The Economic Effects of Highway Congestion

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Abstract

This paper examines the link between highway congestion, labor productivity, and output in a sample of California counties for the years 1977 through 1987. A county production function is modified to include both the value of each county's highway capital stock and a measure of the congestion on each county's highway network. This allows a comparison of two distinct policies -- expanding the highway stock versus reducing congestion on the existing stock. The productive effects of congestion reduction are significantly positive in five of six regression specifications. The effects of expanding the highway stock are more suspect, and are insignificant in what are arguably the preferred specifications. Overall, the results provide evidence that efficiently using the existing highway network is more likely to yield economic benefits than expanding the highway stock.

Section I. Introduction

During the past several years, many studies have examined how public capital is linked to economic productivity. One shortcoming of almost all of these studies is that the measure of public capital is the dollar value of the public infrastructure stock. (See, e.g., Aschauer 1989; Duffy-Deno and Eberts 1991; Eberts 1986; Garcia-Mila and McGuire 1992; Holtz-Eakin 1994; Hulten and Schwab 1991; Kelejian and Robinson 1994; Munnell 1990a and 1990b.) If infrastructure is productive, it is because of the services it provides. The services provided by public infrastructure are determined not only by the stock of public capital, but also by a host of factors including how efficiently that capital is used. As long as attention is focused only on the link between productivity and the infrastructure stock, policy recommendations that involve using the existing stock more efficiently are likely to be overlooked. This study begins to bridge that gap by measuring how the services provided by one type of public capital, highway infrastructure, are related to measures of economic output and productivity.

Section II. Public Capital Inputs and Service Flow Outputs

Bradford, Malt, and Oates (1969) noted that public goods are characterized both by inputs and by service flow outputs. This framework can be adapted in a useful way for public infrastructure. In the case of infrastructure, the dollar value of the stock represents an input. Those inputs are productive to the extent that they produce some useful service flow output (U.S. Department of Transportation 1992; Kessides 1993). Adapting the framework of

Bradford, Malt, and Oates (1969) to the case of public capital, infrastructure services are the output of a production function which has discounted investment flows as inputs, as shown below.

$$S_T = f\left(\sum_{t=1}^{T} \frac{1}{(1+\delta)^{T-t}} G_t \quad , \quad \mathbf{z}_T\right) \tag{1}$$

where S_T = the services produced by public capital in time period "T"
G_t = public capital investment in time period "t"
δ = a discount rate that measures the depreciation of G_t
$\mathbf{z}_T$ = a vector of other variables which affect infrastructure service flows

The vector **z** includes factors such as congestion, how efficiently the stock is used, the suitability of the stock design (or technology) to the problem at hand, and anything else that could affect service flows from a given discounted public capital investment.

Most previous studies of public capital and productivity have measured infrastructure as the present value of the stock, using a perpetual inventory method that is compatible with the discounted investment flow that is the first argument on the right-hand side of equation (1). (See, e.g., Aschauer 1989; Duffy-Deno and Eberts 1991; Garcia-Mila and McGuire 1992; Holtz-Eakin 1994; Munnell 1990a and 1990b.) The shortcomings of that technique are twofold. The first problem is a measurement issue. As the formulation in (1) makes clear, the services provided by public capital are potentially mismeasured by looking at only the value of the stock. The second problem is that many infrastructure policy recommendations involve using the existing stock more efficiently, a point that is missed when the value of the stock is the only variable that measures public capital services.

This mismatch between research and policy is not a minor issue. Consider the case of highway infrastructure, which constitutes one-third of all the public capital stock in the United States (Gramlich 1994, p. 1178). At least since the work of Mohring and Harwitz (1962) and Vickrey (1963), authors have recognized that many urban highways in the United States are underpriced, especially when those roadways are congested. The congestion pricing literature has argued for years that unpriced highways are an inefficient use of the transportation infrastructure stock. (See, e.g., Keeler and Small 1977; Small 1983; Small, Winston and Evans 1989, especially chapter 5.) As such, one policy for increasing the service flow from urban highways is to price the existing stock more efficiently, rather than to build more stock (Gramlich 1994; Winston 1990).

This research looks at the specific case of highway capital. As in past studies (e.g. Aschauer 1989; Duffy-Deno and Eberts 1991; Garcia-Mila and McGuire 1992; Garcia-Mila, McGuire and Porter 1996; Holtz-Eakin 1994) a measure of the highway infrastructure stock is included in an aggregate production function. The innovation here is based on equation (1). Highway capital is only part of what is needed to measure the services produced by highways. This study also uses a measure of how efficiently the highway stock moves traffic.

The measure of efficiency is the inverse of a congestion measure. Broadly speaking, a given stock of highway capital moves traffic more efficiently if the highways are less congested. By examining the effects of changes in the congestion measure, while holding highway infrastructure constant, this paper provides insights into policies such as congestion pricing that can reduce congestion.[1]

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[1] It would be ideal to use a measure of optimal road pricing as the gauge of efficiency. Yet since true congestion pricing in the United States is limited to a handful of recently (continued...)

Since highway services are measured both by the highway capital stock and by an inverse congestion measure, the resulting production function is

$$Q = f(L, K, H, A) \tag{2}$$

Where Q = output
L = labor inputs
K = private capital stock inputs
H = highway stock inputs
A = an inverse congestion measure which will be defined more formally later.

Note that a production function such as equation (2) gives comparisons of the output effects of two distinct infrastructure policies -- expanding the highway stock and reducing congestion on the existing stock. As such, this research both conforms more closely to the Bradford, Malt, and Oates (1969) specification for service flows from public goods and provides results that are relevant to current highway pricing debates.

The remainder of the paper proceeds in five parts. The next section briefly summarizes the recent research on infrastructure and economic productivity. After that, Section IV describes the data used for an empirical test of the hypothesis that highway congestion affects economic output. This includes a description of a congestion measure that is based on highway capacity adequacy data which were obtained from the California Department of Transportation for the years 1977 through 1987. Section V describes the empirical specification and gives regression results. Section VI analyzes the economic impacts of congestion reduction, given the coefficient estimates from Section V. Lastly,

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[1](...continued)
proposed experiments (National Research Council, 1994, volume 1), this is not possible. Thus the efficiency measure is based on road pricing's intended target -- congestion.

Section VII summarizes the findings.

Section III. Background: Recent Studies on Public Infrastructure and Economic Productivity

The literature on public infrastructure and economic productivity has been very ably summarized in Gramlich (1994) and Munnell (1992), so the discussion here will be brief. Broadly speaking, the econometric literature on this topic can be divided into three groups. The first studies used time series data for the entire United States. Those works typically found large and statistically significant elasticities of output with respect to public capital. (See, e.g., Aschauer 1989; Munnell 1990b). The second group of studies used panel data on U.S. states. These papers usually found statistically significant infrastructure elasticities, but the magnitude of the effect was somewhat smaller than in the time series studies (e.g. Garcia-Mila and McGuire 1992; Munnell 1990a). The third group of studies used a panel of data on metropolitan areas within the U.S. These studies also found significantly positive effects from public capital, although again the magnitude was somewhat smaller than in the national time series studies (e.g. Duffy-Deno and Eberts 1991; Eberts 1986).

Some authors (e.g. Jorgenson 1991; Tatom 1991) suggested that the time series relationship between public capital and output is a spurious correlation caused by unit roots in the time series. One motivation for using panel data is to get additional information by exploiting cross-sectional variation in infrastructure stocks across states or metropolitan areas. Both Evans and Karras (1994) and Holtz-Eakin (1994) noted that a panel study of infrastructure should allow for unobservable state effects which could be linked to both infrastructure stocks and private sector output. After controlling for unique state effects, Evans and Karras (1994) and Holtz-Eakin (1994) both showed that the public capital elasticity is not significantly different from zero in a panel study of U.S. states. Garcia-Mila, McGuire, and Porter (1996) also found that the public capital elasticity is insignificant after controlling for state effects. A comparable approach has not been applied to the panel data for metropolitan areas.

Overall, while a large number of studies have found that infrastructure is associated with increased economic output, econometric corrections for unit roots and unobserved heterogeneity cast doubt on this finding. Given that, it is difficult to draw a firm conclusion from the recent research, although the more sophisticated studies often find public capital elasticities that are not statistically different from zero.

What is most important for this study is that no prior work has compared the effects of increasing the infrastructure stock with the effects of using the existing stock more efficiently. As such, even after the wealth of work on public capital, we still have only indirect information on how more efficient use of existing public capital can affect private sector economic performance.

Section IV. Data and Study Area

The empirical approach used in this paper amounts to modifying an aggregate production function to include both the stock of highway capital and a measure of congestion on the highway network. Data are available on gross output, employment, private capital stock, highway capital stock, and highway network congestion in a sample of California counties for the years 1977 through 1987. The sources for the output, labor, private capital, and highway capital data, and the methods used to construct the private capital stock variable, are described in Boarnet (1995). Since the output, labor, private capital and highway capital data are constructed similarly to the measures used in state and national studies (e.g. Aschauer 1989; Garcia-Mila and McGuire 1992; Holtz-Eakin 1994; Munnell 1990a and 1990b), the focus here is on describing a congestion measure that can be used in a production function of the form shown in equation (2).

If highways are productive, it is because they facilitate travel. Stated in a way that corresponds to the discussion in Section II, travel is the service that highways provide. From equation (1), policy-makers can increase the service flow from highways either by increasing the highway stock or by using the existing stock in ways that facilitate more efficient travel.[2]

One measure of the ability of highways to facilitate travel is congestion. More congested highways move travel at slower speeds. Of course congestion occurs at particular places and times on a network. Yet for this research we need to measure congestion

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[2] If the highway stock is increased in a congested urban area by building more highways, the phenomenon of latent demand suggests that the new roads will soon also be congested. In the extreme, highway construction might not provide congestion relief. (See, e.g., Downs 1992, Chapter 2 for a discussion.) Yet if new roads are built, even once they congest, on net more traffic can be moved. Thus the service flow from highways can increase. The framework in equation (1) is especially useful by noting that highway services can be increased either by moving more traffic at existing congestion levels (i.e. building more highways that will congest due to latent demand) or by reducing congestion on the existing highway network, and thus moving possibly less traffic but moving that traffic more efficiently. For a discussion of the efficiency properties of congestion reduction, especially as it relates to congestion pricing, see, e.g., Mills and Hamilton (1989, pp. 261-264).

throughout the entire highway network in a county. While such county-wide congestion measures do not exist, one can be constructed from available data from the California Department of Transportation (Caltrans).

Caltrans keeps annual records of highway capacity adequacy for every mile marker on the state highway system. The state highway system includes all interstate, federal, and state highways, and the records on capacity adequacy are available annually from 1977 through 1987 (California Department of Transportation 1977-1987). A mile marker is simply a designated location on a highway, and markers do not necessarily appear every mile.[3]

For any mile marker, capacity adequacy is the ratio of the highway's rated capacity divided by a measure of peak hour travel flow, multiplied by 100. The capacity adequacy measure is defined formally below.

$$CA = \left(\frac{\text{rated volume capacity}}{\text{volume during present design hour}}\right)*100 \qquad (3)$$

The present design hour is defined as the 30th highest volume hour for rural mile markers and the 200th highest volume hour for urban mile markers. Thus the capacity adequacy (CA) variable is the inverse of a congestion (or volume/capacity) measure. Locations with a CA greater than 100 could carry more traffic at peak hour (i.e. they are not congested). Locations with a CA of less than 100 are carrying more than their rated capacity

[3] The number of mile markers on the state highway system ranges from 3,108 in 1977 to 3,774 in 1987. In 1987, Los Angeles county had the most mile markers (269), and Alpine County had the fewest (13). In general, highways in urban areas have more markers at closer distance intervals than do highways in rural areas.

at peak hour (i.e. they are congested.)

Since the CA variable measures the inverse of congestion at a particular point on the highway network, CA needs to be aggregated to the county level. That aggregation was done in two steps. First, for each county, CA was summed for each highway. The sum is weighted by average daily travel (ADT) at a mile marker. The result is a congestion measure for a highway segment, as shown below.

$$HWYCA_{j,k} = \sum_{i=1}^{N} \frac{ADT_{i,j,k}}{TOTADT_{j,k}} CA_{i,j,k} \tag{4}$$

where $HWYCA_{j,k}$ = congestion measure for highway "j" in county "k"
$CA_{i,j,k}$ = CA at marker "i" on highway "j" in county "k"
$ADT_{i,j,k}$ = average daily travel at marker "i" on highway "j" in county "k"
N = the number of mile markers on highway "j" in county "k"

and

$$TOTADT_{j,k} = \sum_{i=1}^{N} ADT_{i,j,k} \tag{5}$$

such that $TOTADT_{j,k}$ = sum of the ADT at each marker "i" on the segment of highway "j" that is in county "k"

The highway segment CA variable, $HWYCA_{j,k}$, weights CA by ADT. Thus the CA at a particular mile marker is more important if the traffic flow (measured by ADT) is large at that mile marker. Intuitively, this suggests that a bottleneck (i.e. low CA) will affect the congestion measure more if it occurs at a heavily traveled section (and thus affects a large number of drivers).

Once $HWYCA_{j,k}$ is calculated for each highway segment in a county, those segment variables are summed into a county measure. Again the sum is weighted by ADT, as shown below.[4]

$$ACCESS_k = \sum_{j=1}^{M} \frac{TOTADT_{j,k}}{CNTYADT_k} HWYCA_{j,k} \qquad (6)$$

where $ACCESS_k$ = the congestion measure for county "k"
M = the number of highways in county "k"

and

$$CNTYADT_k = \sum_{j=1}^{M} TOTADT_{j,k} \qquad (7)$$

such that $TOTADT_{j,k}$ = sum of highway segment TOTADT's for county "k"

The result, ACCESS, is a weighted average of CA within the county.[5] ACCESS is an inverse congestion measure. Larger values of ACCESS imply less congestion, and hence

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[4] Note that, in equation (6), $HWYCA_{j,k}$ is weighted by $TOTADT_{j,k}$, where $TOTADT_{j,k}$ is the sum of the ADT on the highway segment rather than an average ADT for the segment. One reason to prefer a summed ADT for the weight is that this makes longer highways more important in the $ACCESS_k$ variable. For two highways with the same average ADT, if one is longer, it is arguably more important in the network. This suggests that HWYCA for the longer highway should be weighted more heavily. The formula in (6) does that.

[5] Note that ACCESS is similar to the measures of volume to capacity and levels of service which are described in Meyer (1994), yet ACCESS has two advantages when compared to those measures. First, ACCESS can be collected for an entire state for several years, while most other congestion measures are unique to metropolitan areas. Second, ACCESS measures differences in congestion levels on already congested networks, while many other measures are truncated once a highway or location congests. For a more detailed discussion of congestion measures used in previous research, see Meyer (1994).

easier travel (or access) to locations throughout the network. The name "ACCESS" is simply a mnemonic to denote the opposite of congested travel, and is not meant to imply any broader definition of accessibility.

Table 1 lists ACCESS for 1987 for all California counties. (For informational purposes, Table 1 also lists each county's population density, in persons per acre of land area.) Note that the more urbanized counties (e.g. San Francisco, Los Angeles, Orange, San Diego, Alameda) have lower values of ACCESS, reflecting higher peak hour congestion in those counties.

Figure 1 shows the time series graph of ACCESS for selected counties from 1977 through 1987. The time series for all counties is similar to those shown in Figure 1. Note that ACCESS generally trends down over the sample period. Also note that ACCESS follows the business cycle. In recessions (e.g. 1982 and 1983), ACCESS often improves, presumably due to less peak hour work-based travel. In expansions (e.g. 1984 and 1985) ACCESS typically drops.

One obvious implication of this is that ACCESS is endogenous to the local economy, both in the time series (or business cycle) sense, and to the extent that the more urbanized (and more prosperous) counties have lower ACCESS. For that reason, ACCESS was instrumented in the regression results reported in Section V. Before that is discussed further, consider a regression model of county production, based on equation (2), that includes ACCESS as the congestion measure.

Section V: Empirical Model

As constructed above, values of ACCESS that are less than 100 correspond to a highway network that is, on average, congested. Values over 100 correspond to county networks that are, on average, uncongested. Reducing congestion on uncongested networks ought to have no productive effect, since travel was presumably already flowing freely. Thus the effect of ACCESS in a production function such as (2) should be non-linear, with a kink or turning point at values near 100. For that reason, ACCESS is modelled quadratically in all regressions that follow.[6]

Given that, including year dummy variables in a log-linear version of equation (2) yields

$$\begin{aligned} \log(Q_{c,t}) &= \alpha_0 + \alpha_1 \log(ACCESS_{c,t}) + \alpha_2 \log(ACCESS_{c,t})^2 \\ &+ \alpha_3 \log(L_{c,t}) + \alpha_4 \log(K_{c,t}) + \alpha_5 \log(H_{c,t}) \\ &+ \sum_{i=0}^{9} \alpha_{6+i} YEAR_{1978+i} + \varepsilon_{c,t} \end{aligned} \tag{8}$$

where Q = county output
L = labor inputs
K = private sector capital stock
H = highway capital stock
ACCESS = the inverse congestion measure defined in Section IV
$YEAR_{1978}$ = 1 for 1978, zero otherwise; similarly for $YEAR_{1978+i}$ variables

"c" indexes counties ; "t" indexes years

There are two potential problems with estimating any regression based on equation (8).

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[6] Since all regressions are estimated in log-linear form, the quadratic specification includes log(ACCESS) and the square of log(ACCESS).

First, ACCESS is likely endogenous, for the reasons discussed in Section IV. Second, unit roots in the time series could cause spurious correlations between the dependent and independent variables (Jorgenson 1991; Tatom 1991).

Consider first the problem of unit roots. Table 2 shows augmented Dickey-Fuller tests for unit roots in log(Q), log(L), log(K), and log(H). (See the top part of column B.) If the coefficient on the lagged variable (z_{t-1} in the notation at the bottom of Table 2) is not significantly different from zero, then the hypothesis that the variable has a unit root cannot be rejected. Given that, a t-test for whether the coefficient on the lagged variable is different from zero in Table 2 can be used to test the hypothesis that a variable has a unit root.[7]

Note that the hypothesis of a unit root is not rejected for log(Q), log(L), and log(K). This suggests that the regression in equation (8) must be transformed to eliminate the unit roots. Similar work on states has also demonstrated the appropriateness of transforming the production function to eliminate unit roots (Tatom 1991; Kelejian and Robinson 1994; Garcia-Mila, McGuire, and Porter 1996). The most common transformations are either to difference the data or to re-write the regression in terms of ratios of the variables. Both techniques will be used here.

Assume that equation (8) is derived from a specification that includes log(ACCESS) and $\log(\text{ACCESS})^2$ as shift factors, as shown below.[8]

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[7] The augmented Dickey-Fuller test uses the modified t-tables reported in Fuller 1976, p.373, and also reported in Davidson and MacKinnon 1993, p. 708. The critical t-value, at the 5% level, for the unit root tests in Table 3 is -3.41.

[8] Letting the shift factor include log(ACCESS) and $\log(\text{ACCESS})^2$ is equivalent to taking a second-order translog expansion of g(s) where s includes only one variable, ACCESS.

(continued...)

$$Q = g(s)\, f(L, K, H) \tag{9}$$

Where $\log(g(s)) = \beta_o + \alpha_1 \log(ACCESS) + \alpha_2 \log(ACCESS)^2$
β_0 = a constant
f(L,K,H) is Cobb-Douglas
county and time subscripts have been suppressed
and year dummy variables are not shown.

Assuming constant returns to scale in f(·) allows one to rewrite equation (9) as

$$\frac{Q}{L} = g(s)\, f(\frac{K}{L}, \frac{H}{L}) \tag{10}$$

Taking logs of both sides, assuming f(·) is Cobb-Douglas, and including year dummy variables and an error term gives

$$\begin{aligned} \log(\frac{Q_{c,t}}{L_{c,t}}) &= \alpha_o + \alpha_1 \log(ACCESS_{c,t}) + \alpha_2 \log(ACCESS_{c,t})^2 \\ &+ \alpha_3 \log(\frac{K_{c,t}}{L_{c,t}}) + \alpha_4 \log(\frac{H_{c,t}}{L_{c,t}}) \\ &+ \sum_{i=0}^{9} \alpha_{5+i} YEAR_{1978+i} + e_{c,t} \end{aligned} \tag{11}$$

Column A of Table 2 shows that log(Q/L) and log(K/L) do not have unit roots, although the hypothesis of a unit root cannot be rejected for log(H/L).

Since ACCESS is likely endogenous, it was instrumented. A valid instrument must measure exogenous characteristics of the county's development and road network which affect

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[8](...continued)
For a discussion of translog functional forms, see, e.g., Deaton and Muellbauer (1980), pp. 73-75. For a similar translog expansion of a shift factor, see Henderson (1986).

the ability of highways to facilitate travel. One strategy is to use an instrument that reflects the basic design character of each county's road network. While travel, and thus congestion, are likely endogenous to county output, this research assumes that fundamental highway network design characteristics are pre-determined by highway construction decisions made years earlier.

The variable chosen to measure each county's transportation infrastructure "design character" is the ratio of state highway miles divided by total road miles in the county. Because the choice between highways and arterial streets is heavily influenced by factors such as existing development densities, available land, and past highway and road building, this ratio is assumed to be pre-determined with respect to the year-to-year output levels that are the dependent variable in equations (8) and (11). In 1987, the ratio of state highway miles divided by total road miles ranged from 0.038 for San Francisco County to 0.218 for Amador County.

The log of ACCESS was regressed on a constant and the ratio of state to total road miles. The resulting coefficient estimates were used to get a predicted value of log(ACCESS).[9] The predicted value was used in place of log(ACCESS) in the regressions reported below. The predicted value is denoted by log(ACCESS)-$\wedge$. Column A of Table 2 shows that log(ACCESS)-$\wedge$ and log(ACCESS)-$\wedge^2$ both do not have unit roots.

The results of using log(ACCESS)-$\wedge$, with pooled cross-section time series data in

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[9] Other variables, such as log(L), log(K), and log(H), were not used as instruments to avoid generating a unit root in the predicted value of log(ACCESS). In the first differences specification that is presented later, a more complete two-stage least squares instrument is used, since any unit roots in the predicted value of log(ACCESS) can be eliminated by differencing.

equation (11), are shown in column A of Table 3. As expected, both log(ACCESS)-$\wedge$ and log(ACCESS)-$\wedge^2$ are statistically significant and have opposite signs. The effect of increasing ACCESS is positive for values of ACCESS less than 129, and negative for larger values. This verifies the hypothesis that congestion improvements only have a positive effect for uncongested or nearly congested county highway networks.

Note also that the coefficients on both private capital, log(K/L), and highway infrastructure, log(H/L), are significantly positive. Yet one should be suspicious of the coefficient on log(H/L), since that variable has a unit root in the time series. Lastly, note that the elasticity of private capital is 0.32 in column A, which is consistent with magnitudes from similar production function studies (Aaron 1990).

Column B of Table 3 adds population density to the shift factor to be certain that ACCESS is not proxying for density. (Recall that Table 1 shows a clear relationship between ACCESS and population density.) The shift factor, g(s), now is represented as a second order translog expansion of ACCESS and population density.[10] The log of population density is denoted by log(PDEN).

Again, the coefficient on log(ACCESS)-$\wedge$ is significantly positive and the coefficient on log(ACCESS)-$\wedge^2$ is significantly negative. Evaluating the slope at sample means for 1987, the effect of increasing ACCESS is positive for values less than 128 -- the same result as in column A.

The effect of density and its square are both significantly negative, giving no evidence

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[10] Recall that this is consistent with column A of Table 3. In column A, g(s) contains one argument, and the quadratic representation of log(ACCESS)-$\wedge$ is a second order translog expansion of that more simple g(s).

of urbanization economies, which is consistent with previous research (Henderson 1986). The interaction term is significantly positive, implying that reducing congestion increases the returns to density. The coefficients on log(K/L) and log(H/L) are similar to column A.

Column C of Table 3 shows a specification with H in the shift factor, rather than in the production function. Again, g(s) is represented as a second order translog expansion of its arguments -- ACCESS and H. The results are similar to columns A and B. Evaluating the results at sample means for 1987 shows that the effect of congestion reduction is positive for values of ACCESS less than 125. The interaction between log(ACCESS)-$\wedge$ and log(H) is significantly positive; the returns to highways are greater where there is less congestion. The effect of log(H) is significantly negative. While possibly surprising, significantly negative highway capital elasticities have been found in some specifications in other studies (e.g. Evans and Karras 1994; Holtz-Eakin 1994; Kelejian and Robinson 1994).

Overall, the results are quite stable. ACCESS has the expected quadratic effect, and the relationship changes sign near the hypothesized value.

Equation (8) was also estimated without enforcing the assumption of constant returns to scale. Since the levels of log(Q), log(L), and log(K) have unit roots, equation (8) was estimated in first differences.

Recall that only one instrument for log(ACCESS) was used previously, since the predicted value could not have a unit root in the specification in equation (11). That is no longer a concern, since equation (8) will be estimated in first differences. Now, in addition to the ratio of state highway to total road miles, the instruments also include the density of state highway miles (state highway miles divided by land area), the density of total road miles, the number of state highway miles, the number of total road miles, and population density. All of these variables were assumed to be predetermined by the degree of urbanization and available land in the county and past road construction decisions. Following two-stage least squares, the other inputs in the regression were also used as instruments. Squares and cross-products of all instruments and exogenous inputs were also included in the first-stage regression.[11] Column B of Table 2 shows that both the predicted value of log(ACCESS) and its square have unit roots when this expanded set of instruments is used. This is further evidence that equation (8) should be estimated in first differences.

Augmented Dickey-Fuller tests (not reported here) show that the hypothesis of a unit root is rejected, at better than the 0.01 significance level, for the first differences of all variables used to estimate equation (8). (Test results are available upon request.) First differences has the added advantage of accounting for county-specific fixed effects, as suggested by Evans and Karras (1994), Garcia-Mila, McGuire, and Porter (1996), and Holtz-Eakin (1994) in similar work with state data.

Column A of Table 4 shows that the coefficient on log(ACCESS)-$\wedge$ is significantly positive and the coefficient on log(ACCESS)-$\wedge^2$ is significantly negative. The quadratic effect changes sign at values of ACCESS equal to 103. The estimated coefficients for the inputs are generally smaller in Table 4 than in Table 3, and labor is the only input that is

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[11] This is equivalent to assuming that the first stage regression is

$$\log(ACCESS) = g(I) + f(\log(K), \log(L), \log(H))$$

where both $g(\cdot)$ and $f(\cdot)$ are represented by second order expansions and I equals a vector of the six instruments described above.

consistently significant in Table 4.

Column B includes population density in the shift factor. As in Table 3, the shift factor is a second order translog expansion of its arguments. Now the squared term, log(ACCESS)-$\wedge^2$, is not significant at the 5% level, although it is significant at the 10% level. The coefficient magnitudes suggest that the quadratic effect changes sign at ACCESS equal to 110, which is similar to other results.

Column C shows the effect of including log(H) in the shift factor, instead of making it an input to production. This is the only specification that does not verify the hypothesis that ACCESS affects output. Yet note that the interaction term, log(ACCESS)-$\wedge$*log(H), is significantly positive. This suggests that ACCESS has a positive effect on the returns to highways.

Note that highway capital is not statistically significant in any specification in Table 4. This is consistent with findings from state studies that used fixed effects. Those studies (e.g. Evans and Karras 1994; Garcia-Mila, McGuire, and Porter 1996; Holtz-Eakin 1994; Kelejian and Robinson 1994) generally found that the elasticities of both all public capital and only highway capital were not significantly positive.

Section VI: The Economic Effects of Reduced Congestion

The specifications reported in Tables 3 and 4 can be evaluated using sample data to get elasticities. Table 5 lists the estimated ACCESS elasticity for counties using 1987 data. Counties are listed in ascending order based on the 1987 value of ACCESS. In other words, counties are listed from the most to the least congested in Table 5. The five columns in Table 5 correspond, respectively, to columns A through C of Table 3 and columns A and B of Table 4. Column C of Table 4 is not evaluated, since neither log(ACCESS)-$\wedge$ nor log(ACCESS)-$\wedge^2$ were statistically significant.

Given the quadratic specification for ACCESS, many counties have negative ACCESS elasticities. Those negative elasticities might reflect the inefficiency of reducing traffic on already uncongested roads.[12] On the other hand, traffic reductions on uncongested roads might yield zero, but non-negative, output effects. In that case, the negative externalities might be an artifact of the quadratic specification.

The important point is that either interpretation is consistent with the viewpoint that congestion reduction will only yield economic benefits for already congested highway networks. As theory would suggest, policies to promote congestion reduction (or more efficient use of the highway infrastructure) should focus on areas where congestion is a problem.[13]

The pattern across counties is similar in all columns in Table 5. More congested counties have larger ACCESS elasticities. Yet the range of magnitudes is sensitive to the regression specification. Most notably, the elasticities based on Table 4, where log(Q) was

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[12] If maintenance costs and externalities are ignored, travel on uncongested roads is non-rival. With the focus limited to congestion reduction, eliminating traffic from uncongested roads is inefficient.

[13] This is similar to the insight that one gets from viewing congestion tolls as peak-load pricing. In that case, tolls for traffic reduction should only be charged when traffic is congested. For a discussion of this, see, e.g., Small, Winston and Evans 1989, pp. 84-86.

the dependent variable, are much smaller than those based on Table 3.

This has two interpretations. One could infer that the ACCESS elasticity of labor productivity (the dependent variable in Table 3) is much larger than the ACCESS elasticity of output. In other words, congestion reduction could have a much larger effect on labor productivity than on output. While possible, such a statement should be justified by a model of the relationship between county labor productivity and output. Since such a model has not been developed here, the dramatic differences in the effect of congestion reduction on labor productivity and output is suggested only as a possibility.

The other interpretation is that the elasticities from Table 4 should be preferred. Table 4 relaxes the constant returns to scale assumption used in Table 3, and Table 4 also has the advantage of using county fixed effects. For that reason, the most cautious interpretation focuses on the elasticities in columns D and E of Table 5.

Section VII: Conclusion

Comparing the effects of reducing congestion and increasing the highway stock gives interesting results. The positive effects of congestion reduction are somewhat robust. The effects of increasing the highway stock are more suspect, since the coefficient on that variable was only significant in Table 3, and log(H/L) has a unit root in that specification.

Overall, the evidence supports those who argue that using the existing highway network more efficiently will yield more productive effects than building additional highways. Efficient highway pricing on congested networks appears to have the potential for yielding economic benefits above and beyond the travel time savings that are typically considered by pricing advocates. While the productive effects of highway pricing might be modest, especially given the coefficient estimates in Table 4, they are statistically significant in five of the six specifications tested here.

The idea that urban traffic congestion can be best managed by pricing is well established in academia. A focus on the infrastructure stock obscures the potential for efficient pricing policies to yield economic benefits. This work suggests that additional economic benefits from highways can best be realized by using the existing stock more efficiently, rather than by pouring more concrete.

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Table 1: ACCESS and Population Density by County for 1987

County	ACCESS	pop. dens.	County	ACCESS	pop. dens.
Alameda	59.21	2.6164	Orange	71.09	4.4293
Alpine	210.66	0.0025	Placer	80.27	0.1628
Amador	105.81	0.0669	Plumas	163.19	0.0120
Butte	133.96	0.1591	Riverside	114.47	0.1992
Calaveras	82.07	0.0450	Sacramento	89.63	1.5059
Colusa	130.04	0.0200	San Benito	126.45	0.0372
Contra Costa	63.89	1.5835	San Bernardino	112.71	0.0933
Del Norte	136.25	0.0302	San Diego	96.40	0.8403
El Dorado	77.37	0.1032	San Francisco	67.40	25.75
Fresno	104.52	0.1564	San Joaquin	113.19	0.4926
Glenn	154.19	0.0273	San Luis Obispo	122.71	0.0951
Humboldt	150.96	0.0497	San Mateo	79.32	2.1459
Imperial	291.96	0.0398	Santa Barbara	89.33	0.1957
Inyo	195.64	0.0028	Santa Clara	61.72	1.5232
Kern	125.01	0.0968	Santa Cruz	63.64	0.7934
Kings	165.12	0.0985	Shasta	129.64	0.0557
Lake	145.21	0.0632	Sierra	155.59	0.0055
Lassen	198.38	0.0091	Siskiyou	180.07	0.0106
Los Angeles	77.14	3.2653	Solano	87.59	0.5630
Madera	125.52	0.0584	Sonoma	62.29	0.3508
Marin	63.47	0.6842	Stanislaus	117.11	0.4446
Mariposa	203.14	0.0150	Sutter	138.71	0.1552
Mendocino	109.62	0.0334	Tehama	150.73	0.0241
Merced	129.77	0.1310	Trinity	148.65	0.0067
Modoc	380.42	0.0036	Tulare	143.52	0.0941
Mono	174.13	0.0047	Toulumne	81.23	0.0308
Monterey	102.36	0.1613	Ventura	101.86	0.5302
Napa	84.94	0.2169	Yolo	132.66	0.1949
Nevada	90.58	0.1179	Yuba	124.94	0.1366

Table 2: Unit Root Tests

Column A		Column B	
variable	coef. on lagged var.	variable	coef. on lagged var.
log(Q/L)	-0.0314 (-3.728)	log(Q)	0.001 (0.719)
log(K/L)	-0.0650 (-5.007)	log(L)	0.001 (0.763)
log(H/L)	-0.003 (-1.049)	log(K)	0.002 (0.517)
log(ACCESS)-Λ	-0.059 (-4.271)	log(H)	0.004 (4.443)
log(ACCESS)-Λ^2	-0.061 (-4.392)	log(ACCESS)-Λ	-0.030 (-2.818)
		log(ACCESS)-Λ^2	-0.035 (-3.289)

The test Regression for a variable, z, is:

$$\Delta z_t = \alpha_0 + \beta_1 z_{t-1} + \beta_2 \Delta z_{t-1} + \gamma t + \varepsilon$$

The estimated coefficient for the lagged variable, z_{t-1}, is shown in the table. That is the estimated value of β_1. The t-statistic for β_1 is in parentheses below the coefficient estimate. The critical t-values needed for a test of the hypothesis that β_1 is equal to zero are tabulated in Fuller (1976), p. 373. The 5% critical t-value for β_1 is -3.41. For a discussion of the above test regression, see Davidson and McKinnon (1993), pp. 710-715. The hypothesis of a unit root can be rejected for any variable where the t-statistic shown in parentheses is less than -3.41. Column A shows unit root tests for the variables used to estimate equation (11). (Regression results for equation 11 are reported in Table 3.) Column B shows unit root tests for the levels of the variables in equation (8). (Regression results for equation 8, estimated in first differences, are shown in Table 4.) The number of observations for the test regression is 522 in both columns A and B.

Table 3: Regression Results -- Dependent Variable = log(Q/L)

Independent Variable	Column A	Column B	Column C
log(ACCESS)-Λ	60.451 ** (4.394)	12.667 * (5.251)	22.824 ** (8.398)
log(ACCESS)-Λ^2	-6.215 ** (0.444)	-1.194 * (0.545)	-3.403 ** (0.661)
log(PDEN)		-2.337 ** (0.287)	
log(PDEN)^2		-0.013 ** (0.002)	
log(ACCESS)-Λ*log(PDEN)		0.485 ** (0.060)	
log(H)			-2.563 ** (0.781)
log(H)^2			0.001 (0.006)
log(ACCESS)-Λ*log(H)			0.509 ** (0.125)
log(K/L)	0.322 ** (0.023)	0.240 ** (0.020)	0.314 ** (0.023)
log(H/L)	0.072 ** (0.011)	0.205 ** (0.017)	
constant	-139.998 ** (10.822)	-26.617 * (12.698)	-21.401 (26.826)
R^2	0.6254	0.7519	0.6393
R^2_{adj}	0.6170	0.7451	0.6300
N	638	638	638

* statistically significant at the 0.05 level
** statistically significant at the 0.01 level

Standard errors are in parentheses.
Coefficients on year dummy variables not reported in table.

Table 4: Regression Results -- Dependent Variable = log(Q)

Independent Variable	Column A	Column B	Column C
log(ACCESS)-Λ	0.640 * (0.254)	0.961 * (0.477)	-0.969 (0.704)
log(ACCESS)-Λ^2	-0.069 ** (0.026)	-0.102 (0.052)	-0.003 (0.378)
log(PDEN)		0.097 (0.109)	
log(PDEN)^2		0.013 (0.010)	
log(ACCESS)-Λ*log(PDEN)		-0.004 (0.015)	
log(H)			-0.826 (1.15)
log(H)^2			0.019 (0.029)
log(ACCESS)-Λ*log(H)			0.048 * (0.020)
log(L)	0.098 ** (0.026)	0.100 ** (0.026)	0.086 ** (0.026)
log(K)	0.024 (0.017)	0.022 (0.017)	0.0354 * (0.0177)
log(H)	0.129 (0.072)	0.129 (0.072)	
R^2	0.6213	0.6226	0.6254
R^2_{adj}	0.6112	0.6105	0.6140
N	580	580	580

* statistically significant at the 0.05 level
** statistically significant at the 0.01 level

Results are from first differences specification.
Standard errors are in parentheses.
Coefficients on year dummy variables not reported in table.

Table 5: Elasticities, by county

County	column A	column B	column C	column D	column E
Alameda	9.72	3.39	6.05	0.08	0.12
Santa Clara	9.21	3.03	5.83	0.07	0.12
Sonoma	9.09	2.29	5.04	0.07	0.12
Marin	8.86	2.57	4.69	0.07	0.12
Santa Cruz	8.83	2.64	4.48	0.07	0.11
Contra Costa	8.78	2.96	5.25	0.07	0.11
San Francisco	8.11	4.19	4.70	0.06	0.09
Orange	7.45	3.21	4.94	0.05	0.09
Los Angeles	6.43	2.86	5.14	0.04	0.07
El Dorado	6.40	1.18	3.20	0.04	0.08
San Mateo	6.09	2.59	3.69	0.04	0.07
Placer	5.94	1.31	3.07	0.03	0.07
Toulumne	5.79	0.48	2.44	0.03	0.08
Calaveras	5.67	0.64	2.12	0.03	0.07
Napa	5.24	1.32	2.34	0.03	0.06
Solano	4.86	1.71	2.52	0.02	0.05
Santa Barbara	4.61	1.15	2.54	0.02	0.05
Sacramento	4.57	2.13	2.89	0.02	0.04
Nevada	4.44	0.87	1.97	0.02	0.05
San Diego	3.66	1.67	2.90	0.01	0.03
Ventura	2.98	1.32	1.92	0.00	0.02
Monterey	2.92	0.73	1.64	0.00	0.02
Fresno	2.66	0.66	1.76	0.00	0.02
Amador	2.51	0.22	0.46	0.00	0.02
Mendocino	2.07	-0.20	1.06	0.00	0.02
San Bernardino	1.72	0.23	1.48	-0.01	0.00
San Joaquin	1.67	1.03	1.14	-0.01	0.00
Riverside	1.53	0.56	1.36	-0.01	0.00
Stanislaus	1.25	0.90	0.52	-0.02	0.00
San Luis Obispo	0.66	0.04	0.20	-0.02	-0.01
Yuba	0.44	0.17	-0.57	-0.03	-0.02
Kern	0.43	0.00	0.54	-0.03	-0.01

Table 5: Elasticities (continued)

County	column A	column B	column C	column D	column E
Madera	0.38	-0.25	-0.44	-0.03	-0.01
San Benito	0.29	-0.49	-0.91	-0.03	-0.01
Shasta	-0.02	-0.35	-0.17	-0.03	-0.02
Merced	-0.03	0.06	-0.34	-0.03	-0.02
Colusa	-0.06	-0.85	-0.84	-0.03	-0.02
Yolo	-0.30	0.20	-0.33	-0.03	-0.03
Butte	-0.43	0.08	-0.56	-0.04	-0.03
Del Norte	-0.64	-0.77	-0.98	-0.04	-0.03
Sutter	-0.86	-0.02	-1.14	-0.04	-0.04
Tulare	-1.28	-0.34	-0.83	-0.05	-0.04
Lake	-1.43	-0.56	-1.63	-0.05	-0.04
Trinity	-1.72	-1.71	-1.67	-0.05	-0.04
Tehama	-1.89	-1.12	-1.61	-0.05	-0.05
Humboldt	-1.91	-0.77	-1.88	-0.05	-0.05
Glenn	-2.17	-1.11	-2.03	-0.06	-0.05
Sierra	-2.29	-1.91	-2.27	-0.06	-0.05
Plumas	-2.88	-1.64	-2.35	-0.06	-0.06
Kings	-3.02	-0.65	-2.26	-0.06	-0.07
Mono	-3.69	-2.25	-2.60	-0.07	-0.07
Siskiyou	-4.10	-1.94	-2.46	-0.08	-0.08
Inyo	-5.13	-2.79	-3.55	-0.09	-0.09
Lassen	-5.31	-2.24	-3.64	-0.09	-0.10
Mariposa	-5.60	-2.06	-4.13	-0.09	-0.11
Alpine	-6.05	-3.00	-4.70	-0.10	-0.11
Imperial	-10.11	-2.45	-5.81	-0.14	-0.18
Modoc	-13.40	-4.26	-8.31	-0.18	-0.23

Counties listed in ascending order by 1987 value of ACCESS (i.e. from most congested to least congested)

Column A is based on the coefficient estimates in Table 3, column A.
Column B is based on the coefficient estimates in Table 3, column B.
Column C is based on the coefficient estimates in Table 3, column C.
Column D is based on the coefficient estimates in Table 4, column A.
Column E is based on the coefficient estimates in Table 4, column B.

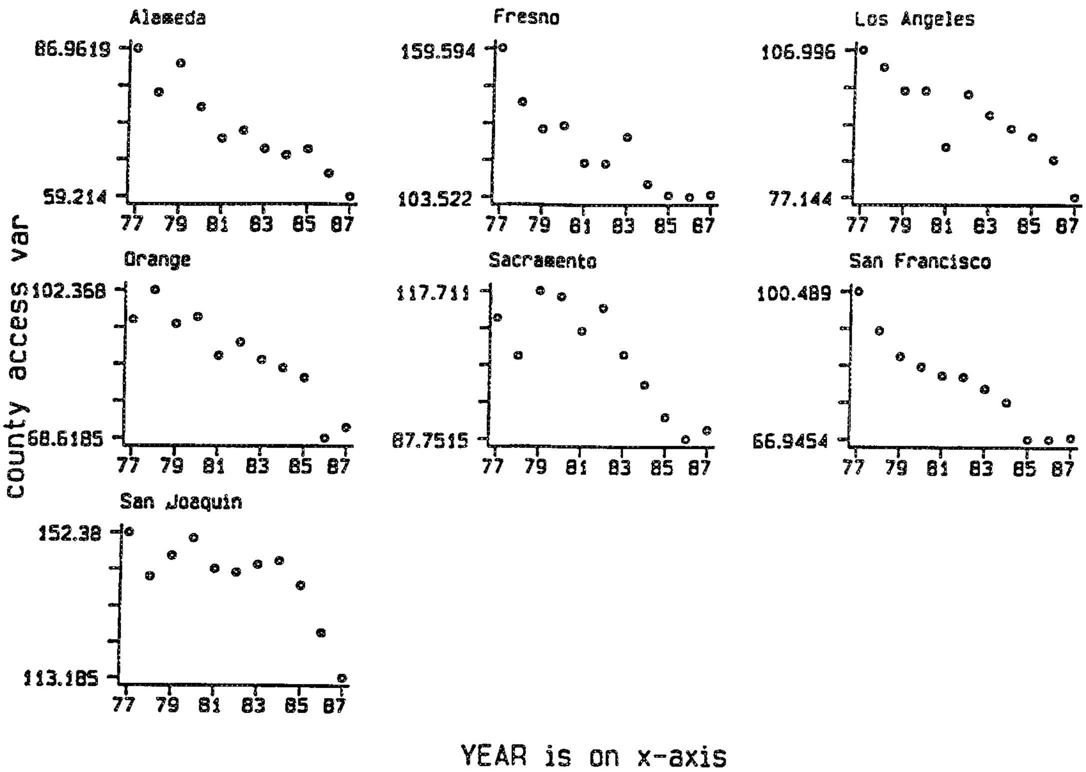

Figure 1: ACCESS by County