment accessibility as our measure of agglomeration economies, we also estimate the wage models using employment density ($\rho_{E,it}$) to represent urban agglomeration economies.

To represent labor productivity, we use the variable real average wage per job, available from the Regional Economic Information System (REIS) of the Bureau of Economic Analysis (BEA). To calculate real average wage per job (w) we use the GDP deflator from the World Bank with base year for 1990. We acknowledge that the variable wage per job is at the level of MSA, not UZA. Nevertheless, as the data is workplace based, the MSA level is relevant as it represents well the labor market related to each UZA. Moreover, even if this creates some measurement error, this is not problematic as it refers to the dependent variable.

In order to avoid issues of omitted variable bias and confounding issues in the estimation of the wage models, we include a set of controls for economic structure, educational attainment, and cost of living. To account for the role of the economic structure of the different UZA, we use a measure of local industry mix based on industry level employment data obtained from the BEA REIS database.[2]

After having computed the shares (in percentage) of employment in each main industry group for each of the 51 UZA, we calculated an expected wage for each UZA given its industrial mix. This is done by estimating a model which measures the impact of each industry's employment share on real average wage per job. We then calculated the expected wage per job for each UZA using the model coefficients. The model used to calculate the expected average wage per job is given by Equation (3):

$$\mathrm{w}_{\mathrm{it}} = \alpha + \beta_1 S_{it}^{manu} + \beta_2 S_{it}^{re} + \beta_3 S_{it}^{fire} + \beta_4 S_{it}^{ser} + \varepsilon_{it} \tag{3}$$

where w_{it} is the real average wage per job in UZA i and year t, α is the constant term, and the terms S^{manu}, S^{re}, S^{fire}, and S^{ser} are the employment shares in the main industry groups manufacturing, retail trade, finance, insurance and real estate, and services respectively. The idea is to estimate the impact of these employment shares on the average wage per job, so that we can capture the effect of the different economic structures on average wages. Based on the model coefficients (β) and observed employment shares for each industry group we compute the expected average wage per job for each UZA and year. The expected average wage (w_{it}^{e}) obtained accounts for the effect of industry mix on wage levels across UZA and can therefore be used in the final wage models to control for the role of economic structure on wage differentials. The results of the estimation of Equation (3) are presented and discussed in Table A.2 of Appendix A.

Human capital is another key variable in determining the level of worker productivity and wage differentials, as proposed by new economic growth theories [e.g. 21] and the literature on human capital externalities in cities [e.g. 22, 23, 24]. It is therefore important to include a measure of human capital (H) because urban areas with better road accessibility are also tend to have higher

[2] Table CA25 (SIC industry classification system for 1990 & 1995) and Table CA25n (NAICS industry classification system for 2001 & 2010). As the industry classification was different for 1990 & 1995 (SIC system) and for 2001 & 2009 (NAICS system), we have matched the data in order to get homogenous measures of employment shares.

levels of human capital. As a result, failing to include a measure of human capital in the model specification is likely to lead to positive omitted variable bias in the coefficient of employment accessibility. To avoid this confounding of effects, we include a measure of human capital in the wage model based on data for educational attainment.

Data for educational attainment were obtained from the decennial Census (for 1990 and 2000) and from the American Community Survey (ACS) for 2009. Using 2000 data for 2001, we had data for 1990, 2001 and 2009. Unfortunately, there was no data available for 1995 as the ACS was conducted for the first time in 1996 in four counties only. To avoid losing one fourth of the observations we interpolated the 1995 educational data using a compound annual growth rate (CAGR) between 1990 and 2000. Although data for educational attainment was collected both at the UA and MSA level, the latter was preferred because it can take account of commuting effects within labor markets. We have calculated the share (in percentage) of population aged 25 years and over holding a bachelor's degree or higher (master's degree, professional school degree and doctorate degree).

The cost of living, particularly housing prices, is another factor thought to play a role in the wage determination process [e.g. 25]. The argument is that larger urban areas pay higher nominal wages to compensate for higher living costs, while real wages are similar across space. To account for the effect of higher living costs in larger urban areas we include a housing price index as a control variable in our wage models. The housing price index (*P*) used consists of the Federal Housing Finance Agency (FHFA) all-transactions index, which is available at the MSA level and is transformed to have 1990 as the base year.

TABLE 1 Descriptive statistics of variables used in the empirical analysis

Variable	Min	Mean	Median	SD	Max
Real average wage per job (w)	20,268	27,883	26,939	5,229	53,182
Employment accessibility, 20 min ($A_{E,i20}$)	192,046	476,428	455,268	148,158	1,101,442
Employment accessibility, 30 min ($A_{E,i30}$)	309,487	824,931	778,857	341,284	2,333,749
Employment accessibility, 40 min ($A_{E,i40}$)	309,487	1,055,435	859,728	631,210	3,377,059
Employment accessibility, 50 min ($A_{E,i50}$)	309,487	1,189,077	859,728	901,759	5,276,655
Employment accessibility, 60 min ($A_{E,i60}$)	309,487	1,275,452	859,728	1,172,149	7,598,383
Employment density ($\rho_{E,it}$)	255	723	674	259	1,849
Industry mix (w^e)	19,675	27,799	28,019	3,983	38,739
% population with bachelor's or higher degree (H)	13.81	26.76	25.82	5.94	47.29
Cost of living (P)	0.80	1.44	1.26	0.49	3.19

Figure 1 illustrates the relationship between the logarithm of employment density (vertical axis) and the logarithm of employment accessibility (horizontal axis) for separate driving time bands. We observe that the two measures of agglomeration economies are positively and strongly correlated, especially up to 30 minutes driving time, after which the correlations appear to be weaker.

Similarly, Figure 2 plots the logarithm of real average wage (vertical axis) against employment density, educational attainment, and employment accessibility within 30 and 60 driving time minutes. The figure depicts a positive association between real average wages, employment density and employment accessibility over time. However, the information contained in these figures can only provide preliminary evidence in support of a positive association between labor productivity and agglomeration economies. To establish a causal relationship between these variables we conduct a comprehensive regression analysis. The next section provides a description of the econometric models used to identify the effect of agglomeration economies on labor productivity, as measured by real average wages.

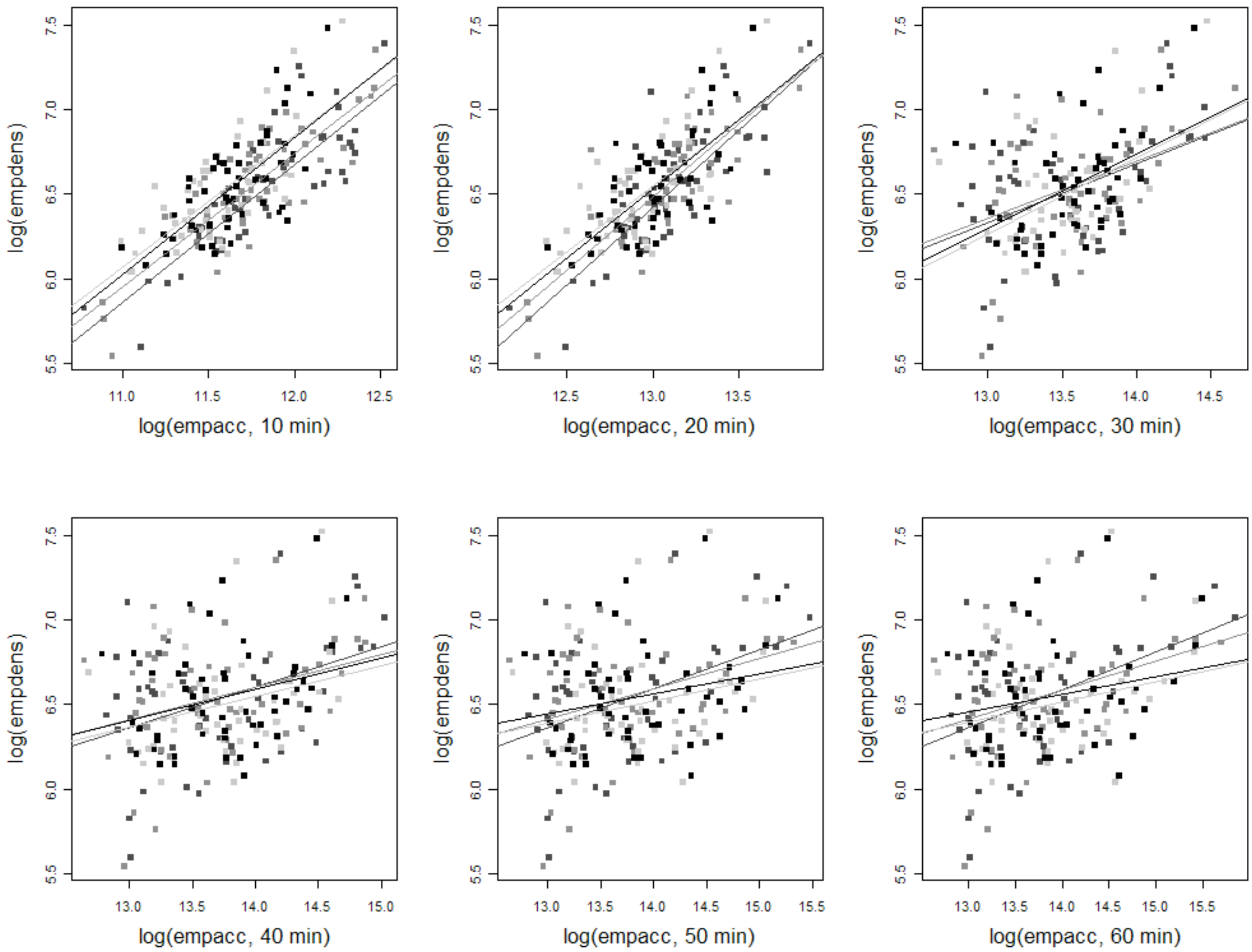

FIGURE 1 Relationship between employment density and employment accessibility
Note: dark line – 2009; dark grey line – 2001; grey – 1995; light grey – 1990.

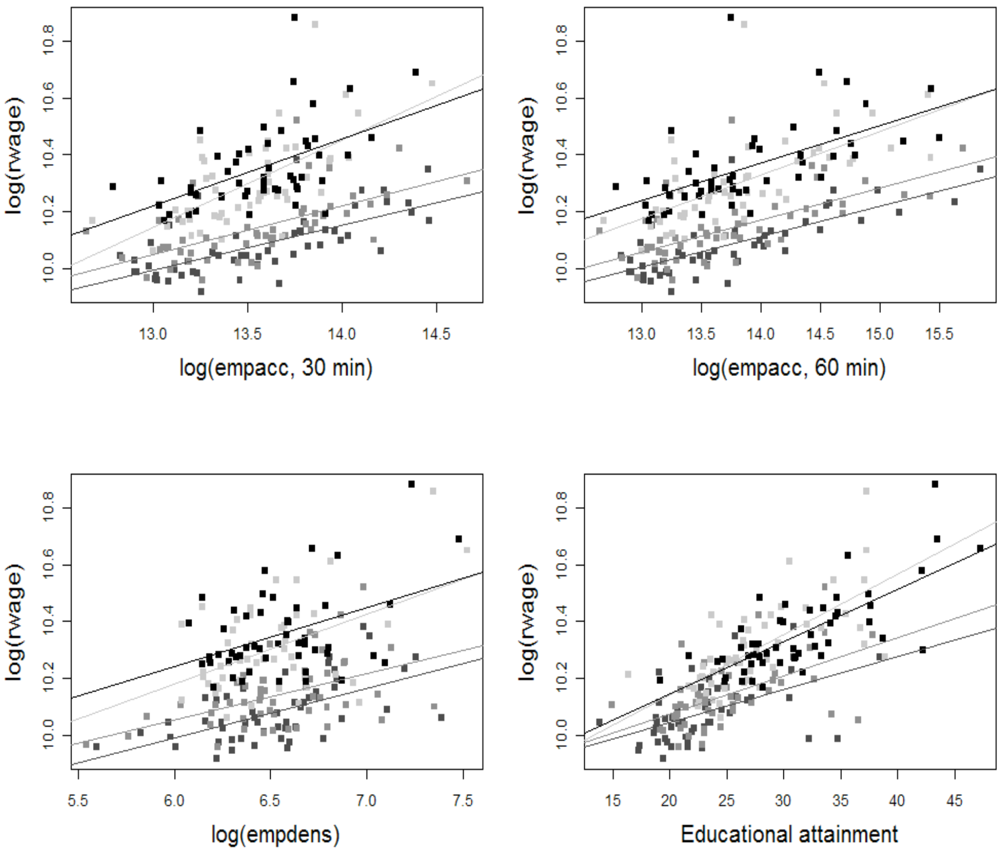

FIGURE 2 The relationship between real average wage per job and employment accessibility, employment density, and educational attainment
Note: dark line – 2009; dark grey line – 2001; grey – 1995; light grey – 1990.

3.2. Empirical model and estimation issues

The literature offers several explanations for the observation of urban wage premiums. A standard explanation proposes that big cities pay higher wages to compensate for higher living costs. This argument suggests that wage differences disappear when real, instead of nominal, wages are considered. An alternative explanation builds on the existence of agglomeration externalities which lead to productivity gains as a result of more efficient labor markets, knowledge spillovers of information sharing, and access to intermediate input and output markets [e.g. 26, 27]. According to this argument, firms prefer to be located in areas where input costs are higher because they enjoy efficiency gains from their higher productivity. Another explanation, parallel to the agglomeration-productivity argument, is that larger urban areas pay higher wages because they attract more skilled workers [e.g. 28, 29, 30].

Under the standard assumption that input factors are paid the value of their marginal products, local input factors will have higher prices in more productive areas. In this context, wage rates should reflect labor productivity and wage equations can be derived from firm profit maximization and used to investigate the existence of an urban wage premium related to agglomeration economies. The general specification of the reduced form wage equation can be represented as shown in Equation (4):

$$\ln(w_{it}) = \beta_0 + \beta_1 \ln(G_{it}) + \beta_2 \ln(w_{it}^e) + \beta_3 H_{it} + \beta_4 P_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{4}$$

where w_{it} denotes the real average wage, β_0 is the model intercept, G_{it} represents agglomeration economies and is measured either by employment accessibility ($A_{E,it}$) or employment density ($\rho_{E,it}$), w_{it}^e denotes the expected average wage variable which captures the effect of industry mix, H_{it} denotes the share of population with a bachelor's degree or higher degree, and P_{it} is the housing price index which is our proxy for cost of living. To account for unobserved shocks that are common to all urbanized areas but vary across time we include year specific effects λ_t. To account for UZA specific unobserved heterogeneity we also include UZA specific effects μ_i. Finally, ε_{it} is the residual error term, which is assumed to be normally distributed while allowing for heteroskedasticity and clustering on urbanized areas.

To look for further evidence on the nonlinear pattern of urban agglomeration effects, we also use semiparametric techniques to examine the presence of nonlinearities in the relationship between productivity and employment density. More specifically, we estimate the wage model using a semiparametric linear additive mixed model [e.g. 31, 32]. The relationship between real average wage per job and industry mix, educational attainment, and cost of living is modelled parametrically, while employment density is modelled non-parametrically. The model to be estimated has the form below:

$$\ln(w_{it}) = \beta_0 + f_1(\ln(\rho_{E,it})) + \beta_2 \ln(w_{it}^e) + \beta_3 H_{it} + \beta_4 P_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{5}$$

where f_1 is a smooth function of employment density, to be estimated using penalized regression techniques [32]; μ_i are independent and identically distributed (i.i.d) random effects defined at the UZA level, and the other terms are defined as in Equation (4). The semiparametric models are estimated with the "gamm" package available from R using Restricted Maximum Likelihood (REML).

The estimation of Equations (4) and (5) is subject to identification and specification problems. We are concerned with the possibility of inconsistent parameter estimates caused by endogenous regressors. In our analysis, this complication can arise from two main sources: (i) confounding due to nonzero correlation between the measures of agglomeration economies, educational attainment, and the error term; (ii) simultaneity between agglomeration economies and worker productivity as measured by real average wages.

We estimate the wage model using various estimators that make distinct assumptions about the correlation between the covariates and the model‘s composite error term. The estimators used are the pooled OLS (POLS), the random-effects estimator (RE), and the fixed-effects estimator (FE). We also combined these estimators with instrumental variables (IV) techniques to address the issue of simultaneity mentioned above.

The main distinction between the different estimators relates to their ability to produce consistent and unbiased parameter estimates. In the presence of nonzero correlation between the urban area specific effects (and hence the error term) and the model covariates, only the FE estimator ensures consistency. Using a comprehensively specified model reduces the scope for unobserved heterogeneity and nonzero correlation between the covariates and the error term, in which case both the pooled OLS and RE estimators provide consistent parameter estimates. While the FE estimator is also consistent in this case, the RE estimator is more efficient because it uses both within and between urbanized area variation.

Although the fixed-effects estimator allows controlling for time-invariant urbanized area specific unobserved heterogeneity, it can result in a reduction of a great deal of variation in the data because only within urbanized area variation is used in the model estimation. The outcome is a loss of efficiency (statistical significance) in the estimation of the coefficients of the regressors that vary little over time, as is typically the case of measures of agglomeration economies.

The second main estimation issue results from the fact that some of our covariates are simultaneously determined with wages, leading to inconsistent parameter estimates. Considering Equation (4), we suspect of reverse causality between the following variables:

(i) Wages and educational attainment: urban areas with higher wages can afford/provide more and better education, and also tend to attract people with higher educational levels;
(ii) Wages and employment density: urban areas with higher wages will attract more people, reinforcing agglomeration economies;
(iii) Wages and employment accessibility: urban areas with higher wages can afford more investment in transport infrastructure, namely road network. A better road network allows for higher levels of employment accessibility.

To correct for reverse causality we use instrumental variable (IV) techniques. We construct a set of instrumental variables based on the Durbin rank method similar to that used by Fingleton [33, 34], and explained by Kennedy [35, p.162-163].[3] The Durbin method ranks the endogenous variable by size and then defines the instrumental variable as the rank order [see 35 for more details on this method].

4. RESULTS AND DISCUSSION

This section presents and discusses the main results obtained from the estimation of the wage models using as measures of agglomeration economies both employment density and employment accessibility for successive driving time bands.

Table 2 presents the pairwise correlation coefficients for the explanatory variables included in the empirical models. As indicated by Figure 1, we observe a strong positive correlation between employment density and employment accessibility for the 10 and 20 minutes time bands: 0.72 and 0.74 respectively. There is also a strong positive correlation between the various measures of employment accessibility (e.g. $A_{E,i10,}$ and $A_{E,i20}$; $A_{E,i30}$ and $A_{E,i40}$; $A_{E,i40}$ and $A_{E,i50}$; and $A_{E,i50}$ and $A_{E,i60}$), a fact that needs to be taken into account in the model specification in order to avoid issues of multicollinearity.

[3] Other similar methods, e.g. two-group method and three-group method, are also explained by Kennedy (2003).

TABLE 2 Correlation matrix

	$A_{E,i10}$	$A_{E,i20}$	$A_{E,i30}$	$A_{E,i40}$	$A_{E,i50}$	$A_{E,i60}$	$\rho_{E,it}$	w^e	H
$A_{E,i10}$	1								
$A_{E,i20}$	0.85	1							
$A_{E,i30}$	0.39	0.68	1						
$A_{E,i40}$	0.22	0.46	0.90	1					
$A_{E,i50}$	0.18	0.38	0.79	0.96	1				
$A_{E,i60}$	0.17	0.35	0.72	0.89	0.97	1			
$\rho_{E,it}$	0.72	0.74	0.53	0.38	0.36	0.35	1		
w^e	-0.08	0.04	0.20	0.24	0.29	0.29	0.17	1	
H	0.05	0.10	0.25	0.26	0.25	0.21	0.26	0.57	1
P	-0.21	-0.12	-0.03	-0.03	0.01	0.00	0.06	0.71	0.52

As discussed in the data and methodology section, the fixed-effects estimator performs poorly when applied to our dataset and results in a general lack of statistical significance for both measures of agglomeration economies. Because agglomeration economies are highly persistent over time, using only within urbanized area variation leads to a large loss of efficiency in the estimation of agglomeration economies. In addition, because the random-effects estimator is more efficient than the pooled OLS estimator, we do not present the results obtained for the latter estimator.[4] As a result, we report the results for the random-effects models, both the version that does not correct for simultaneity bias (RE) and the version that corrects for this source of bias via instrumental variables (IV-RE).

The results obtained from the wage models are reported in Table 3. Model (1) uses employment density to represent urban agglomeration economies. Model (2) uses a quadratic specification of employment density, while Model (3) represents urban agglomeration economies with driving time measures of employment accessibility. The values of the models parameters are shown with respective standard errors and statistical significance levels. The coefficients of determination (R^2 and adjusted R^2), number of observations, and other relevant tests are shown at the bottom of the table. The adjusted R^2 is high for all the models estimated and ranges between 0.83 and 0.86.

Concerning instrument relevance, the first-stage regressions indicate that the instruments have good explanatory power. The first stage F-statistics are always greater than the rule of thumb value 10, and the partial R^2 and Shea R^2 [36] are generally very high. The partial R^2 and Shea R^2 are equal to 0.82 and 0.78-0.81 for educational attainment, and range between 0.62-0.99 and 0.51-0.98 for employment density. There is a wider range for the model using employment accessibility, with values ranging between 0.62-0.99 and 0.51-0.98 for the partial R^2 and Shea R^2 respectively. Moreover, the Kleibergen-Paap [37] rank LM statistic tests always reject the null hypothesis of model underidentification, indicating that our models are identified. In addition, the Kleibergen-Paap [37] Wald rank F weak identification test statistic is also always higher than the Stock and Yogo [38] critical values, suggesting that our instruments are not weak.

Results for Model (1) indicate that doubling employment density increases wages, all else equal, by 4.3% (RE and IV-RE). According to a recent meta-analysis of elasticities of urban agglomeration economies [16], the mean and median values of the elasticity estimates obtained from wage models are 0.034 and 0.032 respectively, which is somewhat below the value obtained for our preferred model (0.043). However, the two sets of values are not exactly comparable because the estimates reviewed in the meta-analysis included measures of urban agglomeration economies other than

[4] The full set of results for the pooled OLS and fixed-effects models can be obtained from the authors upon request.

employment density (e.g. population, population density, market potential, etc.) and various types of estimators (e.g. OLS, fixed-effects, random-effects, etc.).

The results obtained from Model (2), using a quadratic specification of employment density, indicate that the productivity effects of urban agglomeration economies are likely to exhibit a nonlinear shape. This result is not statistically significant for the IV-RE regression, only the RE regression. Part of the explanation for the lack of significance in the IV model is the weaker quality of the instruments used in the quadratic specification.

The overall wage elasticity of employment density, calculated using the sample average, is 0.043. This implies that, similarly to Model (1), doubling employment density increases wages by 4.3% (RE). However, the quadratic specification indicates that the effect of employment density on labor productivity is positive only after a certain density threshold is reached. For our sample of urbanized areas this density threshold is about 484 jobs per square kilometre, while the mean and median values of employment density are 723 and 674 jobs per square kilometre respectively. This threshold may not be applicable to the whole population of urban areas in the US and we see it as being specific to our sample of urban areas, including the largest urbanized areas in the US (e.g. Boston, Chicago, Los Angeles, New York, San Francisco, Washington).

The results obtained from the semi-parametric models also provide evidence in favour of a nonlinear effect of employment density on worker productivity.[5] Figure 3 illustrates the relationship between real wages per job and employment density. The vertical axis displays the value of the smooth function for (the logarithm of) employment density and the horizontal axis displays the values of (the logarithm of) employment density. The two dashed lines lie respectively at two standard errors above and below the estimate of the smooth curve.

The shape of the curve suggests that there is considerable nonlinearity in urban agglomeration effects as measured by employment density. Moreover, the figure also shows that the positive effects from employment density are experienced by urban areas with a logarithm of employment density between about 6.2 (493 jobs per square kilometre) and about 6.8 (898 jobs per square kilometre). The effects became considerably more important for urban areas with logarithmic employment density values greater than 7.2 (1340 jobs per square kilometre), but there is weak evidence of significant effects for urban areas with logarithmic employment density values between 6.8 and 7.2. This suggests that estimating a single elasticity of agglomeration economies for a whole country is likely to misrepresent the actual magnitude of the agglomeration effects on labor productivity.

[5] The results for the model regressors are very similar to those estimated using the parametric models shown in Table 3 and are not reported because the main feature of the semi-parametric model is to test for nonlinearity (Figure 3) in the productivity-agglomeration relationship. The full set of results for the semi-parametric model can be obtained from the authors upon request.

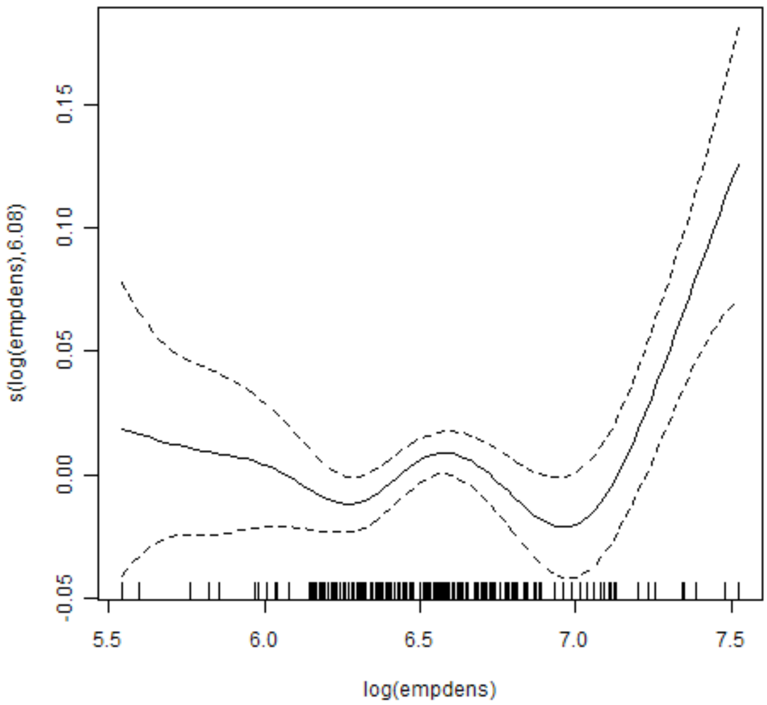

FIGURE 3 Nonlinearities in urban agglomeration economies across US urbanized areas
Note: Dashed lines correspond to two standard error lines above and below the estimate of the smooth curve.

We now consider the results for the wage models using measures of employment accessibility based on driving times (Model (3)). The discussion of the results is based on the preferred IV-RE regression, although the relationships are overall consistent across the two estimators. In comparing our results with those obtained from previous studies using market access type measures, it should be kept in mind that our measure of employment accessibility is predominantly urban in nature because it refers to accessibility to jobs within a given urbanized area. The majority of the studies mentioned in section two, however, use market accessibility measures that also capture inter-urban area and regional effects.

We observe from the IV-RE estimation of Model (3) that doubling the density of jobs accessible within 20 (30) minutes driving time leads to an increase in real average wages of 6.5% (7%). This effect is considerably higher than the effect obtained for employment density (4.3%). Part of the explanation is the homogeneity assumption underlying employment density measures. That is, the assumption that all urban space (i.e. square kilometres) is equal and the corresponding failure to account for spatial decay effects.

The coefficients indicate that the magnitude of the productivity-urban agglomeration effects falls sharply with travel time, from 0.065 within 20 minutes to 0.005 between 20 and 30 minutes. This finding suggests that the effects from urban agglomeration externalities are quite localised (within 20 minutes) and decay sharply. Similar results were found by previous studies using wage models and driving time accessibility measures for the UK [15], and physical distance market potential measures for the US [7], Italy [8], and the UK [18, 19].

In addition to the sharp decrease in the effects of employment accessibility, the spatial reach of these effects appears to extend to 60 minutes, although there appears to be some discontinuity for the time interval between 30 and 40 minutes. The effects re-emerge, although with a rather small magnitude, between 40 and 60 minutes. The interpretation of this result is not straightforward and may result, to some extent, from insufficient variation in employment accessibility across some of the driving time bands, as well as from possible issues of multicollinearity (since the number of jobs 20 to 30 minutes away for the average traveller is not unrelated to the number of jobs 10 to 20 minutes away) (see Table 2). Only in the largest cities are there significant increases in accessibility beyond 30 minutes driving time. In smaller metropolitan areas, 30 or 40 minutes is sufficient for the average resident to drive to the far edge of the city, and thus see no (or few) additional available jobs.

The last part of this section considers the results obtained for the other model covariates, namely, educational attainment, industry mix, and cost of living. As expected, educational attainment does help explain spatial differences in real average wages: an increase of 10 points in the share (in percentage) of population aged 25 years and over holding a bachelor's or higher degree leads to an increase of 11% in average real wages. The magnitude of the effect of educational attainment is consistent across all the models estimated.

The models estimated suggest that the economic structure of the urban areas accounts for a large part of the determination of real average wages. The expected average wage computed based on the industrial mix of the different urban areas in our sample provides an indication of the effect of economic structure on average wages. A 10% increase in the value of the expected average wage corresponds to an increase of 3.9% (RE) and 2.9% (IV-RE) in the real average wage per job.

As for the role of housing prices as a wage determinant, the evidence suggests that real average wages are generally higher in urban areas with higher housing prices. On average, an increase of 10% in the value of the housing price index is associated with a very small increase in real average wages, between 0.7% and 0.8%.

TABLE 3 Results from the estimation of the wage equations

	RE			IV-RE		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
constant	7.233 ***	9.476 ***	6.966 ***	5.962 ***	6.186 ***	6.041 ***
	(1.056)	(1.237)	(1.037)	(0.840)	(1.619)	(0.823)
ln($\rho_{E,it}$)	0.043 **	-0.674 **		0.043 **	-0.142	
	(0.017)	(0.301)		(0.018)	(0.432)	
ln($\rho_{E,it}^2$)		0.054 **			0.014	
		(0.023)			(0.033)	
ln($A_{E,i20}$)			0.065 ***			0.065 ***
			(0.019)			(0.021)
ln($A_{E,i20-30}$)			0.001			0.005 ***
			(0.001)			(0.002)
ln($A_{E,i30-40}$)			0.002 **			0.002
			(0.001)			(0.001)
ln($A_{E,i40-50}$)			0.004 ***			0.004 ***
			(0.001)			(0.001)
ln($A_{E,i50-60}$)			0.003 **			0.003 *
			(0.001)			(0.002)
H	0.010 ***	0.010 ***	0.009 ***	0.007 ***	0.008 ***	0.007 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(w^e)	0.223 **	0.234 ***	0.191 *	0.355 ***	0.391 ***	0.286 ***
	(0.107)	(0.081)	(0.109)	(0.086)	(0.086)	(0.087)
P	0.082 ***	0.082 ***	0.083 ***	0.079 ***	0.074 ***	0.082 ***
	(0.018)	(0.016)	(0.019)	(0.018)	(0.018)	(0.017)
Year dummies	yes	yes	yes	yes	yes	yes
First Stage - Partial/Shea R^2:						
- H(1)					0.82/0.81	0.82/0.78
- ln($\rho_{E,it}$); ln($\rho_{E,it}^2$)(1)					0.89/0.62; 0.89/0.62	
- ln($A_{E,i20}$), ..., ln($A_{E,i50-60}$)(1)						0.51-0.98/0.62-0.99
Underidentification test				71.83 ***	34.93 ***	54.88 ***
Weak identification test(2)				348.09	31.11	24.8
R^2/Adjusted R^2	0.90/0.86	0.90/0.86	0.90/0.85	0.88/0.84	0.87/0.83	0.88/0.83
Observations	204	204	204	204	204	204

Robust standard errors are shown in parentheses. Significance levels: 0.01 ***, 0.05 **, 0.1*.
(1) Instruments: rank of educational attainment, ranks of employment density and ranks of employment accessibility.
(2) Stock-Yogo weak identification test critical values are available from Stock-Yogo (2005).

5. CONCLUSIONS

This paper has undertaken several empirical analyses with the aim of improving the current understanding of the relationship between labor productivity and urban agglomeration economies across a sample of urbanized areas in the US. Agglomeration economies are represented according to both distance-based and time-based measures of employment accessibility. The latter approach allows for an explicit account of the link between (road) transport networks and agglomeration economies.

The results obtained from our preferred models suggest that doubling employment density leads to an increase of 4.3% in average wages. Another important contribution of this study is that it investigates the presence of nonlinearities in the relationship between labor productivity and agglomeration economies for urbanized areas in the US. Evidence of nonlinearities in the relationship between productivity and agglomeration economies has real implications for the appraisal of the wider economic impacts of transport projects, which is typically based on a single point elasticity regardless of where the project takes place. The presence of nonlinearity in transport induced agglomeration effects suggests that estimates of agglomeration elasticities computed for a whole country are likely to misrepresent the actual magnitude of the agglomeration effects on labor productivity.

Finally, we also investigated the spatial decay pattern of the productivity-agglomeration effects. There are various reasons why improving the current understanding of the pattern of spatial decay of agglomeration economies is important. Knowledge about the geographic scale of agglomeration benefits can offer information on the potential success of different policy tools in attempting to exploit the benefits from agglomeration externalities. If the spatial scope of agglomeration benefits is very localised, policy tools that promote close interactions may be preferred to tools that impact preferably on longer distance interactions. Similarly, if the geographic scale over which agglomeration benefits are available to firms and workers is wide enough to encompass different labor markets, then policy tools that improve the frequency and quality of the interactions between the different labor markets is likely to enhance the strength of the productivity benefits from agglomeration economies.

Our findings suggest that the geographical scope of the productivity-agglomeration effects, for the sample of US urbanized areas, can extend up to 60 minutes, but the magnitude of these effects decays very rapidly with driving time. Doubling the number of jobs accessible within 20 minutes of driving time leads to an increase in real average wages of 6.5%, while the impact for a similar increase within 20 to 30 minutes is as small as 0.5%. This finding implies that the effects from urban agglomeration externalities are quite localised. Thinking in terms of the *Marshallian* sources, this suggests that knowledge spillover externalities are likely to be a very important source of agglomeration economies.

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