

# Mutual causality in road network growth and economic development



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## ABSTRACT

This paper investigates the relationship between the growth of roads and economic development. We test for mutual causality between the growth of road networks (which are divided functionally into local roads and highways) and changes in county-level population and employment. We employ a panel data set containing observations of road mileage by type for all Minnesota counties over the period 1988 to 2007 to fit a model describing changes in road networks, population and employment. Results indicate that causality runs in both directions between population and local road networks, while no evidence of causality in either direction is found for networks and local employment. We interpret the findings as evidence of a weakening influence of road networks (and transportation more generally) on location, and suggest methods for refining the empirical approach described herein.

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## 1. Introduction

Transportation networks are frequently cited as one of the primary factors affecting patterns of development at the urban and regional level. Depending on the type of change to the network, new links can lead to greater concentration (agglomeration) or dispersal of activities, altering the balance between the location of households and firms at a given level of aggregation. While comparatively more of the work on the relationship between transportation and development has been focused on at the intra-urban level, due in part to the greater abundance of spatial data at this level, there are also important spatial reorganization effects observable at regional and interregional levels.

In this paper, we examine the relationship between road network growth and economic development at the county level in the State of Minnesota over a 20-year period. In particular, we test for the influence of road network growth on the location of population and employment, and vice versa. We divide the road network into two types of roads, highways and local roads (both measured in terms of road length), and evaluate their impact independently given the possibility that they may have differing impacts on the location of population and employment. Granger causality tests

are applied to the relationship between road networks and development, using temporal precedence to establish the direction of causality between variables. The longitudinal nature of the data set allows for the examination of longer-term adjustments in response to network growth over time.

The rest of the paper is structured as follows. The next section gives a brief review of the evidence on the relationship between road networks and development. The third section describes the underlying theory and empirical specification of our models, along with hypotheses about the estimated coefficients. It also contains a description of the data set constructed to estimate the model. The fourth section discusses the results of the empirical analysis and their implications regarding the direction of causality between road networks and development. The fifth and final section summarizes the empirical results, assesses the soundness of the methodological approach, and draws some implications for further study.

## 2. Literature review

Research in transportation and related fields has long recognized the role of transportation networks in shaping locations patterns. The canonical “monocentric” model of urban structure adopted by urban economists identifies transportation costs as a fundamental factor, along with several others (population, income, agricultural land rent), in determining urban spatial structure.

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Empirical tests have confirmed its importance (Brueckner and Fansler, 1983; McGrath, 2005).

Studies of the decentralization of population and employment within and between urban areas have identified patterns of mutual causation between these processes (White, 1999), with transportation network expansion (primarily highways) often assumed to play an intervening role (Garrison et al., 1959; Meyer et al., 1965; Boarnet, 1994). Employment decentralization is often characterized as a process of jobs following workers to suburban locations, facilitated in part by improvements to highway networks which increase the accessibility of these locations (Gordon and Richardson, 1989; Levinson and Kumar, 1994; Glaeser and Kahn, 2001). Isolating causal relationships is difficult in these situations, and the default assumption that is often made that population and employment are jointly determined (Steinnes, 1977) in a multi-equation framework. Other approaches have attempted to address the identification problem associated with the endogeneity of transportation investment using instrumental variables (IV). For example, a study of the effect of urban highway growth on central city population decline by Baum-Snow (2007) used planned segments of the interstate highway system (including unbuilt segments) as a source of exogenous variation to estimate its effect on population decline in a single-equation model. However, the plausibility of this choice of instrument has been questioned (Cox et al., 2008), and there have been few other published examples of the identification of possible instruments.

The location of residences and places of employment and the role that transportation networks play in shaping them have implications for specific types of policy measures. Policies to encourage jobs-housing balance within local jurisdictions (Cervero, 1989, 1996) have been advocated on the assumption that greater balance between concentrations of employment and housing will lead to greater self-containment of commute and non-commute trips, while also balancing directional network flows. Given the role of transportation networks in changing the relative attractiveness of locations, this would seem like a plausible direction to pursue. Yet evidence on trends in urban form within many US cities indicates that a certain amount of “balancing” at local levels takes place over time even in the absence of explicit policy direction (Giuliano, 1991; Cervero, 1996).

Moreover, many transportation networks, including those in urban areas, are reaching a state of maturity with few new links being added and only modest capacity additions identified in most regional plans. Theories and historical evidence regarding the deployment of transportation networks suggest that the few new links likely to be built at this more mature stage, illustrated in

Fig. 1, will probably exert less influence on growth and location patterns (Garrison and Levinson, 2006).

Mutual causality between transportation network growth and location choice has also been at the heart of a number of studies attempting to explain historical patterns of development. Several of these studies have emphasized the influence that specific modes of urban travel have had on development patterns at a particular time in history. For example, Levinson (2008) identified a feedback process between the growth of underground and surface rail networks in London and population density at the borough level during the late 19th century. Another study by King (2011) examined the relationship between the growth of the New York City subway network and patterns of residential and commercial land use. Results indicated that the growth of the network did not precede development, but rather that it served already-emerging residential areas. In contrast, a study of the co-evolution of residential development and streetcar network growth in the Minneapolis-St. Paul, Minnesota region during the early 20th century found evidence that the growth of the streetcar network led residential development within the region (Xie and Levinson, 2010). In each of these studies, the method of Granger causality was used as the identifying assumption for establishing a causal link between network growth and urban development.

Such methods have also been adopted at broader geographic scales to investigate questions of causality between network growth and regional development. For example, Carlini and Mills (1987) expanded an equilibrium model of population and employment location designed for urban areas to a national scale to identify the causes of county-level growth in the United States during the 1970s. They found evidence that county-level interstate highway density was positively associated with both population and employment density. Another study of major corridor-level highway development and population growth by Chi (2010) used minor civil division-level (city or township) census data on population change in the state of Wisconsin during the 1980s and the 1990s to identify the longer-run influence of highways. Results indicated that the strongest impacts of highway development on population growth occurred in suburban areas, while impacts were weaker in rural areas and not statistically significant in urban areas. More frequently, studies that have focused on a regional or larger scale have identified employment as the critical measure of development. Recent work by Jiwattanakulpaisarn et al. (2009, 2010) examined causality in the relationship between state highway networks and employment, both in terms of total employment and sector-level disaggregation, using a panel vector autoregressive (VAR) framework. Applying this framework to a panel of US states from 1984 to 1997, they find evidence of temporal relationships between changes in state highway network capacity and changes in employment, though certain sectors tend to be impacted more positively (e.g. services), while others are negatively impacted (manufacturing).

Of note, many studies of the relationship between transportation infrastructure and economic growth, including those cited above and the voluminous economic literature on public capital and economic growth, use fairly aggregate measures of the stock of highway infrastructure (measured either in terms of discounted economic value, network length, network capacity, or others). This is in part due to the difficulty of obtaining such measures (in the United States, at least), especially for longer time series, at more disaggregate levels. Those studies that do, including the one by Carlini and Mills (1987), tend to focus on shorter time horizons such as decennial changes which can be measured via published census data. The present study addresses some of these issues by using a 20-year panel of county-level network data furnished by a state department of transportation to probe the relationship between changes in transportation networks and growth in

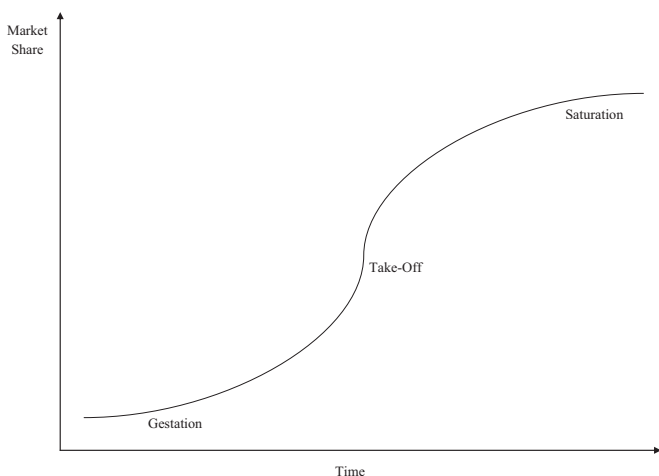


Fig. 1. Deployment curve for transportation networks.

population and employment. In particular, the data set combines the county-level network measures with annual measures of population and employment available from federal data sources to produce a data set with improved temporal and spatial resolution. This comes at a cost of having fewer details about individual local units of observation and a less precise definition of the road network, but allows for examination of changes at sub-state levels and over longer periods of time. The data set will be described in more detail in a subsequent section.

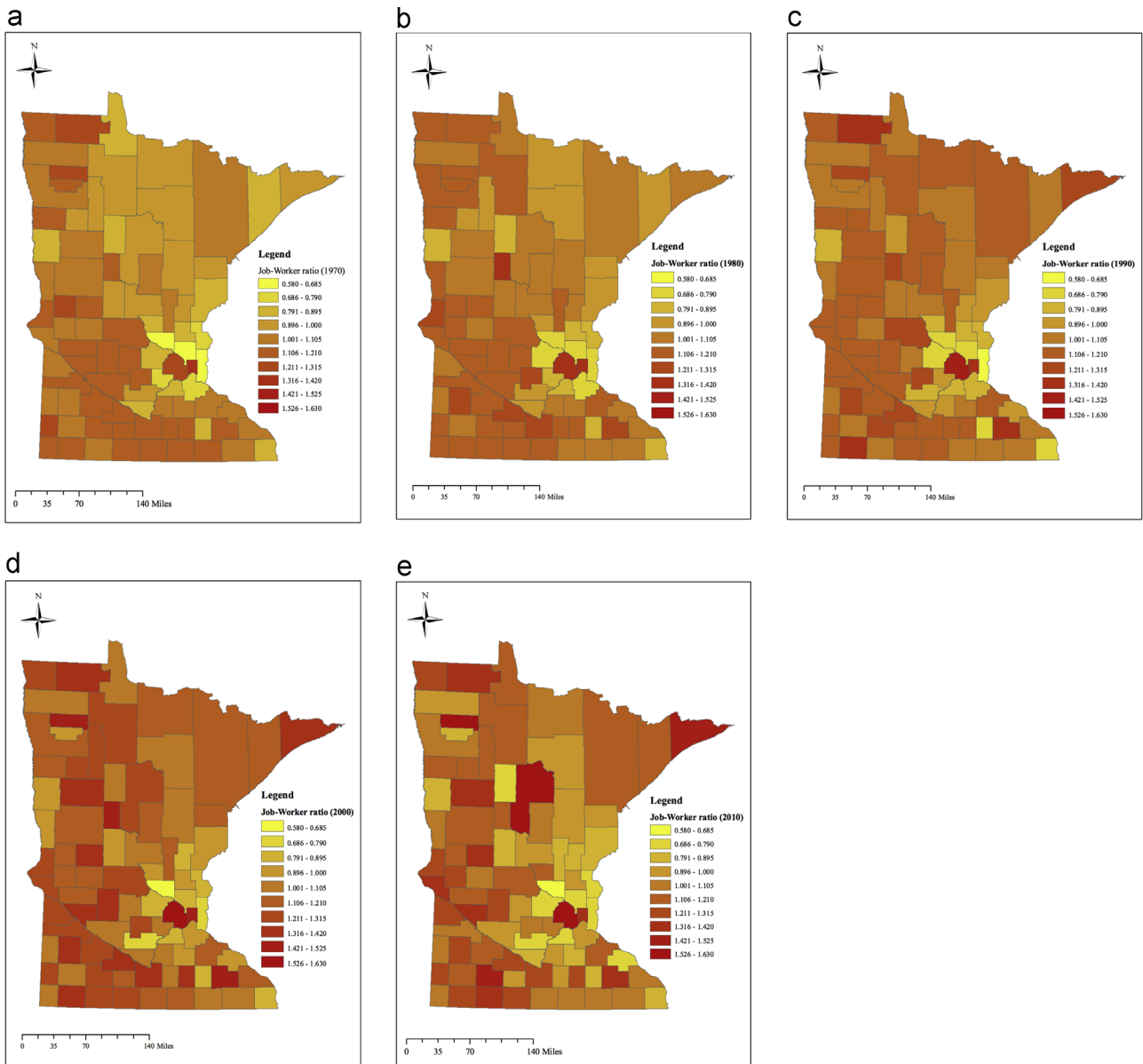
### 3. Trends in the structure of employment and worker location

It is important to note the role that transportation networks play in the evolution of the economic structure of regions. While their role may have been historically larger when networks were less developed, transportation networks were central in serving as a balancing force between the decentralization of population and jobs. They allowed employment centers to emerge in more

peripheral parts of metropolitan areas (Carlino and Chatterjee, 2002), thus bringing greater balance between jobs and workers to these areas, while also allowing for the specialization of production in many small urban and non-metropolitan locations.

As an illustration, Fig. 2 presents statewide data for the state of Minnesota on the ratio of employment to workers at the county level by decade from 1970 to 2010. In addition to the emergence of several “job-rich” counties in the non-metropolitan southern and southwestern part of the state, one of the most notable trends is the greater primacy of the two counties containing the central cities of the Minneapolis-St. Paul region. Their dark red shading indicates their high concentrations of employment relative to their population of resident workers, a trend which has been augmented by significant population losses in recent decades.

In addition to these micro-scale trends, we can also document structural shifts in the relative location of employment and workers statewide over this period. Suppose we measure the shifts in job-worker balance across the state by describing the distribution of job-worker balance by county. Let  $j$  index each of the



**Fig. 2.** Employment/worker ratios in Minnesota counties, 1970 through 2010. (a) 1970 Entropy=0.721, (b) 1980 Entropy=0.725, (c) 1990 Entropy=0.742, (d) 2000 Entropy=0.815, (e) 2010 Entropy=0.873. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

subsets of the distribution (bins of the histogram of job-worker ratios by county) and  $J$  represent the total number of subsets in the distribution. Further, let  $p_j$  represent the proportion of observations within the  $j$ th subset. The evenness of the distribution of job-worker ratios across counties can be described by an entropy statistic taking the form:

$$Entropy = - \sum_j \frac{p_j \ln(p_j)}{\ln(J)} \quad (1)$$

This statistic ranges from zero to one, with a value of zero representing complete homogeneity and a value of one representing complete heterogeneity. Analogously, a value of zero describing the distribution of job-worker ratios among counties would imply that all observations were grouped into one of the bins of the histogram, while values close to one would imply that the ratios were more evenly distributed across a larger number of bins. For consistency, the same intervals are adopted for each set of decennial observations. The value calculated for this statistic in 1970 was 0.721 whereas by 2010 it had increased to 0.873, suggesting a greater number of observations at the more extreme values of the distribution as well as less clustering of values near its center. Values for the intervening years are 0.725 (1980), 0.742 (1990), and 0.815 (2000).

The entropy values for these two years correspond to the patterns observed in Fig. 2a–e, where several new employment centers emerge outside of the state's largest metropolitan area (Minneapolis–St. Paul), reflected in their high job-to-worker ratios. Many of these centers have been identified as micropolitan areas for statistical purposes by the US Census Bureau. The evidence from these entropy measures is suggestive, but more evidence is required if we are to accept the role of transportation network growth as an explanatory factor in driving these trends.

## 4. Methods and data

### 4.1. Empirical specification

In order to investigate the role of transportation network growth as a determinant of patterns of development (and vice versa), we propose a simple empirical model that ties together the location of road networks, employment and population. Our model assumes that population densities, employment densities, and road network densities (measured as road miles per square mile) in a given location are determined as a function of three sets of variables.

The first set of variables represents prior (lagged) levels of each variable and indicates the importance of initial conditions in influencing future levels of each variable. Road networks are divided into two types of roads (local roads and highways) to emphasize their functional differences and to test whether they have differing effects on the location of population and employment.

The second set of variables measures *changes* in the level of population, employment and road networks between periods  $t-5$  and  $t$ . This set of variables is perhaps the most important, since it yields an indication of the magnitude of the response to changes in each of the variables at the margin over the most recent period.

The third group of variables measures changes in the corresponding statewide values for each variable over the same period. These variables are included to capture secular trends over the study period, such as broader demographic trends which might affect population growth or macroeconomic trends which affect industries that comprise a significant share of the state's employment base, and thus may influence trends at more local levels. They may also serve to capture the effect of actions at a distance,

such as increases in the utility of highway networks to local users brought about by expansion in non-local jurisdictions, a pure “network effect”. Thus, local employment or population densities might be affected by non-local changes to the road network. This represents an alternative method to the use of spatial weight matrices in order to capture the effects of action at a distance.

Five-year changes were chosen in order to allow sufficient time for adjustment to changes in road networks or population/employment levels. Other values, including shorter-term changes, were also tested but not found to add significant explanatory power. All of the variables in this specification are transformed into their natural logarithms. Variables expressed in differenced form represent changes in the logged level of that variable.

This model structure will form the basis for our examination of causality among population, employment, and road networks. Each of the equations is estimated separately via a fixed-effects (“within”) estimator with a correction for first-order autocorrelation in the disturbance term using the Prais–Winsten technique. This technique allows for time-invariant, county-specific unobserved effects while also accounting for the temporal aspects of the panel data set. A procedure for fitting this model with a correction for correlation across each panel in the data set is available in the Stata software package (the “xtpcse” procedure) and was applied to obtain the parameter estimates.

Within this framework, the four individual estimating equations can be written as

$$E_{c,t} = \alpha_E + \sum_{i=1}^4 (\beta_{x,i} x_{i,c,(t-5)} + \beta_{\Delta x,i} \Delta x_{i,c,(t-5,t)} + \beta_{\Delta S,i} \Delta S_{i,(t-5,t)}) + \epsilon_E \quad (2)$$

$$P_{c,t} = \alpha_P + \sum_{i=1}^4 (\pi_{x,i} x_{i,c,(t-5)} + \pi_{\Delta x,i} \Delta x_{i,c,(t-5,t)} + \pi_{\Delta S,i} \Delta S_{i,(t-5,t)}) + \epsilon_P \quad (3)$$

$$L_{c,t} = \alpha_L + \sum_{i=1}^4 (\lambda_{x,i} x_{i,c,(t-5)} + \lambda_{\Delta x,i} \Delta x_{i,c,(t-5,t)} + \lambda_{\Delta S,i} \Delta S_{i,(t-5,t)}) + \epsilon_L \quad (4)$$

$$H_{c,t} = \alpha_H + \sum_{i=1}^4 (\eta_{x,i} x_{i,c,(t-5)} + \eta_{\Delta x,i} \Delta x_{i,c,(t-5,t)} + \eta_{\Delta S,i} \Delta S_{i,(t-5,t)}) + \epsilon_H \quad (5)$$

where:

$i$  = indicator variable,  $i = 1 = E$ ,  $i = 2 = P$ ,  $i = 3 = L$ ,  $i = 4 = H$ .

$E_{c,t}$  = Private, non-farm employment density in county  $c$  in year  $t$

$P_{c,t}$  = Population density in county  $c$  in year  $t$

$L_{c,t}$  = Local road density in county  $c$  in year  $t$

$H_{c,t}$  = Highway density in county  $c$  in year  $t$

$x_{i,c,(t-5)}$  = lagged variable  $i$  observed in county  $c$  in year  $t-5$

$\Delta x_{i,c,(t-5,t)}$  = Change in variable  $i$  observed in county  $c$  between  $t-5$  and  $t$

$\Delta S_{i,(t-5,t)}$  = Change in statewide variable  $i$  between years  $t-5$  and  $t$

$\epsilon$  is a well-behaved, normally-distributed error term

$\alpha$ ,  $\beta$ ,  $\pi$ ,  $\lambda$ , and  $\eta$  are sets of parameters to be estimated

The following variables are forced to 0 to avoid co-linearity ( $\beta_{\Delta x,1}, \pi_{\Delta x,2}, \lambda_{\Delta x,3}, \eta_{\Delta x,4} = 0$ )

For each of the four models listed above, a separate, restricted model will be estimated and the residuals used to test for Granger causality. For example, the employment equation listed above will be fit with and without the road network variables. The restricted model, without the road variables, forms the basis for the null hypothesis that changes in road network variables have no

influence on employment growth in the subsequent period (that is, that they are jointly equal to zero).

#### 4.2. Hypotheses

We formulate a set of specific hypotheses regarding the interactions among employment, population, and the road networks within the model framework previously outlined. These include

- Employment increases in response to expansion of the highway network, as the increased accessibility to labor markets and suppliers improves the relative attractiveness of a given location to existing and prospective firms ( $\beta_{x,4}, \beta_{\Delta x,4}, \beta_{\Delta S,4} > 0$  (Eq. (2))).
- Growth in population follows the growth of local roads, as new residents are able to take advantage of the provision of new infrastructure ( $\pi_{x,3}, \pi_{\Delta x,3}, \pi_{\Delta S,3} > 0$  (Eq. (3))).
- Local roads increase with the growth of the local population, as new roads are required to serve new development ( $\lambda_{x,2}, \lambda_{\Delta x,2}, \lambda_{\Delta S,2} > 0$  (Eq. (4))).
- Highway networks grow in response to growth in local employment, as new employers need to draw on a larger labor pool and networks serving existing employment centers become more heavily burdened ( $\eta_{x,1}, \eta_{\Delta x,1}, \eta_{\Delta S,1} > 0$  (Eq. (5))).
- Highways and local roads are complements, that is, increases in highways are followed by expansion of local road networks and vice versa ( $\lambda_{x,4} > 0$  (Eq. (4));  $\eta_{x,3} > 0$  (Eq. (5))).
- Employment and population are complements, that is, jobs attract people and vice versa ( $\beta_{x,2} > 0$  (Eq. (2));  $\pi_{x,1} > 0$  (Eq. (3))).
- Trends in each of the variables are persistent over time ( $\beta_{x,1}, \pi_{x,2}, \lambda_{x,3}, \eta_{x,4} \approx 1$ ).

The first four of these hypotheses essentially posit feedback loops between the expansion of the road network and the location of residents and jobs. While the effects are assumed to be positive overall, there may also be some variation in outcomes by location. For example, road improvements in less populated areas may lead some residents to leave by lowering the cost of accessing locations with greater opportunities. Likewise, improvements in rural areas could, in principle, lower employment levels by exposing local firms to a greater level of spatial competition from firms in neighboring jurisdictions.

The fifth hypothesis suggests complementarity between different parts of a hierarchical road network, that is, more highways are often accompanied by the extension of the local road network. An alternative hypothesis might be that the two types of networks are substitutes. The sixth suggests that people follow jobs and vice versa, and the seventh simply states that trends in each of the variables are persistent, while noting that this relationship should be stronger in the case of the population variable, whose value is estimated rather than observed for intercensal years by the US Census Bureau.

#### 4.3. Data

The road network data we use to test our hypotheses regarding the direction of causality among road networks, population and employment comes from the Minnesota Department of Transportation (MnDOT). MnDOT has collected and published a data series on roadway miles and vehicle-miles of travel by county and roadway classification dating back to 1988 (Minnesota Department of Transportation, 2012). It has also begun more recently to add data on lane-miles of roadway by type, though this series only goes as far back as 2002, making it of limited use in the present study. Though data on roadway miles are also available for more

recent years, we limit our data set to observations through 2007, as errors in coding in subsequent years have led to large discontinuities in the data series. The errors appear in the most recent years of the data set and give the appearance of sharp increases in the size of the network (on the order of several percentage points) at a time during which spending levels on roads and other infrastructure in the state were relatively flat. Thus, we focus our analysis on the data that are available for the 20-year period between 1988 and 2007. This choice also allows us to focus on the years prior to the subsequent deep recession which had dramatic and adverse effects on employment levels both locally and nationally, and which were unrelated to the variables of interest in this study.

We do not consider freight or passenger rail networks in our analysis. While freight railroads still play a somewhat prominent role in the state's movement of goods, rail networks have changed very little since the beginning of the study period, and so are unlikely to be an important source of variation in economic activity. Passenger rail networks are also very sparse relative to countries in Europe and Asia, and so do not figure prominently in the locations of households at the county level.

Population data in our data set are yearly estimates from the Census Bureau's archive of intercensal population estimates (United States Census Bureau, 2013), with the exception of data points for census years (1990 and 2000). We chose to use the population estimates in order to both match the periodicity of the employment and road network data and to increase the size of our sample.

Employment data used in the study are annual totals of private, non-farm employment by county, collected from the Bureau of Economic Analysis' Regional Economic Information System (REIS) (United States Bureau of Economic Analysis, 2012). These data include all full-time and part-time employment identified by place of work. Fig. 3 depicts the trend in employment growth statewide from 1990 to 2007. Employment growth over this period averaged about 1.9 percent per year. For comparison, the trend in road network growth over the same period is plotted on the same graph. Road-miles of highways and local roads in Fig. 3 are indexed to a value of 100 in 1990 along with employment to permit comparison on a similar scale. Three-period moving averages are used to smooth out some of the discontinuities in the road network data, which explains why the data in the figure begin in 1990 rather than 1988. The size of the local road network grew by only about three percent over this 20-year period. The growth of the highway network was even more modest—it only expanded by about 0.5 percent over the same period. Note, however, that these totals only represent road miles and not lane-miles. Thus, they likely understate the real growth in network capacity, especially in urban areas. Descriptive statistics for the full set of variables to be included in the model are listed in Table 1. The data set contains 1305 observations representing each of the state's 87 counties observed over 15 years (the full data set contains 20 years of observations, but five are lost due to the use of 5-year lags and differences in the covariates).

## 5. Empirical results

The estimation results for each of the four equations in the model are presented in Table 2. We report parameter estimates for each of the covariates with five-period lags and differences. Other, shorter lag periods were also tested but found to add little to the explanatory power of the models. Granger causality tests are run to test each of the hypotheses identified previously regarding the direction of causality between road networks and the location of population and employment. For example, the first hypothesis is

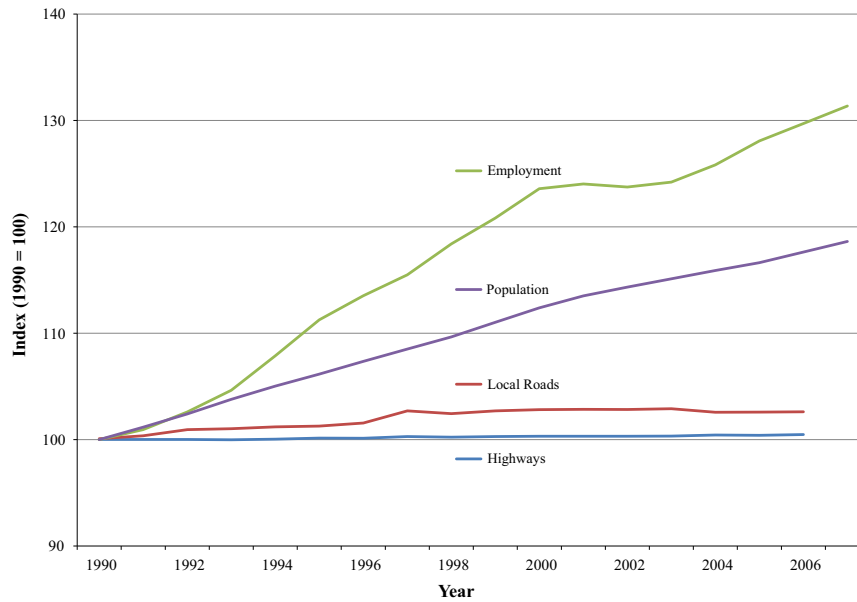


Fig. 3. Growth in employment, population, and road network size in Minnesota, 1990 to 2007.

tested by estimating the employment change model with and without the highway network variables. This hypothesis can then be tested by comparing the residual sums of squares from the restricted and unrestricted models using an F-test. Statistical output for each of the restricted models are not reported in Table 2, but are available from the authors.

The results from the employment equation in Table 2 indicate that lagged population and employment levels are among the strongest predictors of employment density levels in the subsequent period. Changes in population density also appear to be strongly and positively correlated at both local and statewide scales. The coefficients on the local road density variables have mixed signs, but all are relatively small in magnitude and statistically insignificant. Also, contrary to our hypotheses, lagged levels and changes in highway density are both negatively and significantly correlated with employment. Lagged employment levels also appear to be significant indicating a persistence in employment trends, though the coefficient is significantly below one. A

formal test of the significance of the local road and highway variables in causing changes in employment using the F-test just described yields test statistics of 4.53 and 7.01 respectively, for an F-distribution with (3, 1293) degrees of freedom. The results of these tests and tests for Granger causality among the other pairs of variables in the remaining three equations are reported below in Table 3. The test statistics are significantly above the critical value of 2.60 (corresponding to a 0.05 level of significance), indicating that the null hypothesis of no causality can be rejected.

The second equation predicts county population density. Lagged population density is the strongest predictor of population density in the subsequent period, with a coefficient slightly above one. Statewide population density changes also appear to be positive and significant. The one other covariate that correlates positively with employment density is changes in local employment density. Both of the road network density change variables also appear to be positively associated with subsequent population levels, though neither are statistically significant and the

Table 1  
Descriptive statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Employment density ( $\ln x_{E,c,t}$ )	1305	2.558	1.412	-0.417	7.623
Population density ( $\ln x_{P,c,t}$ )	1305	3.424	1.300	0.263	8.011
Local road density ( $\ln x_{L,c,t}$ )	1305	0.182	0.576	-2.119	2.212
Highway density ( $\ln x_{H,c,t}$ )	1305	-0.564	0.457	-2.569	0.833
Employment density, t-5 ( $\ln x_{E,c,(t-5)}$ )	1305	2.456	1.397	-0.634	7.599
Population density, t-5 ( $\ln x_{P,c,(t-5)}$ )	1305	3.397	1.270	0.140	8.011
Local road density, t-5 ( $\ln x_{L,c,(t-5)}$ )	1305	0.175	0.572	-2.119	2.210
Highway density, t-5 ( $\ln x_{H,c,(t-5)}$ )	1305	-0.566	0.457	-2.569	0.833
$\Delta$ Employment density ( $\Delta x_{E,c,(t-5,t)}$ )	1305	0.102	0.107	-0.301	0.517
$\Delta$ Population density ( $\Delta x_{P,c,(t-5,t)}$ )	1305	0.027	0.066	-0.141	0.290
$\Delta$ Local road density ( $\Delta x_{L,c,(t-5,t)}$ )	1305	0.007	0.022	-0.063	0.141
$\Delta$ Highway density ( $\Delta x_{H,c,(t-5,t)}$ )	1305	0.002	0.012	-0.056	0.132
$\Delta$ Statewide employment density ( $\Delta S_{E,(t-5,t)}$ )	1305	0.096	0.033	0.028	0.153
$\Delta$ Statewide population density ( $\Delta S_{P,(t-5,t)}$ )	1305	0.052	0.009	0.036	0.063
$\Delta$ Statewide local road density ( $\Delta S_{L,(t-5,t)}$ )	1305	0.008	0.007	-0.002	0.017
$\Delta$ Statewide highway density ( $\Delta S_{H,(t-5,t)}$ )	1305	0.001	0.001	0.000	0.003

**Table 2**  
Estimated coefficients for employment, population, and road network models.

Variable	ln(Employment)			ln(Population)			ln(Local roads)			ln(Highways)		
	Coeff.	S.E.	t-value	Coeff.	S.E.	t-value	Coeff.	S.E.	t-value	Coeff.	S.E.	t-value
ln $x_{E,c,(t-5)}$	0.8025	0.0501	16.02	-0.0012	0.0134	-0.09	-0.0094	0.0069	-1.36	-0.0061	0.0027	-2.27
ln $x_{P,c,(t-5)}$	0.2212	0.0590	3.75	1.0508	0.0173	60.67	0.0206	0.0095	2.16	0.0090	0.0035	2.55
ln $x_{L,c,(t-5)}$	0.0226	0.0199	1.14	-0.0649	0.0121	-5.36	0.9894	0.0088	112.73	0.0101	0.0028	3.61
ln $x_{H,c,(t-5)}$	-0.0804	0.0239	-3.36	-0.0169	0.0134	-1.26	-0.0061	0.0129	-0.47	0.9807	0.0050	194.75
$\Delta x_{E,c,(t-5,t)}$				0.1005	0.0148	6.80	-0.0011	0.0071	-0.15	-0.0138	0.0041	-3.35
$\Delta x_{P,c,(t-5,t)}$	0.7633	0.0847	9.01				0.0501	0.0365	1.37	0.0381	0.0169	2.25
$\Delta x_{L,c,(t-5,t)}$	-0.0138	0.0910	-0.15	0.0524	0.0658	0.80				-0.0298	0.0375	-0.80
$\Delta x_{H,c,(t-5,t)}$	-0.3967	0.0988	-4.02	0.0559	0.0662	0.84	-0.0934	0.0695	-1.34			
$\Delta S_{E,(t-5,t)}$	-1.0145	0.8397	-1.21	0.0333	0.0490	0.68	-0.0388	0.0131	-2.96	0.0119	0.0162	0.74
$\Delta S_{P,(t-5,t)}$	0.9033	0.1942	4.65	0.8437	0.1989	4.24	-0.0125	0.0578	-0.22	-0.0310	0.0670	-0.46
$\Delta S_{L,(t-5,t)}$	-0.1728	4.6811	-0.04	-0.2396	0.2189	-1.09	0.9375	0.0507	18.50	0.0648	0.0770	0.84
$\Delta S_{H,(t-5,t)}$	-0.0889	0.9105	-0.10	0.9245	1.0660	0.87	0.8037	0.2948	2.73	1.3512	0.3724	3.63
Constant	-0.2664	0.0875	-3.04	-0.1996	0.0295	-6.77	-0.0464	0.0214	-2.17	-0.0279	0.0086	-3.22
$\rho$	0.7480			0.8289			0.7486			0.6384		
Adjusted $R^2$	0.993			0.999			0.996			0.998		
N	1305			1305			1305			1305		

Notes: Parameter estimates are within-group estimates using deviations from variable means.  $\rho$  is the (first-order) autoregressive parameter of the disturbance term.

**Table 3**  
Test statistics for causality between pairs of variables.

Causality	F statistic
Population – Employment	183.37 <sup>b</sup>
Local Roads – Employment	4.53 <sup>b</sup>
Highways – Employment	7.01 <sup>b</sup>
Employment – Population	202.40 <sup>b</sup>
Local Roads – Population	62.53 <sup>b</sup>
Highways – Population	10.47 <sup>b</sup>
Employment – Local Roads	3.22 <sup>a</sup>
Population – Local Roads	34.33 <sup>b</sup>
Highways – Local Roads	24.67 <sup>b</sup>
Employment – Highways	1.97
Population – Highways	13.09 <sup>b</sup>
Local Roads – Highways	11.60 <sup>b</sup>

Note:

<sup>a</sup> Statistically significant at  $p < 0.05$  level of significance.

<sup>b</sup> Statistically significant at  $p < 0.01$  level of significance.

magnitude of their effect is relatively small. The coefficients on the local road network variables, which are the focus of our second hypothesis, again have mixed signs. While lagged local road density is negatively and significantly correlated with subsequent population density, the variable representing 5-year changes in local roads are positively correlated with subsequent population density levels, albeit at a low level of significance. The magnitudes of both are relatively small, indicating a rather weak effect on population density. Subjecting the local road variables to the same F-test that was applied to the employment equation yields a test statistic of 62.53, indicating a fairly high level of significance. Applying the same test to the highway density variables in the population equation produces a test statistic with a value greater than 10, again indicating significance at the  $p > 0.01$  level.

Our third hypothesis represents the converse of the second, namely that growth in the local road network also follows local population growth, in addition to population growth following the provision of local roads. The estimated coefficients for the local road network density equation in Table 2 indicate that while lagged employment density levels do not appear to significantly

affect the size of the local road network, lagged population levels and changes do. The coefficient on the population density change variable indicates that a 10 percent increase in population density is associated with a roughly 0.5 percent increase in the density of the local road network. This estimate may also mask a significant amount of variation among urban, suburban and rural counties. Applying the test for Granger causality, the inclusion of the population density variables to the restricted model containing only road network and employment density variables yields a test statistic of over 34, providing strong evidence against the null hypothesis of no causality. Applying the same test to investigate whether employment density is a significant predictor of local road density yields less conclusive results. The test statistic of 3.22 indicates significance at the  $p < 0.05$  level, providing modest evidence that employment Granger causes local roads.

The fourth equation in Table 2 presents the coefficients for the model predicting highway network density. While local population density appears to positively influence the size of the highway network in subsequent years, local employment does not seem to have the same effect, as our fourth hypothesis suggested. Changes in employment over the previous five years appear to correlate negatively with highway density as well. These results may indicate that many of the new highway links built during the study period were designed to serve fast-growing suburban areas where population growth was high, rather than counties where most employment growth took place. The test statistics reported in Table 3 confirm these results, with strong evidence that population density Granger causes highway network density but no evidence of a similar causal relationship between employment density and highways.

Our fifth hypothesis assumed complementarity between highways and local road networks. Looking at the estimated coefficients for the local road density and highway density equations, we see that there is no significant evidence that highways influence local road density. On the contrary, highway network density does appear to be correlated with the lagged level of road network density, while recent changes in local road density do not appear to have any effect. We conclude that there is only weak evidence that the two types of roads are complements and that local road density is more likely to influence subsequent highway networks than the opposite.

The sixth hypothesis regarding the complementarity of employment and population also seems to be corroborated. Residents demand non-basic (service) employment. Employment growth attracts local residents. While at the very local scale they may be substitutes (a parcel (or downtown) for commercial development may price out residences, as found in Levinson (2008)), at the scale of the county they are complementary.

Our seventh and final hypothesis concerned the persistence of trends in each of the four equations. Evidence for this hypothesis comes from the coefficients on the lagged dependent variables included in each of the models. We find support for this hypothesis in three of the four equations, with the exception being the employment equation which indicates a downward drift in employment change over time, perhaps reflecting the effect of the recession of the early 2000s and relatively slow employment growth in subsequent years.

## 6. Conclusions

Our analysis and discussion of the relationship between the growth in road networks and the growth of population and employment illustrates what we believe to be understudied phenomena. The empirical model of changes in networks and the location of economic activity adapts the model of regional adjustment adopted by Carlino and Mills (1987) and others to examine the reverse causality from population and employment to changes in road networks. Though we do find evidence of feedbacks between population changes and the growth of local networks, we found surprisingly little evidence of similar relationships between employment changes and highway networks. We interpret the latter as evidence of a weakening in the traditional relationship between road networks and the location of employment due to the maturity of the highway network. Indeed, the limited amount of expansion in the statewide highway network itself (as depicted in Fig. 3) over the 20-period examined here is indicative of its maturity. It is worth noting the caveat that the results apply specifically to the context in which the data was collected. While we may suggest that the results are typical of many U.S. urban areas, it is certainly possible that different results could be obtained in less developed settings, or in locations where denser road networks and systems of cities predominate (e.g. western Europe, Japan, South Korea). It is also quite possible that other location factors (human capital levels, tax rates, natural amenities, etc.) have become just as important, if not more, than transportation network considerations.

It is worthwhile to consider the implications of these trends for future research into the relationship between road network investment and regional growth. We suggest that in addition to established lines of research linking transportation infrastructure to economic growth via aggregate output and cost functions some emphasis should be placed on identifying the indirect effects of transportation improvements through their impacts on the location of factors of production. Some progress has already been made in this area with attention being paid to the role of transportation networks in fostering agglomeration economies (Haughwout, 1999; Graham and Kim, 2008). This is one of the key considerations among studies investigating the possibility of “wider effects” (Banister and Berechman, 2001; Vickerman, 2000, 2007) from major transportation network improvements.

We also believe the framework presented in this study might be usefully expanded upon, though improvements to available data might be required to do so. One shortcoming of the present approach, as identified previously, is the reliance upon road length as a measure of the size of highways and local road networks. This approach understates the growth in road capacity, particularly in

urban areas where improvements to highways are more likely to take the form of expansions of existing links as opposed to the construction of new ones. This compromise may have created a downward bias in the response of road networks to population and employment growth. Another issue is the ability to capture the full adjustment of population and employment to network expansions, a process that can take place over longer periods of time than those represented in the present study. A number of other similar empirical studies have chosen long differences (10 years or more) as a way to capture the long-term adjustment process (Carlino and Mills, 1987; Boarnet, 1994; Carruthers and Vias, 2005). 10-year changes are convenient due to the ability to observe decennial census counts and collect data on other location factors that have been found to influence the decisions of firms and households. However, they tend to come at the expense of having a limited amount of longitudinal detail to observe and being able to identify feedbacks between transportation networks and the places they serve that span multiple decades. There is, at present, no ideal data source that can capture both the spatial and temporal detail that the present study requires. We suggest that a useful place to start would be to begin building historical data sets describing the size and capacity of road networks, ideally at annual intervals and at a sub-state geographic level, that cover several decades worth of changes.

Lastly, there is a need to consider the flow of services made possible by transportation networks. The basic output of most transportation networks is accessibility. Improvements to networks can be measured by the degree to which they lower the cost of accessing other destinations in terms of travel time, out-of-pocket cost, convenience, or any other valued aspect of travel. Changes to patterns of accessibility, either at urban or larger regional levels, may change the shape or spatial extent of markets and lead to the kinds of reorganization of activities that are the focus of this study. They may also lead to the emergence of network effects, whereby some locations may receive additional benefit due to an advantageous location within the network relative to other urban areas. We suggest that future studies of this kind attempt to make explicit links between the level of accessibility provided the network and whichever measure of economic activity is chosen for investigation.

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## References

- Banister, D., Berechman, Y., 2001. Transport investment and the promotion of economic growth. *J. Transp. Geogr.* 9 (September (3)), 209–218.
- Baum-Snow, N., 2007. Did highways cause suburbanization? *Q. J. Econ.* 122 (May (2)), 775–805.
- Boarnet, M.G., 1994. An empirical model of intrametropolitan population and employment growth. *Pap. Reg. Sci.* 73 (2), 135–152.
- Brueckner, J.K., Fansler, D.A., 1983. The economics of urban sprawl: theory and evidence on the spatial sizes of cities. *Rev. Econ. Stat.* 65 (August (3)), 479–482.
- Carlino, G.A., Chatterjee, S., 2002. Employment deconcentration: a new perspective on America's postwar urban evolution. *J. Reg. Sci.* 42 (3), 455–475.
- Carlino, G.A., Mills, E.S., 1987. The determinants of county growth. *J. Reg. Sci.* 27 (1), 39–54.
- Carruthers, J.I., Vias, A.C., 2005. Urban, suburban, and exurban sprawl in the Rocky Mountain West: evidence from regional adjustment models. *J. Reg. Sci.* 45 (1), 21–48.
- Cervero, R., 1989. Jobs-housing balancing and regional mobility. *J. Am. Plan. Assoc.* 55 (2), 136–150.



- Cervero, R., 1996. Jobs-housing balance revisited: trends and impacts in the San Francisco Bay Area. *J. Am. Plan. Assoc.* 62 (4), 492–511.
- Chi, G., 2010. The impacts of highway expansion on population change: an integrated spatial approach. *Rural Sociol.* 75 (1), 58–89.
- Cox, W., Gordon, P., Redfean, C.L., 2008. Highway penetration of central cities: not a major cause of suburbanization. *Econ J Watch* 5 (January (1)), 32–45.
- Garrison, W., Levinson, D., 2006. *The Transportation Experience: Policy, Planning, and Deployment*. Oxford University Press, New York, NY.
- Garrison, W.L., Berry, B., Marble, D.F., Nystuen, J.D., Morrill, R.L., 1959. *Studies of Highway Development and Geographic Change*.
- Giuliano, G., 1991. Is jobs-housing balance a transportation issue? *Transp. Res. Rec.: J. Transp. Res. Board* 1305, 305–312.
- Glaeser, E., Kahn, M.E., 2001. Decentralized employment and the transformation of the American city. *Brookings-Wharton Papers on Urban Affairs*, 2001, pp. 1–47.
- Gordon, P., Richardson, H.W., 1989. Congestion, changing metropolitan structure, and city size in the United States. *Int. Reg. Sci. Rev.* 12 (1), 45–56.
- Graham, D.J., Kim, H.Y., 2008. An empirical analytical framework for agglomeration economies. *Ann. Reg. Sci.* 42, 267–289.
- Haughwout, A.F., 1999. State infrastructure and the geography of employment. *Growth Change* 30, 549–566 (Fall).
- Jiwattanakulpaisarn, P., Noland, R.B., Graham, D.J., 2010. Causal linkages between highways and sector-level employment. *Transp. Res. Part A* 44, 265–280.
- Jiwattanakulpaisarn, P., Noland, R.B., Graham, D.J., Polak, J.W., 2009. Highway infrastructure and state-level employment: a causal spatial analysis. *Pap. Reg. Sci.* 88 (March (1)), 133–159.
- King, D., 2011. Developing densely: estimating the effect of subway growth on New York City land uses. *J. Transp. Land Use* 4 (Summer (2)), 19–32.
- Levinson, D., 2008. Density and dispersion: the co-development of land use and rail in London. *J. Econ. Geogr.* 8, 55–77.
- Levinson, D.M., Kumar, A., 1994. The rational locator: why travel times have remained stable. *J. Am. Plan. Assoc.* 60 (3), 319–332.
- McGrath, D.T., 2005. More evidence on the spatial scale of cities. *J. Urban Econ.* 58, 1–10.
- Meyer, J.R., Kain, J.F., Wohl, M., 1965. *The Urban Transportation Problem*. Harvard University Press, Cambridge, MA.
- Minnesota Department of Transportation, September 2012. *Roadway data: data products*. website.
- Steinnes, D., 1977. Causality and intraurban location. *J. Urban Econ.* 4, 69–79.
- United States Bureau of Economic Analysis, November 2012. *Regional economic accounts: local area income and employment*. website.
- United States Census Bureau, March 2013. *Population estimates: historical data*. website.
- Vickerman, R., 2000. Evaluation methodologies for transport projects in the United Kingdom. *Transp. Policy* 7, 7–16.
- Vickerman, R.W., 2007. Cost-benefit analysis and large-scale infrastructure projects: state of the art and challenges. *Environ. Plan. B: Plan. Des.* 34, 598–610.
- White, M.J., 1999. Urban areas with decentralized employment: theory and empirical work. In: Mills, E.S., Chesire, P. (Eds.), *Handbook of Regional and Urban Economics*. Elsevier, pp. 1375–1412 (Chapter 36).
- Xie, F., Levinson, D.M., 2010. How streetcars shaped suburbanization: a Granger causality analysis of land use and transit in the Twin Cities. *J. Econ. Geogr.* 10, 453–470.