The Effects of Public Transit Supply on the Demand for Automobile Travel*

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Abstract

Public transit is often advocated as a means to address traffic congestion within urban transportation networks. We estimate the effect of past public transit investment on the demand for automobile transportation by applying an instrumental variable approach that accounts for the potential endogeneity of public transit investment, and that distinguishes between the substitution effect and the equilibrium effect, to a panel dataset of 96 urban areas across the U.S. over the years 1991-2011. The results show that, owing to the countervailing effects of substitution and induced demand, the effects of increases in public transit supply on auto travel depend on the time horizon. In the short run, when accounting for the substitution effect only, we find that on average a 10% increase in transit capacity leads to a 0.7% reduction in auto travel. However, transit has no effect on auto travel in the medium run, as latent and induced demand offset the substitution effect. In the long run, when accounting for both substitution and induced demand, we find that on average a 10% increase in transit capacity is associated with a 0.4% increase in auto travel. We also find that public transit supply does not have a significant effect on auto travel when traffic congestion is below a threshold level. Additionally, we find that there is substantial heterogeneity across urban areas, with public transit having significantly different effects on auto travel demand in smaller, less densely populated regions with less-developed public transit networks than in larger, more densely populated regions with more extensive public transit networks.

JEL Classifications: D62, H23, H54, Q58, R41, R42, R48, R53

Keywords: traffic congestion, public transit investment, urban transportation, automobile travel, induced demand

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1 Introduction

Anyone who has idled in traffic anxiously watching the clock is all too familiar with the costs of traffic congestion. Congestion is ubiquitous across urban roadways and is a persistent topic of policy debate. The external costs of congestion – which include increased operating costs for both private and freight vehicles, increased fuel usage and emissions, and, most significantly, the delay costs and uncertain travel times confronting motorists – are substantial and have been steadily increasing.[1] In 2011, these costs of traffic congestion alone have been estimated to have exceeded \$121 billion in the U.S. (Schrank, Eisele and Lomax, 2012). Congestion has steadily increased in recent decades: from 1983 to 2001, for example, average car travel time increased by 30% and average transit travel time increased by 62.5% for a sample of large metropolitan statistical areas in the U.S. (Berechman, 2009).[2]

Congestion costs represent the majority of the external costs of automobile travel for urban commuters in the U.S.: of the combined per vehicle-mile costs of congestion, accidents, and environmental externalities for urban commuters in the U.S., congestion costs represent 71.7% of the short-run average variable social cost of auto travel and 74.3% of the short-run marginal variable social cost (Small and Verhoef, 2007).[3]

As one component of broader urban transportation policy, public transit is often advocated as a means to decrease traffic congestion and reduce emissions from automobiles. Additionally, large-scale public transit investments are often championed due to purported local and/or regional economic development benefits accompanying the construction and operation of the new transit system. In the U.S., in addition to annual transit operating expenses of \$38 billion per year, recent expenditures on public transit capital have exceeded \$18 billion per year (American Public Transportation Association, 2012).

Public transit investments should be evaluated on their contribution to overall net social welfare, taking into account the cost of the investment and any associated operating costs. While the broader question as to how public transit should be funded and its role in the U.S. urban transportation sector is important and has been addressed by others such as Viton (1981) and Winston and Shirley (1998), the congestion-reduction effect of public transit is a potentially important com-

[1] Congestion can be particularly costly if individuals exhibit preferences for urgency owing to time constraints, schedule constraints, and possible penalties for being late (Bento, Roth and Waxman, 2017).

[2] In addition, as we show in Section 3 using the population-weighted mean values across 96 large urban areas in the U.S., total hours of delay attributable to congestion increased by 55% over the period 1991 to 2011.

[3] Similarly, of the externalities associated with gasoline consumption that Lin and Prince (2009) analyze in their study of the optimal gasoline tax for the state of California, the congestion externality is the largest and should be taxed the most heavily, followed by oil security, accident externalities, local air pollution, and global climate change.

ponent of this overall evaluation process, and to date there has not been an empirical consensus on the magnitude of this effect.[4]

Although policymakers may wish to use public transit investment as a policy instrument to both reduce congestion and spur economic activity, these two objectives are often incompatible.[5] On the one hand, an increase in transit supply may cause some commuters to substitute transit travel for trips previously taken by automobile (the "substitution effect"), thereby decreasing auto travel. On the other hand, by reducing congestion, increasing accessibility, increasing economic activity, and/or attracting additional residents and workers to the area, transit investment may generate additional automobile trips that were previously not undertaken (the "induced demand effect"). The "equilibrium effect" accounts for both the substitution effect and the induced demand effect.

In this paper, we consider the effect of public transit supply on the volume of auto travel. Specifically, we address the following questions:

1. Have past public transit investments been effective in reducing the demand for automobile travel in the U.S.?

2. Is it possible to disentangle the substitution effect and the induced demand effect due to public transit supply?

Our measure of public transit supply is the public transit capacity in vehicle-revenue miles, where public transit includes commuter rail, light rail, heavy rail, hybrid rail, monorail, automated guideway, bus rapid transit, bus, and trolleybus. We empirically estimate the effect of past public transit investment on the demand for automobile transportation by applying an instrumental variable approach that accounts for the potential endogeneity of public transit investment, and that distinguishes between the substitution effect and the equilibrium effect, to a panel dataset of 96 urban areas across the U.S. over the years 1991-2011.

The results show that, owing to the countervailing effects of substitution and induced demand, the effects of increases in public transit supply on auto travel depend on the time horizon. In the short run, when accounting for the substitution effect only, we find that on average a 10% increase in transit capacity leads to a 0.7% reduction in auto travel. However, transit has no effect on auto travel in the medium run, as latent and induced demand offset the substitution effect. In the long

[4] Beaudoin, Farzin and Lin Lawell (2018) develop a theoretical model of optimal public transit investment to evaluate whether public transit investment has a role in reducing congestion in a second-best setting when a Pigouvian congestion tax cannot be levied on auto travel.

[5] For example, employment growth, a common public policy goal, can lead to a number of unwanted environmental, social, and economic costs – particularly in high growth communities – due to its impact on peak-hour traffic. Morrison and Lin Lawell (2016) find that for each additional 10 workers added per square kilometer, travel time increases by 0.171 to 0.244 minutes per one-way commute trip per commuter in the short run, which equates to \$0.07 to \$0.20 in travel time cost per commuter per day.

run, when accounting for both substitution and induced demand, we find that on average a 10% increase in transit capacity is associated with a 0.4% increase in auto travel. We also find that public transit supply does not have a significant effect on auto travel when traffic congestion is below a threshold level.

Additionally, we find that there is substantial heterogeneity across urban areas. When accounting for the substitution effect only, the magnitude of the elasticity of auto travel with respect to transit capacity varies from approximately -0.008 in smaller, less densely populated regions with less-developed public transit networks; to approximately -0.215 in larger, more densely populated regions with more extensive public transit networks. When accounting for both the substitution effect and the induced demand effect in the long run, the elasticity of auto travel with respect to transit capacity varies from approximately 0.005 in smaller, less densely populated regions with less-developed public transit networks; to approximately 0.129 in larger, more densely populated regions with more extensive public transit networks.

By using a broader set of urban areas over a longer time period than previous studies; by distinguishing between the substitution effect and the equilibrium effect; and by accounting for regional heterogeneity across urban areas where transit investments occur, our empirical analysis helps explain the previous literature's seemingly conflicting empirical results on the relationship between transit supply and traffic congestion.

The balance of our paper proceeds as follows. We review the related literature in Section 2. We present a conceptual model and our empirical models for analyzing public transit and the demand for automobile travel in Section 3. We describe our data in Section 4 and present our results in Section 5. Section 6 concludes.

2 Literature Review

The link between pricing and investment in auto travel was recognized in the seminal papers by Mohring and Harwitz (1962) and Vickrey (1969), with a recent treatment by Lindsey (2012). While investment in roadway infrastructure may lead to short-term reductions in congestion, it may be ineffective in the long run in the absence of efficient pricing, as improvements in travel conditions will induce additional demand for auto travel (Hau, 1997). This predicted effect is known as the 'fundamental law of traffic congestion' and traces back to Downs (1962); it is analogous to the Tragedy of the Commons associated with any non-excludable and congestible resource, and has been demonstrated empirically by Duranton and Turner (2011), who show that auto travel volumes increase proportionally with the available auto capacity.

The concept of induced auto travel following improved travel conditions is also applicable to investment in public transit. Increasing the relative attractiveness of transit travel may initially cause a subset of commuters to switch from auto to transit. However, by reducing congestion, increasing accessibility, increasing economic activity, and/or attracting additional residents and workers to the area, transit investment may generate additional automobile trips that were previously not undertaken. As Small and Verhoef (2007) note, the introduction of Bay Area Rapid Transit (BART) service between Oakland and San Francisco in the early 1970s led to 8,750 automobile trips being diverted to BART; however, 7,000 new automobile trips were subsequently generated, diminishing the net reduction in travel during peak periods. Additionally, investments in mass transit may lead to localized economic development and land-use changes, which, even if considered to be 'transit-oriented development', may still generate automobile trips that countervail potential traffic congestion reductions due to the initial cross-modal travel substitution (Stopher, 2004; Small and Verhoef, 2007).

Existing empirical studies of the relationship between public transit investment and traffic congestion can be summarized as follows.[6] Baum-Snow and Kahn (2005) analyze 16 new and/or expanded rapid rail transit systems in large, dense U.S. cities over the period 1970-2000. They find that rail transit investment does not reduce congestion levels and that variation in metropolitan area structure (primarily population density) both within and between regions is an important factor leading to heterogeneous responses of commuters with respect to mode choice following expanded rail service. Winston and Langer (2006) analyze the effects of roadway expenditures on the cost of congestion in 72 large urban areas in the U.S. over the period 1982-1996. They find that rail transit mileage leads to a decrease in congestion costs, but that increases in bus service actually exacerbate congestion costs. Winston and Maheshri (2007) examine 25 rail systems in the U.S. from 1993-2000. They estimate that in 2000 these rail systems generated approximately $2.5 billion in congestion cost savings. This estimate is derived by comparing observed congestion costs with those that would arise in the counterfactual scenario where the rail systems were not constructed, based on the empirical results of Winston and Langer (2006); their approach does not provide an estimate of the marginal congestion reduction attributable to incremental changes in existing rail service levels. Nelson et al. (2007) use a simulation model calibrated for Washington, DC and find that rail transit generates congestion-reduction benefits large enough to exceed total rail subsidies.

Duranton and Turner (2011) find empirical support for the 'fundamental law of traffic congestion'

[6] See Beaudoin, Farzin and Lin Lawell (2015) and Beaudoin and Lin Lawell (2017) for detailed discussions and comparisons of these studies. There is also a burgeoning literature on public transit investment and air quality (Anas and Timilsina, 2009; Cutter and Neidell, 2009; Chen and Whalley, 2012; Sexton, 2012; Lalive, Luechinger and Schmutzler, 2013; Rivers, Saberian and Schaufele, 2017; Bauernschuster, Hener and Rainer, 2017; Beaudoin and Lin Lawell, 2018); see Beaudoin, Farzin and Lin Lawell (2015) and Beaudoin and Lin Lawell (2018) for reviews and discussions of this literature.

and convincing evidence of induced demand: increases in road capacity are met with commensurate increases in auto travel. In the course of their analysis, they also find that the level of public transit service does not affect the volume of auto travel, though they do not estimate the effect on congestion *per se*. Controlling for the potential endogeneity of transit service and auto travel, their analysis covers 228 Metropolitan Statistical Areas in the U.S. for the years 1983, 1993, and 2003.

Anderson (2014) uses a regression discontinuity design based on a 2003 labor dispute within the Los Angeles transit system, and finds that average highway delay increases by 47% when transit service ceases operation. He also finds that heterogeneity in congestion levels within a city leads to congestion reduction from transit roughly six times larger than when there is homogeneous congestion levels facing commuters. As was the case with Winston and Maheshri (2007), Anderson (2014) provides strong evidence of the effects of transit on congestion at the *extensive* margin (i.e. comparing the outcome of an existing transit network with the counterfactual absence of any transit services), but in addition to only being a short-term effect that may potentially be specific to the Los Angeles transportation network, it does not address the effect of transit on congestion at the *intensive* margin (i.e. comparing incremental changes in the level of transit service provided relative to the existing network).

The effects of mass transit have recently been examined in various contexts. Bauernschuster, Hener and Rainer (2017) use a similar research design to Anderson (2014) and find that transit strikes in Germany resulted in an 11-13% increase in total hours spent in cars during these strikes, and a commensurate increase in accident and emission externalities. Using a regression discontinuity framework, Yang et al. (2018) find that subway openings in Beijing in the last decade led to an average reduction in travel delays of approximately 15% across Beijing, following a near doubling of the rail network in the city. Mayer and Trevien (2017) estimate that commuter rail openings in Paris led to localized employment increases, but no detectable effect on overall population growth.

Hamilton and Wichman (2018) study the impact of bicycle-sharing infrastructure on urban transportation, and find that the availability of a bikeshare reduces traffic congestion upwards of 4% within a neighborhood. They also estimate heterogeneous treatment effects using panel quantile regression, and find that the congestion-reducing impact of bikeshares is concentrated in highly congested areas.

Overall, the existing empirical evidence of the effect of transit investment on traffic congestion is mixed. Anderson (2014) summarizes the literature by recognizing that while public transit service may have a minimal impact on total travel volumes, it may still have a large impact on congestion levels, depending on how induced demand occurs along the various margins of the travel decision (whether to travel, which mode to use, which route to take, and the timing of the trip if taken).

The conflicting conclusions of previous studies may also be due to differences in empirical methodologies employed and the characteristics of the dataset used. Our paper adds further evidence to this issue by using a broader set of urban areas over a longer time period than previous studies; by distinguishing between the substitution effect and the equilibrium effect; and by accounting for regional heterogeneity across urban areas where transit investments occur. The importance of the time horizon and of regional heterogeneity that our results indicate helps reconcile the literature's seemingly conflicting evidence.

3 Public Transit and the Demand for Automobile Travel

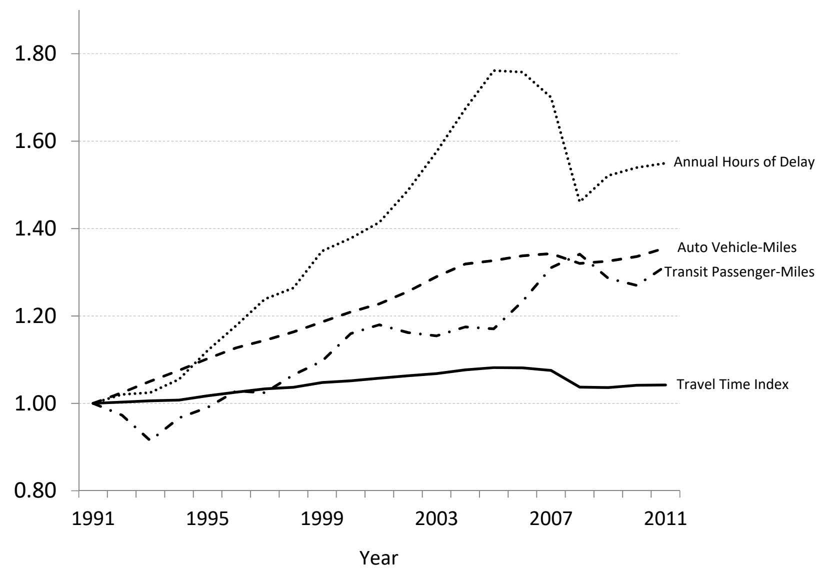
Figure 1 displays the growth in congestion and travel volumes for a representative urban area in the U.S. over the period 1991 to 2011, calculated using the population-weighted mean values across 96 large urban areas (UZAs) in the U.S.,[7] with the indices for the 1991 values normalized to 1.00. Auto data are from the Texas Transportation Institute's Urban Mobility Report and transit data are from the Federal Transit Administration's National Transit Database; both are described in detail in Section 4. On average, the total hours of delay attributable to congestion increased by 55% over this period, associated with a 36% increase in auto travel and a 34% increase in transit travel, respectively. Travel times have increased by 4% over this same period, with the total delay hours being relatively higher due to the growing population and more commuters being exposed to the congestion externality.

Figure 2 provides an overview of U.S. public transit over the period 1991 to 2011, using data from the Federal Transit Administration's National Transit Database, which is described in detail in Section 4. Indices are again a population-weighted average across the 96 urban areas (UZAs) and normalized so that their 1991 value is 1.00. Transit service frequency (as measured by vehicle revenue-miles per directional route-mile) has remained fairly steady over time, while overall transit network coverage (directional route-miles) has increased by 18%, which suggests that the increased transit ridership is mostly associated with increased transit accessibility.

Some analysts (e.g., Rubin and Mansour (2013)) have argued that increased congestion in the presence of increased public transit supply indicates that public transit is an ineffective tool to reduce congestion. However, one must consider the counterfactual congestion that would exist in the absence of this change in transit supply and assess congestion levels within the context of growing population and per capita income over time (see Noland (2001), Berechman (2009) and Litman (2014) for a discussion of the underlying contributors to auto travel growth). These considerations

[7] As described in detail in Section 4, an 'urban area' (UZA) is defined by the U.S. Census Bureau and refers to a region that is centered around a core metropolitan statistical area (MSA).

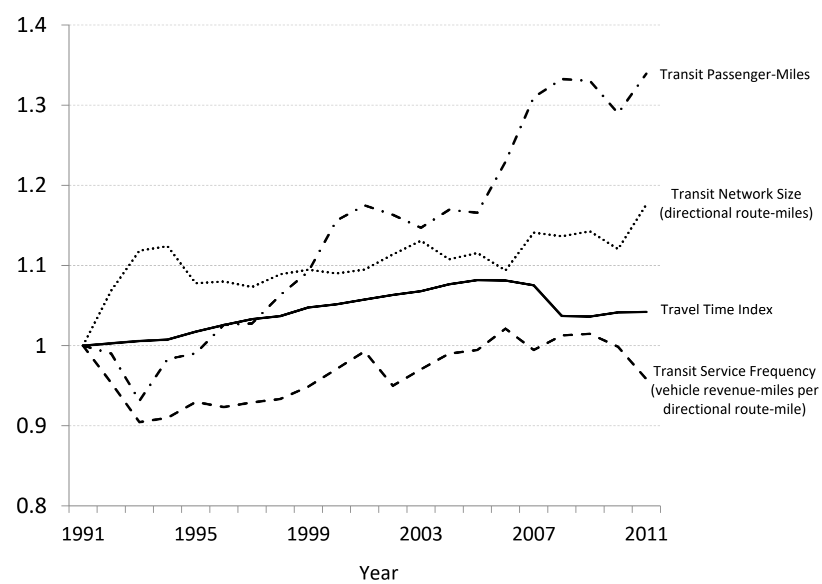
Figure 1: Growth in congestion and travel volumes



Note: The graph shows trends in traffic congestion, auto travel, and transit travel for a representative urban area in the U.S. over the period 1991 to 2011, calculated using the population-weighted mean values across 96 large urban areas (UZAs) in the U.S., with the indices for the 1991 values normalized to 1.00.

Data Sources: Auto data are from the Texas Transportation Institute's Urban Mobility Report and transit data are from the Federal Transit Administration's National Transit Database.

Figure 2: Overview of U.S. public transit



Note: The graph shows trends in traffic congestion, transit travel, and transit supply over the period 1991 to 2011. Indices are a population-weighted average across 96 large urban areas (UZAs) and normalized so that their 1991 value is 1.00.

Data Source: Federal Transit Administration's National Transit Database.

of induced demand are especially important in the equilibrium framework one should use to evaluate public transit investment.

The ability of public transit supply to reduce congestion levels hinges on the degree to which auto users switch to transit following a reduction in the cost of transit travel, which depends on both the substitution effect and the induced demand effect. We now present our conceptual model and then our empirical models for disentangling the effects of modal substitution and induced demand following increases in transit supply.

3.1 Conceptual Model

We begin with a simple conceptual model that explains the substitution effect and the induced demand effect, and how changes in public transit capacity may change auto travel demand in the short run, medium run, and long run. For a more detailed theoretical model of the effects of public transit investment on auto travel demand, see Beaudoin, Farzin and Lin Lawell (2018).

The level of public transit supplied in a region influences the demand for automobile travel in two ways: (1) by determining the total volume of travel across the urban transportation network, and (2) by influencing the modal distribution of trips across the transit and automobile modes. Moreover, the incentive to substitute across modes is subject to the regulations in place regarding urban auto travel; notably, in the absence of a Pigouvian tax on auto travel in congested conditions, the ratio of the marginal private cost of travel and the marginal social cost of travel across modes is distorted.

We are interested in estimating the net effect of changes in the supply of transit on observed levels of automobile travel, in the absence of a Pigouvian congestion tax on auto travel. In other words, we are estimating the effect of transit given existing policies in place, and therefore must account for induced auto demand due to the inefficient pricing of auto travel.

An increase in the supply of transit affects the relative cost of auto and transit travel. The marginal private cost of auto travel is given by the sum of the monetary cost of auto travel (which includes the variable out-of-pocket expenses such as fuel), the monetized value of time spent traveling, and the per-unit tax levied on auto travel (if any). Similarly, the marginal private cost of transit travel is given by the sum of the transit fare and the monetized values of the access, wait, and travel times required for transit trips. Both the equilibrium volume of total travel and the modal distribution of trips are functions of the equilibrium values of these generalized costs.

An increase in transit supply primarily reduces the access and wait times associated with public transit use, which has been demonstrated to have a much more significant effect on modal choice than changes in monetary costs (Wardman, 2004). This reduction in the generalized cost of transit travel may lead to a downward shift in the auto demand curve following an increase in transit capacity, if the cross-elasticity between modes is positive.

In the short run, an increase in transit supply may therefore cause some commuters to substitute transit travel for trips previously taken by automobile (the "substitution effect"), thereby decreasing auto travel. In the medium and long run, by reducing congestion, increasing accessibility, increasing economic activity, and/or attracting additional residents and workers to the area, transit investment may generate additional automobile trips that were previously not undertaken (the "induced demand effect"). The "equilibrium effect" accounts for both the substitution effect and the induced demand effect.

A complementary view of the induced demand effect relies on a spatial equilibrium model of an open urban city. In equilibrium, individuals must be indifferent across cities. Transportation costs are a potential source of inter-regional compensating variation, and investment in public transit can lead to inter-regional migration in the long run. Thus, any short-run increase in income levels and/or decrease in transportation costs following improved transit supply will induce migration into the city in the long run, until these differentials are eroded by increased population and traffic congestion. Additionally, there may be positive agglomeration externalities associated with large-scale transit projects, for example from network effects following accessibility improvements, which may also attract additional residents and workers to the area in the long run. Both of these effects would lead to an upward shift in the auto demand curve in the long run.

More formally, spatial equilibrium requires the equalization of utility $U_{irt}(\cdot)$ across individuals i and across regions r, so that the following condition must hold at time t for all individuals i and for all regions r and r' in the long run:

$$U_{irt}\left(P_{rt}\left(n_{rt}\right), Y_{irt}\left(n_{rt}\right), g_{irt}\left(n_{rt}, K_{rt}^{T}\right), a_r\right) = U_{ir't}\left(P_{r't}\left(n_{r't}\right), Y_{ir't}\left(n_{r't}\right), g_{ir't}\left(n_{rt}, K_{r't}^{T}\right), a_{r'}\right),$$

where, Y_{irt} is individual i's income; and where for each region r, n_{rt} is the population in region r at time t; K_{rt}^{T} is the supply of public transit; a_r is a vector of amenities; P_{rt} is a vector of non-transportation prices (including housing); and g_{irt} is the generalized cost of travel for individual i, which reflects the monetary and non-monetary costs of a trip, including congestion costs. Assuming individuals choose to take the lower cost mode of travel, the generalized cost of travel is given by $g_{irt} = min\left\{g_{irt}^{T}, g_{irt}^{A}\right\}$, where T denotes transit and A denotes auto.

In the short run, an increase in public transit K_{rt}^{T} leads to a decrease in the generalized cost of travel g_{irt} and an increase in utility U_{irt}, which subsequently leads to an increase in the population n_{rt} in region r, with the rate of population growth dependent on the transaction costs and frictions associated with relocation. This increase in population then reduces utility U_{irt} by increasing non-transportation prices, decreasing income, and/or increasing transportation costs, and migration between regions will continue until utility levels are again equalized across regions.

It follows that the level of auto travel will be affected by transit investment over time. In the short run, individuals may switch from auto to transit as the generalized cost of transit travel g_{irt}^T falls. However, in the medium run, this will lead to induced auto travel for two reasons: (1) any initial substitution away from auto travel will lower the cost of auto travel by reducing congestion and this will then lead to replacement auto trips, and (2) population growth in the region due to the mechanism outlined in the model above. In the long run, this population growth will have a more significant effect on auto travel as the inter-region migration flows increase.

To disentangle the effects of modal substitution and induced demand following transit supply increases, we estimate three different models of the effect of transit supply on auto travel volumes. We now describe these empirical models for estimating the substitution effect, the medium-run equilibrium effect, and the long-run equilibrium effect, respectively.

3.2 Modal Substitution Effect

To estimate the modal substitution effect, we analyze the effect that transit supply has on observed auto traffic levels in region r at year t while controlling for factors that would lead to induced demand, including employment rate, income, and population. Our regression model for the substitution effect is given by:

$$\begin{aligned}\text{Auto travel}_{rt} = \;&\beta_1\cdot\text{Transit Capacity}_{rt} + \beta_2\cdot\text{Freeway Capacity}_{rt} + \beta_3\cdot\text{Arterial Road Capacity}_{rt}\\ &+ \beta_4\cdot\text{Fuel Cost}_{rt} + \beta_5\cdot\text{Transit Fare}_{rt} + \beta_6\cdot\text{Employment}_{rt} + \beta_7\cdot\text{Income}_{rt}\\ &+ \beta_8\cdot\text{Population}_{rt} + \text{Year Effects} + \text{UZA Fixed Effects} + \varepsilon_{rt},\end{aligned} \tag{1}$$

where the observed level of auto travel is measured as the number of vehicle-miles traveled per freeway lane-mile, transit supply is measured as the total transit in terms of vehicle revenue-miles,[8] and auto capacity is measured by the number of lane-miles (distinguishing between freeway and arterial roads). The monetary cost of auto travel is measured by the fuel cost per vehicle-mile

[8] The level of transit supplied is measured most accurately by the total capacity of the network, given by the vehicle-revenue miles of service provided (Small and Verhoef, 2007). It is not possible to separately identify the effects of transit accessibility (directional route-miles) and transit capacity (vehicle revenue-miles) at the aggregate level of the transportation network, given the significant collinearity of the two measures: the correlation between these measures is 0.907 and there is very little spatial and temporal variation in vehicle revenue-miles traveled per directional route-mile.

traveled and the transit fare is the average per-trip fare revenue received. Socioeconomic and regional control variables include employment rate, income, and population. Year effects and urban area (UZA) fixed effects are also included. The standard errors are clustered at the UZA level.[9]

For this model, our key parameter of interest is β_1, the coefficient on transit capacity. Using a panel of urban areas, we estimate β_1 using regional fixed effects to remove all time-invariant effects that vary across regions and influence the estimated effect of transit investment on auto travel volume, such as the physical design of the transportation network, which is very slow to evolve. Variation in travel volumes and transit levels within a region over time enables us to best estimate the substitution effect, given the differences in the structure and existing equilibria across transportation networks, and after controlling for factors that would lead to induced demand (including employment rate, income, and population), as the fixed effects absorb the heterogeneity in congestion and transit levels unique to each region.

3.3 Equilibrium Effect Accounting for Induced Demand

When increases in transit supply are considered in a dynamic context with no congestion tax in place, the fundamental law of road congestion must be accounted for. Although an increase in transit supply may decrease auto travel in the short run via the substitution effect, this decrease in auto travel may be offset by the induced demand effect in the medium and long run. In the medium and long run, by reducing congestion, increasing accessibility, increasing economic activity, and/or attracting additional residents and workers to the area, transit investment may generate additional automobile trips that were previously not undertaken. The equilibrium effect accounts for both the substitution effect and the induced demand effect.

To estimate the medium-run equilibrium effect accounting for both the substitution effect and the medium-run induced demand effect, we replace the factors associated with the induced demand effects of the spatial equilibrium model – employment rates, income, and population – with their 5-year lagged values. Thus, unlike our empirical model of the substitution effect, whose coefficient on transit capacity yields the marginal effect of transit on auto travel holding employment rates, income, and population constant, the coefficient on transit capacity in our empirical model of the medium-run equilibrium effect accounts for both the substitution effect and the medium-run induced demand effect that may have been induced by resulting changes in employment rates, income, and population in the medium run. Our empirical model of the medium-run equilibrium effect therefore allows for medium-run adjustments in employment rates, income, and population, and enables us to estimate the *net* effect of transit supply on equilibrium auto travel volumes once

[9] ε_{rt} are stochastic error terms assumed to be independent and identically distributed across regions and time, and may be heteroskedastic across regions.

these medium-run mechanisms of induced demand over this period are factored in. Our regression model for the medium-run equilibrium effect is given by:

$$\begin{aligned}\text{Auto travel}_{rt} = {} & \gamma_1 \cdot \text{Transit Capacity}_{rt} + \gamma_2 \cdot \text{Freeway Capacity}_{rt} + \gamma_3 \cdot \text{Arterial Road Capacity}_{rt} \\ & + \gamma_4 \cdot \text{Fuel Cost}_{rt} + \gamma_5 \cdot \text{Transit Fare}_{rt} + \gamma_6 \cdot \text{Employment}_{r,t-5} + \gamma_7 \cdot \text{Income}_{r,t-5} \\ & + \gamma_8 \cdot \text{Population}_{r,t-5} + \text{Year Effects} + \text{UZA Fixed Effects} + \varepsilon_{rt}.\end{aligned} \tag{2}$$

For the medium-run equilibrium model, we control for the 5-year lagged values of employment, income, and population, but not their contemporaneous values, as we wish to allow for the effect of transit capacity to lead to changes in regional structure over the medium run. For this model, we use the panel setting to exploit variations in transit supply and auto travel volumes within and across regions over time. For this model, our key parameter of interest is γ_1.

We choose 5 years as the time horizon for the medium run because it is a reasonable medium-run time horizon for some changes in employment, income, and population to take place, but still short enough to give us enough observations when we run the model with 5-year lags. To further examine the dynamics of the induced demand effect, we also vary the number of years we lag the auto demand determinants (employment, income, and population) in the medium-run equilibrium effect in equation (2) from 0 to 10 years, representing different medium-run time horizons ranging up to 10 years.

To estimate the long-run equilibrium effect accounting for both the substitution effect and the long-run induced demand effect, we remove as controls the factors associated with the induced demand effects of the spatial equilibrium model: employment rates, income, and population. Thus, unlike our empirical model of the substitution effect, whose coefficient on transit capacity yields the marginal effect of transit on auto travel conditional on contemporaneous employment rates, income, and population, the coefficient on transit capacity in our empirical model of the long-run equilibrium effect accounts for both the substitution effect and the long-run induced demand effect that may have been induced by changes in employment rates, income, and population. Our empirical model of the long-run equilibrium effect therefore allows for long-run adjustments in employment rates, income, and population, and enables us to estimate the *net* effect of transit supply on equilibrium auto travel volumes once the long-run mechanisms of induced demand are factored in. Our regression model for the long-run equilibrium effect is given by:

$$\begin{aligned}\text{Auto travel}_{rt} = {} & \alpha_1 \cdot \text{Transit Capacity}_{rt} + \alpha_2 \cdot \text{Freeway Capacity}_{rt} + \alpha_3 \cdot \text{Arterial Road Capacity}_{rt} \\ & + \alpha_4 \cdot \text{Fuel Cost}_{rt} + \alpha_5 \cdot \text{Transit Fare}_{rt} + \text{Year Effects} + \text{UZA Fixed Effects} + \varepsilon_{rt}.\end{aligned} \tag{3}$$

For the long-run equilibrium model, we do not control for employment, income, or population, as we wish to allow for the effect of transit capacity to lead to changes in regional structure over time.

For this model, we use the panel setting to exploit variations in transit supply and auto travel volumes within and across regions over time. For this model, our key parameter of interest is α_1.

We expect the substitution effect to be non-positive, with $\beta_1 \leq 0$. Similarly, the induced demand effect should be non-negative; depending on the values of the substitution effect and the induced demand effect, the net equilibrium effect could take on any value. The implied value of the induced demand effect is then the difference between β_1 and γ_1 in the medium run, and the difference between β_1 and α_1 in the long run. An alternative interpretation is that the net equilibrium effect of public transit supply on the volume of automobile travel in the medium run and in the long run depends on the relative magnitudes of the short-run substitution effect and the respective medium- and long-run induced demand effect.

3.4 Identification Strategy

Anderson (2014) identifies the effect of changes in transit supply on congestion along the extensive margin by employing a regression discontinuity design. As we are interested in estimating the effect along the intensive margin relative to existing public transit supply, our identification strategy relies on a panel data setting. We seek to identify the causal effect of public transit supply on auto travel demand by exploiting both time series and cross-sectional variation in transit capital and auto congestion levels and by using an instrumental variable to address the endogeneity in the supply of public transit across urban areas of the U.S.

There are two potential sources of time-varying endogeneity of urban transportation investment to observed congestion levels. First, there may be omitted variable bias, as transportation investment is more likely to occur in densely populated urban areas that are also likely to have higher *ex ante* (and/or anticipated) levels of congestion. Similarly, new investments may be used as a policy measure to address existing congestion and/or as a component of a regional growth and development strategy; in both cases, we would expect congestion and transportation investment to be positively correlated. This has been a prevalent issue in analogous studies evaluating the effects of road investment on auto travel. As Cervero (2002, pp. 7) notes, "road investments are not made at random but rather as a result of conscious planning based on anticipated imbalances between demand and capacity. This implies that, irrespective of any traffic inducement effect, road supply will generally correlate with road use." A second source of endogeneity is that travel demand and congestion are simultaneously determined through the speed-flow relationship and the generalized travel cost function.

To address the potential endogeneity of transit with respect to congestion, we instrument for public transit investment. To identify the effect of transit investment on congestion, our instrument must be correlated with the level of investment, while the exclusion restriction requires that our instrument has no effect on congestion beyond the direct effect on public transit investment.

The instrument we use for public transit investment is the level of Federal funds provided for transit capital in the region from two years prior. From 1991-2011, the regions studied received 66.7% of capital funding and 17.3% of operating funding from Federal sources on average, with the remainder via State and Local sources. As Libermann (2009, pp. 87) states: "...most [Federal] highway, transit and safety funds are distributed through formulas that only indirectly relate to needs and may have no relationship to performance. In addition, the programs often do not use the best tools or best approaches, such as using more rigorous economic analysis to select projects." Although State and Local funds may be correlated with unobserved factors affecting regional congestion, conditional on time-invariant region-specific unobservables that are absorbed by the regional fixed effects, changes in Federal funds two years ago are orthogonal to current changes in such potential factors. This supposition is consistent with Berechman (2009, pp. 219-222):

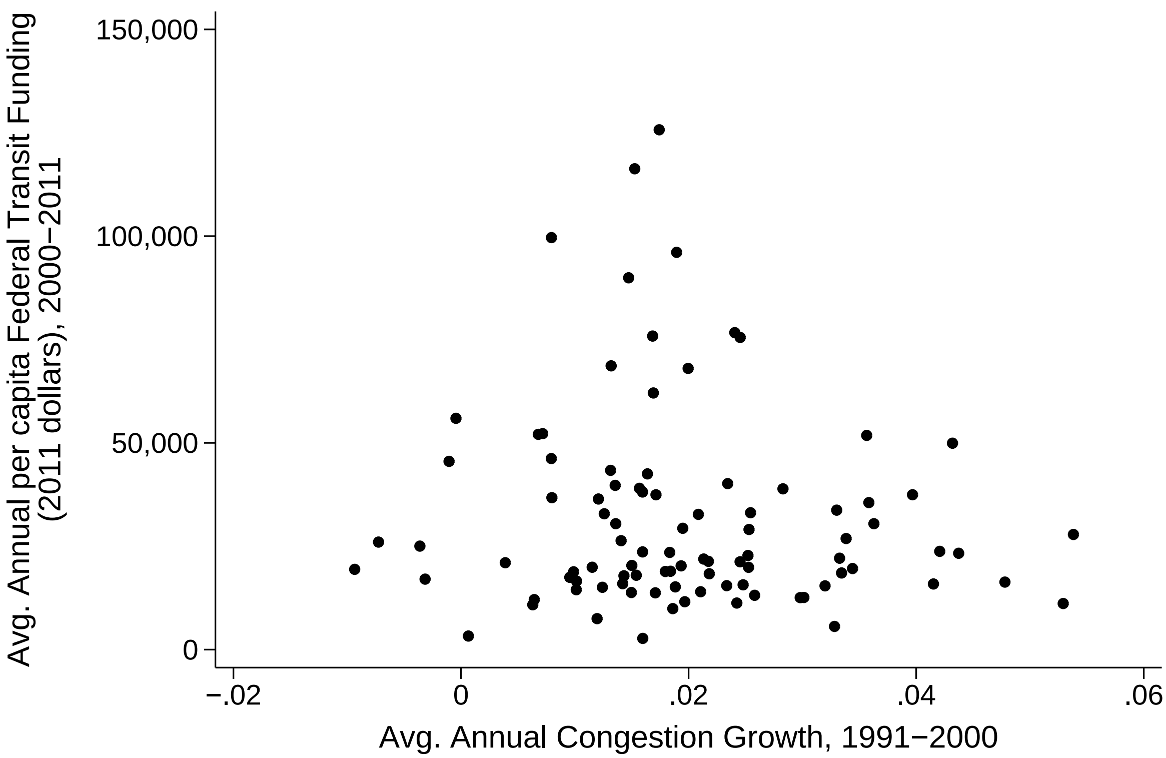
> "...the proclivity of local decision makers to accept a project regardless of its actual benefits and risks increases with the proportion of funding obtained from higher levels...This observation also explains why US federal subsidies to local public transit inherently provide incentives for selecting capital-intensive projects irrespective of their efficiency or effectiveness...Our hypothesis states that local authorities, as recipients of federal and state money, tend to regard external funding as "costless" and as political benefits. They are therefore predisposed to promoting infrastructure projects containing a large external funding component...this tendency promotes the implementation of inefficient projects, selected without any regard for their social rate of return."

There is little evidence that Federal transit funds have been directed towards the most congested regions. As seen in the scatterplot in Figure 3, there is no clear relationship between the growth in congestion experienced by urban areas over the period 1991-2000 and the subsequent per capita Federal transit funds allocated to the region in 2000-2011. The scatterplot therefore provides evidence that areas with the highest levels of congestion growth did not receive greater Federal transit funding in response. Further, there appears to be a very limited tradeoff between Federal transit funding and investment in roads.[10]

We are interested in estimating the effect of transit investment on auto travel demand, holding fixed the level of auto capacity. While aggregate auto capacity has increased fairly steadily over the period 1991-2011, this growth rate is very low and the scatterplot in Figure 4 shows that there is no evidence that auto capacity investment has systematically occurred in the most congested regions. The scatterplot therefore provides evidence that areas with the highest levels of initial

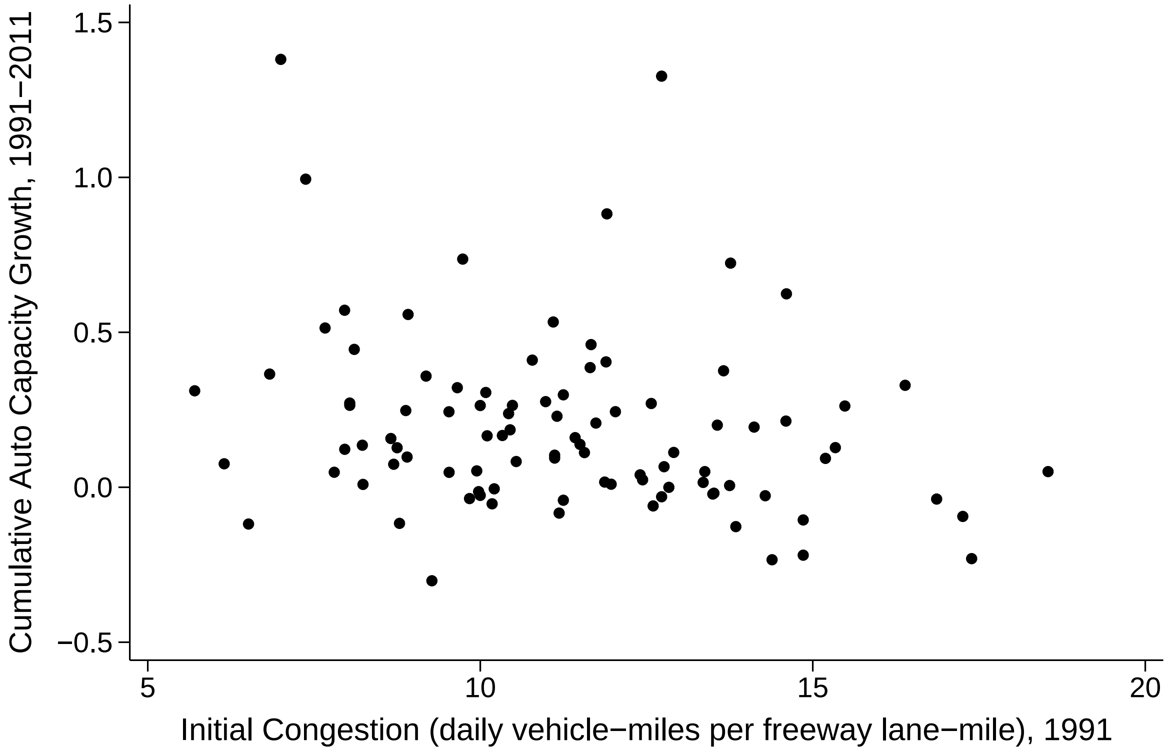
[10] The correlation between auto freeway capacity per capita and Federal transit funding per capita is -0.17 for capital funding and -0.10 for operating funding.

Figure 3: Congestion growth and subsequent Federal transit funding



Note: The scatterplot shows, for each of the 96 urban areas (UZAs) in our data set, the average annual growth in congestion (as measured by the percent change in daily vehicle-miles per freeway lane-mile) experienced by the urban area over the period 1991-2000, and the subsequent per capita Federal transit funds allocated to the region in 2000-2011. Each point on the scatterplot corresponds to one of the 96 urban areas (UZAs) in our data set. The scatterplot provides evidence that areas with the highest levels of congestion growth did not receive greater Federal transit funding in response.

Figure 4: Auto capacity investment and baseline congestion levels



Note: The scatterplot shows, for each of the 96 urban areas (UZAs) in our data set, the initial level of congestion (in daily vehicle-miles per freeway lane-mile) in the urban area in 1991, and the subsequent cumulative auto capacity growth (as measured by the percent change in freeway lane-miles) in the urban area over the period 1991-2011. Each point on the scatterplot corresponds to one of the 96 urban areas (UZAs) in our data set. The scatterplot provides evidence that areas with the highest levels of initial congestion did not receive greater roadway investment in response.

congestion did not receive greater roadway investment in response. Overall, the road networks of the developed urban regions of the U.S. evolve very slowly and we view road capacity as exogenous within our sample.

As seen in Table 1, the correlations between changes in Federal capital funding for transit and changes in lagged determinants of auto travel (employment, income, and population) are extremely low. The low correlations provide additional evidence that determinants of auto demand are not correlated with Federal capital funding for transit, and therefore provide further support for the exogeneity of our Federal transit capital funding instrument.

Conditional on urban area fixed effects and the other controls (including employment, income, and population), our instrument is therefore plausible, as there should not be any other significant

Table 1: Correlation between Changes in Federal Capital Funding and Changes in Lagged Determinants of Auto Demand

Correlation between Changes in Federal Capital Funding in year t and Changes in:

Year	**Employment Rate**	**Income**	**Population**	**VMT per Freeway Lane-Mile**
t	−0.000	−0.010	0.103	−0.018
$t-1$	0.053	0.081	0.050	0.020
$t-2$	0.039	0.048	−0.130	0.034
$t-3$	0.033	−0.000	0.034	−0.018
$t-4$	−0.036	−0.053	−0.031	0.018
$t-5$	−0.052	−0.093	0.055	0.008
$t-6$	−0.037	−0.037	0.058	0.002
$t-7$	−0.028	−0.045	−0.047	−0.024
$t-8$	0.029	0.061	0.100	−0.014
$t-9$	−0.006	0.019	−0.003	0.003
$t-10$	0.010	−0.009	−0.095	−0.002

Note: The table shows correlations, calculated using the data from each of the 96 urban areas (UZAs) in our data set, between changes in Federal capital funding for transit in year t in an urban area, and changes in contemporaneous and lagged determinants of auto travel (employment, income, and population) for the preceding 1-10 years in that urban area. The low correlations provide evidence that determinants of auto demand are not correlated with Federal capital funding for transit.

economic changes that are correlated with travel demand and changes in our instrument.[11] To further test the validity of our instrument, we also conduct weak-instrument-robust inference tests, and their results are reported along with our regression results below. The instrument passes these tests, and the first-stage Angrist-Pischke F-statistics are greater than 10.[12]

4 Data

To estimate equations (1) - (3), we construct a panel dataset spanning 21 years from 1991 to 2011, covering 96 urban areas within 351 counties and 44 states across the U.S. An 'urban area' (UZA) is defined by the U.S. Census Bureau and refers to a region that is centered around a core metropolitan statistical area (MSA). A UZA does not align directly with other geographic and/or political boundaries; while each UZA has a core MSA, a UZA can be contained within multiple MSAs, counties, and/or States, and a UZA is smaller in overall size than an MSA.[13]

Appendix A contains further details of our dataset. Table A.1 displays summary statistics, while Table A.2 lists the regions included in the analysis and gives an overview of these regions across several relevant characteristics. As Figure 5 shows, the UZAs included in the analysis are spread across the U.S., and there is significant variation in the attributes of the UZAs. The average pop-

[11] In our sample, there is very little residual correlation between congestion and the instrument after conditioning on the other covariates in the model.

[12] Tables A.5 - A.7 in Appendix A present the first-stage regression results.

[13] The 96 UZAs in our dataset are the 96 UZAs with both auto and transit data after merging the Texas Transportation Institute's Urban Mobility Report auto data and the Federal Transit Administration's National Transit Database transit data below.

ulation of the UZAs in 2011 was 1.8 million, ranging from 0.2 million in Brownsville, TX to 18.9 million in New York-Newark, NY-NJ-CT. The average area was 501 square miles, with Laredo, TX being the smallest at 43 square miles and New York-Newark being the largest at 3,353 square miles.

Data relating to the auto travel components of each UZA's transportation networks are primarily from the Texas Transportation Institute's Urban Mobility Report (Schrank, Eisele and Lomax, 2012), which are the "best available means of comparing congestion levels in different regions and tracking changes in regional congestion levels over time" (Downs, 2004, pp. 17). While we measure auto travel as the daily vehicle-miles traveled per freeway lane-mile, Schrank, Eisele and Lomax (2012) contains additional measures of traffic congestion: the Travel Time Index, which measures actual travel time relative to free-flow travel time; total annual hours of delay; percentage of peak vehicle-miles traveled under congested conditions; and the Roadway Congestion Index, which measures the aggregate traffic density of an urban area relative to the capacity of the transportation network.[14] As seen in Table A.3 in Appendix A, these various measures of congestion are highly correlated. Table A.4 in Appendix A summarizes congestion levels across UZAs from 1991-2011. As presented and discussed below, our empirical results are robust to the particular measure of congestion used.

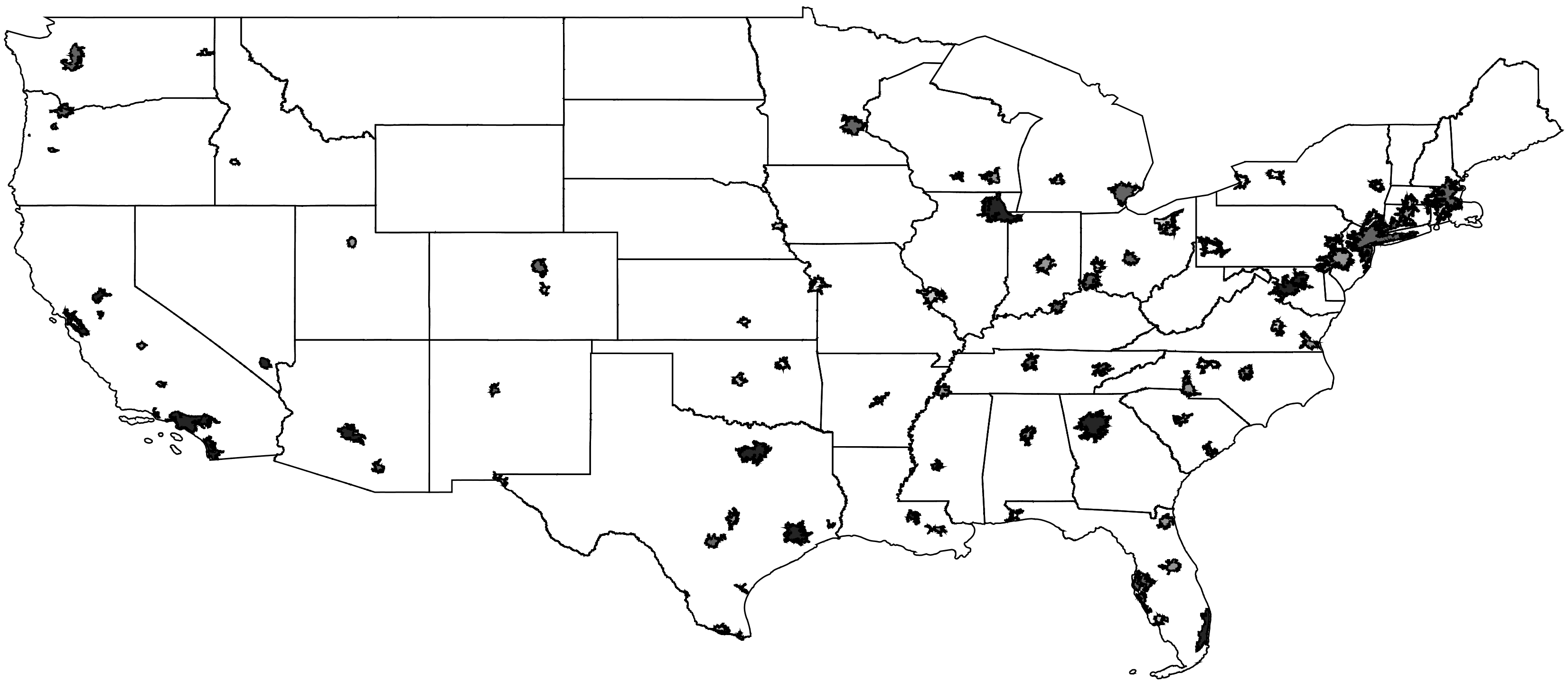
The per-mile fuel cost of auto travel is derived from the Federal Highway Administration's Highway Statistics records. The average state-wide fuel efficiency (gallons per vehicle-mile traveled) in each year is derived from the total gallons of fuel used and the annual vehicle-miles traveled in each state. This value is then multiplied by the average cost of fuel (dollars per gallon) in the state (from TTI's Urban Mobility Report) to compute the cost of fuel on a per vehicle-mile basis. The primary state of each UZA is used in assigning this value, as the underlying data are not available at the UZA level, and the fuel price control variable can thus be considered exogenous with respect to the congestion levels of the UZA. These current values are then converted to 2011 U.S. Dollars via the Consumer Price Index.

Transit data are obtained from the Federal Transit Administration's National Transit Database.[15] For each UZA's transit system, the network size is measured by directional route-miles and capacity is measured by vehicle-revenue miles. Transit travel is measured by annual passenger-miles traveled, while operating and capital funding is disaggregated by source (fares, Federal, State, Local, and other). Our two measures of transit fares for the UZA are calculated by dividing total transit fare revenue by (1) passenger-miles traveled on transit or by (2) the total number of unlinked transit trips. Since transit fares are very sticky, they are also assumed to be exogenous with respect

[14] The Urban Mobility Report measures traffic delay using data from the U.S. Department of Transportation on traffic volumes and the characteristics of the city (see Winston and Langer (2006) for discussion).

[15] www.ntdprogram.gov/ntdprogram/data.htm.

Figure 5: Urban areas (UZAs) included in the analysis



Note: Map shows the 96 urban areas (UZAs) in our data set, which span 351 counties and 44 states across the U.S. An ‘urban area’ (UZA) is defined by the U.S. Census Bureau and refers to a region that is centered around a core metropolitan statistical area (MSA).

to the congestion level of the UZA.[16] Operational transit data are distinguished by modal type - fixed guideway modes with separate rights-of-way for the transit vehicle versus mixed traffic modes that share the roadways with automobiles. The fixed guideway modes included are: commuter rail, light rail, heavy rail, hybrid rail, monorail and automated guideway, and bus rapid transit. The mixed traffic modes are: bus and trolleybus. We include fixed schedule service and exclude demand-response modes (such as those typically provided for passengers with mobility issues). In 2011, the modes included in our analysis represent approximately 74% of vehicle-revenue miles and 97% of unlinked passenger trips across the UZAs in our analysis.

Socioeconomic data relating to employment rate, income, and population are compiled for the central MSA comprising each UZA and obtained from the Bureau of Economic Analysis's Regional Data records.[17]

5 Empirical Results

We now discuss the empirical results from estimating the models outlined in Section 3.

5.1 Overall Results

Table 2 contains our baseline results from estimating the substitution effect using equation (1). Specification (1) presents OLS estimates, while specifications (2) and (3) present the IV estimates excluding and including UZA fixed effects, respectively.[18] To interpret the coefficient estimates in specification (3), which is our preferred specification, we also present the results of specification (3) in terms of the average elasticity of auto travel with respect to the associated variable across the 96 UZAs.[19]

Our results for the substitution effect show that in the short run, when accounting for the substitution effect only, and after controlling for the underlying factors that generate auto traffic growth, increases in transit capacity do lead to a reduction in traffic congestion. The coefficient estimate for the substitution effect implies a statistically significant average elasticity of auto travel with respect to transit capacity of -0.07 across the 96 UZAs, which indicates that on average a 10%

[16] Though some transit agencies differentiate peak and off-peak fares, there has been little variation in the average transit fare over time.

[17] www.bea.gov/iTable/index.cfm under *Local Areas Personal Income and Employment, Economic profiles (CA30).*

[18] The results of the first-stage regression are presented in Table A.5.

[19] The elasticity of auto travel with respect to transit capacity referred to throughout this section is $\frac{\%\Delta\text{Auto travel}}{\%\Delta\text{Transit capacity}}$. Holding auto capacity fixed, the elasticity of auto travel with respect to transit capacity reflects the change in auto travel volume due to changes in transit supply.

increase in transit capacity is expected to lead to a 0.7% reduction in auto travel in the short run.

Our elasticity estimate relates to a change in transit capacity along the intensive margin, which may not extrapolate to large transit investments. At the individual level, there may be a diminishing marginal modal substitution rate as the level of transit capacity increases, since those for whom the initial generalized cost of transit travel only slightly exceeds the generalized cost of auto travel will be the first induced to switch modes, and progressively larger reductions in transit travel costs will be required to induce further modal substitution. Additionally, the estimated elasticity may differ if the scale of the public transit network changes significantly; applying the Lucas critique, the parameter estimates of the travel choices of individuals will depend on the characteristics of the modal choices available to them when those choices are observed.

By comparing the OLS and IV coefficient estimates for the substitution effect in specifications (1) and (3), respectively, of Table 2, we see that while ignoring the endogeneity of transit supply levels still leads to a statistically significant negative coefficient on transit capacity, it would understate the congestion-reduction benefit of transit by approximately 26%.[20]

There are several secondary results of interest. The elasticity of auto travel with respect to freeway capacity is -0.28, implying that a 10% increase in road capacity leads to a 2.8% reduction in the volume-to-capacity ratio. Since this effect is holding employment, income, and population constant and removing the effect of the time trend, this suggests that there is still a small amount of induced demand associated with capacity expansion beyond these underlying auto demand growth factors, as a value of -1 would be expected if there were no induced demand. In comparing our results with the induced demand effect found by Duranton and Turner (2011) – which would imply an auto capacity coefficient of 0 in our model – it should be noted that their estimate should be interpreted as a long-run elasticity (as their observations occur at 10-year intervals), whereas our elasticity is a short-run elasticity based on annual data.

The price of transit travel (as represented by the transit fare) is found to have no effect on the level of congestion. While the previous literature (Glaister and Lewis, 1978; Parry and Small, 2009) shows that there is theoretical justification for transit fare subsidization if auto travel is underpriced, the result is consistent with their conclusion that transit fare subsidies will nonetheless have a minimal effect on equilibrium congestion levels due to a very low cross-price elasticity of auto demand with respect to transit fares (Button, 1990).[21]

[20] A Hausman test rejects the null hypothesis that transit capacity is exogenous, and a Davidson-MacKinnon test of exogeneity soundly rejects the null hypothesis that OLS would yield consistent estimates of the coefficients.

[21] Additionally, since existing transit fares are generally below average cost (indicated by the sizable operating subsidy provided to transit agencies), our estimate of the effect of transit fares is for a marginal change relative to the existing (subsidized) fare, which could be expected to have a small influence at the margin on transit ridership, as

The price of auto travel (as represented by the fuel price) is found to have a small or insignificant effect on auto travel volumes. This result is unsurprising, as the low elasticity of auto travel demand with respect to fuel prices has been well documented: Graham and Glaister (2004) survey the literature and summarize the elasticity of auto travel with respect to fuel price as -0.15 in the short run and -0.31 in the long run. The fuel price does not vary by time and location, and aside from the effect of congestion on per-unit fuel consumption, is largely independent of the degree of congestion; as a result, this should not be construed as indicating that road pricing would not be an effective tool in addressing congestion.

Population growth appears to be the main determinant of auto travel increases; the elasticity of auto travel with respect to population is 0.45. The average elasticity of auto travel with respect to per capita income is 0.14. The employment rate does not have a significant effect on auto travel.

Table 3 contains our baseline results from estimating the medium-run equilibrium effect, which includes the potential for induced auto demand in the 5 years following transit supply increases, using equation (2). Specification (1) presents OLS estimates, while specifications (2) and (3) present the IV estimates excluding and including UZA fixed effects, respectively.[22] To interpret the coefficient estimates in specification (3), which is our preferred specification, we again present the results of specification (3) in terms of the average elasticity of auto travel with respect to the associated variable across the 96 UZAs to facilitate comparisons.

Results from specification (3) show that, in the medium run, an increase in transit capacity has no significant effect on auto travel, as latent and induced demand offset the substitution effect, yielding no net effect.

To further examine the dynamics of the induced demand effect, we also vary the number of years we lag the auto demand determinants (employment, income, and population) in the medium-run equilibrium effect in equation (2) from 0 to 10 years, representing different medium-run time horizons ranging up to 10 years. We graph the resulting elasticities of auto travel with respect to transit capacity as a function of the length of the medium-run time horizon. As seen in Figure 6, transit reduces auto travel in the short run (0 to 4 years), but in the longer run (>4 years) it has no effect on auto travel, as latent and induced demand offset the substitution effect.[23]

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the transit fare is a relatively low fraction of the total generalized cost of transit travel.

[22] The results of the first-stage regression are presented in Table A.6.

[23] One can view the long run as the limit as the number of years we lag the auto demand determinants in Figure 6 becomes very large. As our data set spans 21 years, our long run captures a 21-year horizon. Because the sample size decreases with the number of years we lag the auto demand determinants, we do not lag the auto demand determinants more than 10 years. However, even with lags of 9 or 10 years, one can see that the point estimate becomes positive when the time horizon is long enough.

Table 2: Substitution Effect

Dependent variable is Daily Auto VMT per freeway lane-mile (000s)				
	Coefficient (Std. Err.)			**Avg. Elasticity**
	(1) OLS	(2) IV	(3) IV	(3) IV
Transit capacity	-0.032***	-0.041***	-0.043*	-0.07*
(total vehicle revenue-miles, millions)	(0.009)	(0.003)	(0.019)	
Auto capacity: freeways	-4.237***	-0.192	-4.376***	-0.28***
(total lane-miles, thousands)	(0.533)	(0.158)	(0.576)	
Auto capacity: arterials	-0.170	-0.732***	-0.118	-0.02
(total lane-miles, thousands)	(0.230)	(0.129)	(0.251)	
Fuel price	-0.811	0.750	1.574	0.01
($ per vehicle-mile)	(6.043)	(6.729)	(6.379)	
Transit fare	0.060	-0.234	0.050	0.00
($ per unlinked trip)	(0.070)	(0.166)	(0.062)	
Employment rate	2.984	-2.625*	0.414	0.02
(total employed per capita)	(2.890)	(1.215)	(3.141)	
Income	0.022	0.126***	0.046	0.14
(real per capita income)	(0.027)	(0.011)	(0.027)	
Population	4.079***	2.833***	4.333***	0.45***
(millions)	(0.581)	(0.266)	(0.949)	
Year fixed effects	Yes	Yes	Yes	Yes
UZA fixed effects	Yes	No	Yes	Yes
N	1997	1802	1802	1802
R^2	0.641	0.518	0.581	0.581
p-val. (Prob > F)	0.000	0.000	0.000	0.000
First-stage F-statistic				
First-stage AP F-stat, Transit Capacity	-	108.50	14.12	14.12
Weak-instrument-robust inference				
Anderson-Rubin Wald F test: p-val.	-	0.000	0.027	0.027
Anderson-Rubin Wald χ^2 test: p-val.	-	0.000	0.023	0.023

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses. In (2)-(3), transit capacity is instrumented by Federal transit funding in UZA, lagged two periods.

(Significance levels: $*: p < 0.05$ $**: p < 0.01$ $***: p < 0.001$)

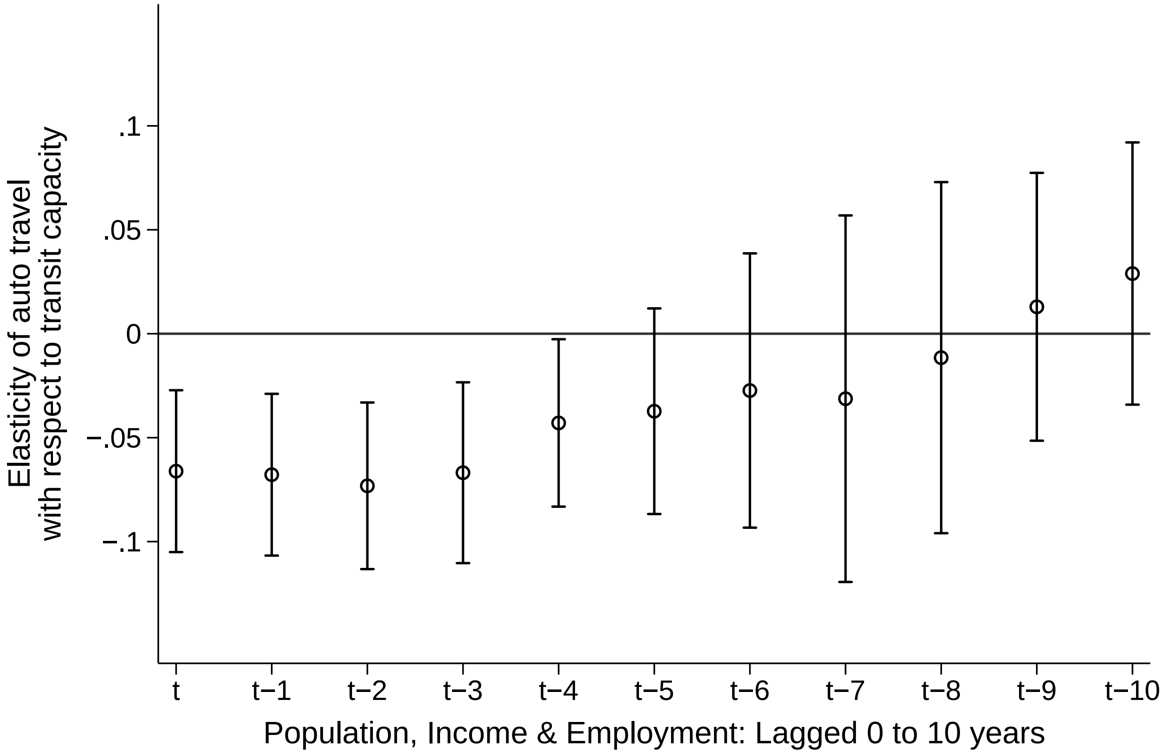
Table 3: Medium-Run Equilibrium Effect with Induced Demand

Dependent variable is Daily Auto VMT per freeway lane-mile (000s)				
	Coefficient (Std. Err.)			**Avg. Elasticity**
	(1) OLS	(2) IV	(3) IV	(3) IV
Transit capacity	-0.005	-0.031***	-0.022	-0.04
(total vehicle revenue-miles, millions)	(0.007)	(0.003)	(0.021)	
Auto capacity: freeways	-4.382***	0.083	-4.461***	-0.31***
(total lane-miles, thousands)	(0.682)	(0.178)	(0.677)	
Auto capacity: arterials	0.019	-0.288	0.068	0.01
(total lane-miles, thousands)	(0.297)	(0.148)	(0.313)	
Fuel price	4.497	6.830	4.725	0.04
($ per vehicle-mile)	(5.368)	(7.155)	(5.304)	
Transit fare	0.080	-0.215	0.054	0.00
($ per unlinked trip)	(0.062)	(0.164)	(0.063)	
Employment rate, 5-year lag	2.689	-3.503*	1.994	0.09
(total employed per capita)	(3.856)	(1.382)	(3.824)	
Income, 5-year lag	0.001	0.137***	0.006	0.02
(real per capita income)	(0.033)	(0.013)	(0.032)	
Population, 5-year lag	2.765***	1.892***	3.235***	0.33***
(millions)	(0.503)	(0.284)	(0.838)	
Year fixed effects	Yes	Yes	Yes	Yes
UZA fixed effects	Yes	No	Yes	Yes
N	1528	1521	1521	1521
R^2	0.432	0.471	0.423	0.423
p-val. (Prob > F)	0.000	0.000	0.000	0.000
First-stage F-statistic				
First-stage AP F-stat, Transit Capacity	-	111.14	12.15	12.15
Weak-instrument-robust inference				
Anderson-Rubin Wald F test: p-val.	-	0.000	0.327	0.327
Anderson-Rubin Wald χ^2 test: p-val.	-	0.000	0.318	0.318

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses. In (2)-(3), transit capacity is instrumented by Federal transit funding in UZA, lagged two periods.

(Significance levels: $*: p < 0.05$ $**: p < 0.01$ $***: p < 0.001$)

Figure 6: Medium-Run Equilibrium Effect for Different Lengths of the Medium-Run Time Horizon



Notes: Graph shows elasticities of auto travel with respect to transit capacity that result from varying the number of years we lag the auto demand determinants (employment, income, and population) in the medium-run equilibrium effect in equation (2). The lags range from 0 to 10 years, representing different medium-run time horizons. Error bars indicate 95% confidence interval.

Table 4 contains our baseline results from estimating the long-run equilibrium effect, which includes the potential for long-run induced auto demand following transit supply increases, using equation (3). Specification (1) presents OLS estimates, while specifications (2) and (3) present the IV estimates excluding and including UZA fixed effects, respectively.[24] To interpret the coefficient estimates in specification (3), which is our preferred specification, we present the results of specification (3) in terms of the average elasticity of auto travel with respect to the associated variable across the 96 UZAs to facilitate comparisons.

The coefficient estimate for the long-run equilibrium effect implies a statistically significant average elasticity of auto travel with respect to transit capacity of 0.04 across the 96 UZAs. This indicates that on average a 10% increase in transit capacity is associated with a 0.4% increase in auto travel in the long run once the long-run induced demand effect is also accounted for; in other words,

[24] The results of the first-stage regression are presented in Table A.7.

the short-run substitution effect is outweighed by the induced demand accompanying population growth over the long run.

Table 4: Long-Run Equilibrium Effect with Induced Demand

Dependent variable is Daily Auto VMT per freeway lane-mile (000s)				
	Coefficient (Std. Err.)			**Avg. Elasticity**
	(1) OLS	(2) IV	(3) IV	(3) IV
Transit capacity	0.017**	-0.013***	0.020*	0.04*
(total vehicle revenue-miles, millions)	(0.005)	(0.001)	(0.008)	
Auto capacity: freeways	-2.400**	1.090***	-2.700**	-0.20**
(total lane-miles, thousands)	(0.813)	(0.189)	(0.893)	
Auto capacity: arterials	0.432	0.440***	0.433	0.09
(total lane-miles, thousands)	(0.283)	(0.050)	(0.243)	
Fuel price	-0.925	31.920***	1.472	0.01
($ per vehicle-mile)	(6.736)	(6.920)	(7.007)	
Transit fare	0.069	-0.121	0.065	0.00
($ per unlinked trip)	(0.074)	(0.083)	(0.059)	
Year fixed effects	Yes	Yes	Yes	Yes
UZA fixed effects	Yes	No	Yes	Yes
N	1997	1802	1802	1802
R^2	0.557	0.410	0.491	0.491
p-val. (Prob > F)	0.000	0.000	0.000	0.000
First-stage F-statistic				
First-stage AP F-stat, Transit Capacity	-	274.55	17.17	17.17
Weak-instrument-robust inference				
Anderson-Rubin Wald F test: p-val.	-	0.000	0.044	0.044
Anderson-Rubin Wald χ^2 test: p-val.	-	0.000	0.039	0.039

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses. In (2)-(3), transit capacity is instrumented by Federal transit funding in UZA, lagged two periods.

(Significance levels: $*: p < 0.05$ $**: p < 0.01$ $***: p < 0.001$)

5.2 Regional Heterogeneity

As seen in Figure 7, urban areas vary significantly across several characteristics that may influence the effect of transit supply on auto travel volumes. In particular, the ability of transit investment to reduce auto congestion depends on several factors that may vary across regions, including the extent of existing congestion, the magnitude of auto demand shifts in response to changes in the generalized cost of transit travel, and the characteristics of the regional transportation network.

To examine the potential heterogeneity of the congestion-reduction benefit of transit across UZAs, we compare the elasticities of auto travel with respect to transit capacity when the models in equations (1) - (3) are applied to a variety of sub-samples of the data, each constructed by stratifying the urban areas (UZAs) in our data set according to characteristics of the region and the transportation network.[25] Table 5 summarizes these results for the substitution effect, the medium-run equilibrium effect, and the long-run equilibrium effect. The medium-run equilibrium effect is not statistically significant. The magnitude of the negative substitution effect is consistently twice the magnitude of the positive long-run equilibrium effect.

When accounting for the substitution effect only, the magnitude of the elasticity of auto travel with respect to transit capacity varies from approximately -0.008 in smaller, less densely populated regions with less-developed public transit networks; to approximately -0.215 in larger, more densely populated regions with more extensive public transit networks. When accounting for both the substitution effect and the induced demand effect in the long run, the elasticity of auto travel with respect to transit capacity varies from approximately 0.005 in smaller, less densely populated regions with less-developed public transit networks; to approximately 0.129 in larger, more densely populated regions with more extensive public transit networks.

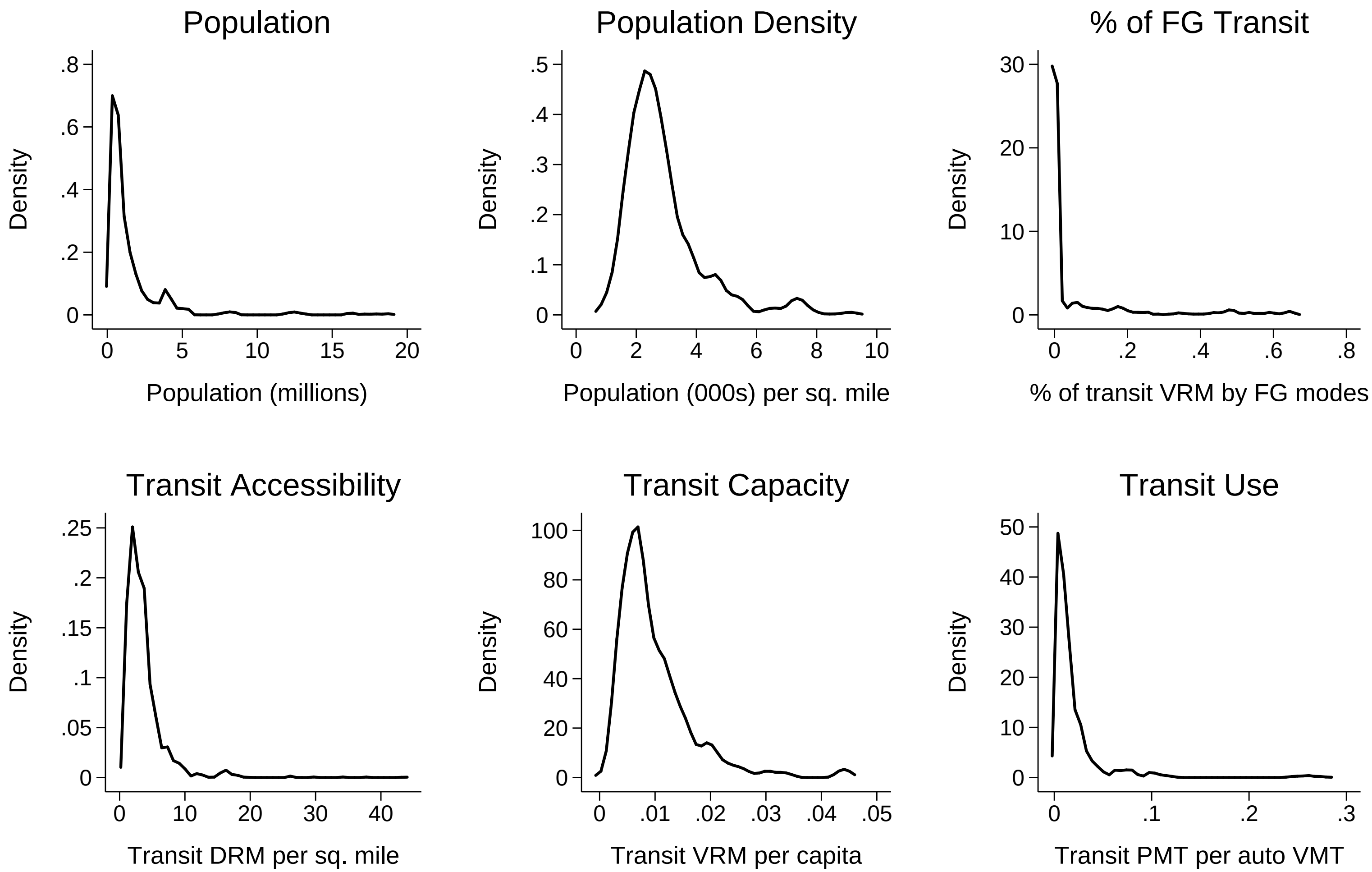
Our baseline results outline the average marginal effect of transit supply on auto travel. We also examine the extent to which this marginal effect varies according to the level of auto travel occurring in a given region. Figure 8 plots our estimates of the elasticity of auto travel with respect to transit capacity when the models in equations (1) - (3) are stratified according to deciles of auto travel. We find that for both the substitution effect and the long-run equilibrium effect, there is a threshold value for the level of traffic congestion above which public transit supply begins to potentially affect auto travel.

For values below this threshold, transit capacity does not influence auto travel demand, but once the volume of auto travel exceeds this threshold, the magnitude of the elasticity of demand for automobile travel with respect to transit capacity increases (becoming more negative for the substitution effect and more positive for the long-run equilibrium effect) and the precision of the estimate decreases with the demand for automobile travel.[26] We provide a more detailed analysis of regional heterogeneity along several different characteristics in Appendix B.

[25] For each characteristic, the UZAs are stratified using each UZA's mean value of that characteristic over the panel duration; as a result, the decile each UZA is in for a particular characteristic is held fixed over time.

[26] Our result that the elasticity varies with congestion provides support for our choice not to estimate a log-log regression model, which assumes that the elasticity does not vary with congestion.

Figure 7: Distributions of urban area (UZA) characteristics



Abbreviations: FG - fixed guideway; VMT - vehicle-miles traveled; DRM - directional route-miles; VRM - vehicle revenue-miles; PMT - passenger-miles traveled

Notes: Graphs show the distributions of urban area (UZA) characteristics. The distributions are plotted as kernel density functions.

Table 5: Elasticity of auto travel with respect to transit capacity

Sample		Substitution Effect	Medium-Run Equilibrium Effect	Long-Run Equilibrium Effect
		Avg. Elasticity in Sample		
Full sample	IV	-0.066^*	-0.037	0.037^*
Population	Above Median	-0.118^*	-0.066	0.068^*
	Below Median	-0.012^*	-0.006	0.005^*
Density	Above Median	-0.101^*	-0.056	0.059^*
	Below Median	-0.028^*	-0.015	0.014^*
Rail Service?	Yes	-0.171^*	-0.096	0.101^*
	No	-0.022^*	-0.011	0.010^*
Rail Service Established Prior to 1991?	Yes	-0.215^*	-0.123	0.129^*
	No	-0.027^*	-0.014	0.013^*
% Fixed Guideway Transit	High	-0.162^*	-0.091	0.095^*
	Low	-0.021^*	-0.010	0.009^*
Transit Accessibility	Above Median	-0.099^*	-0.055	0.056^*
	Below Median	-0.032^*	-0.018	0.017^*
Transit Capacity	Above Median	-0.116^*	-0.066	0.066^*
	Below Median	-0.008^*	-0.014	0.007^*
Transit Usage	Above Median	-0.117^*	-0.067	0.067^*
	Below Median	-0.017^*	-0.009	0.008^*

Notes: Table shows the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) for different time horizons are applied to a variety of sub-samples of the data, each constructed by stratifying the urban areas (UZAs) in our data set according to characteristics of the region and the transportation network. Robust standard errors are clustered by UZA. Transit capacity is instrumented by Federal transit funding in UZA, lagged two periods. Significance level: $*: p < 0.05$.

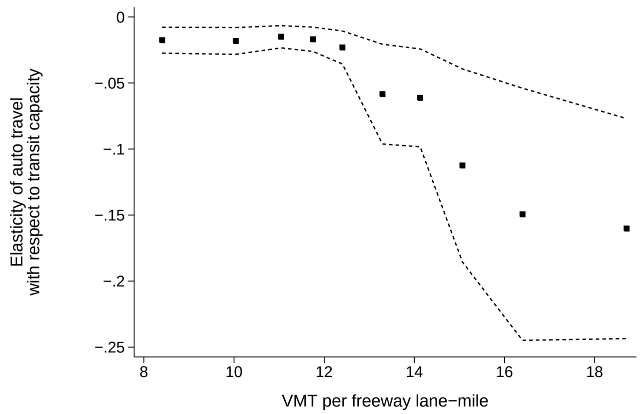
5.3 Robustness

To assess the robustness of the preceding results, several sensitivity analyses were carried out. Very similar results to those in Tables 2 - 4 were obtained using alternative measures of congestion, different combinations of lagged values for the instrument, a quadratic time trend in place of year fixed effects, and a log-linear specification instead of a linear specification.[27]

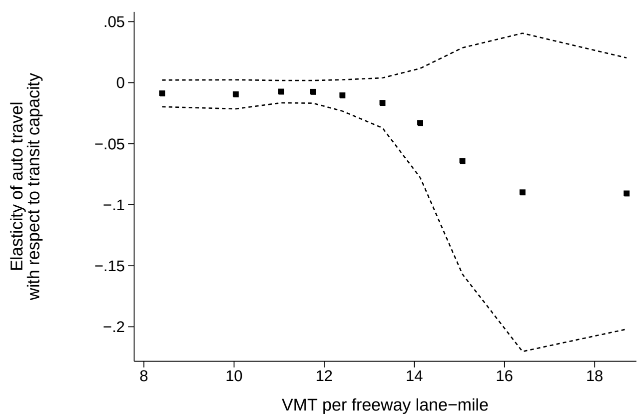
To control for regional time-varying unobservables, including regional policies that might affect auto travel demand, we also estimate the substitution effect, medium-run equilibrium effect, and long-run equilibrium effect controlling for census division-year fixed effects in addition to UZA fixed effects and year effects, where the census divisions are defined by the US Census. To allow for habit formation in the demand for automobile travel, we also estimate a specification for the

[27] As our results above show that the elasticity varies with congestion, we choose not to estimate a log-log regression model, which assumes that the elasticity does not vary with congestion.

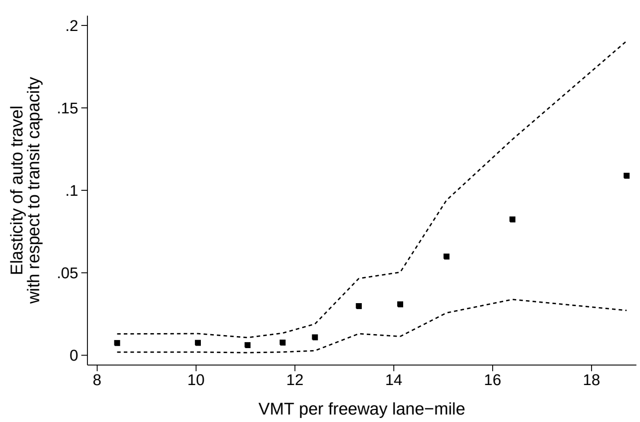
Figure 8: Elasticity of auto travel with respect to transit capacity vs. congestion level



(a) Substitution Effect



(b) Medium-Run Equilibrium Effect



(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of the level of auto travel across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.

substitution effect, medium-run equilibrium effect, and long-run equilibrium effect that includes the lagged dependent variable (i.e., lagged auto travel demand) using the augmented version of the Arellano-Bond (1991) estimator outlined in Arellano and Bover (1995) and fully developed in Blundell and Bond (1998). This dynamic panel estimator for lagged dependent variables is a Generalized Method of Moments estimator that treats the model as a system of equations, one for each time period, and which addresses the issue with the original Arellano-Bond estimator that lagged levels are often poor instruments for first differences, especially for variables that are close to a random walk. As seen in Table A.8 in Appendix A, similar results to those in Tables 2 - 4 were obtained with regressions that also include census division-year fixed effects, and with regressions that include a lagged dependent variable.

There are other possible measures of congestion which yield qualitatively similar results in our analysis, due to the high correlation between the various measures (see Table A.3 in Appendix A). Results using these alternative measures of congestion – including the volume-to-capacity ratio combining travel on freeway and arterial roads; the Travel Time Index; the Roadway Congestion Index; the percentage of peak vehicle-miles traveled in congested conditions; and the annual hours of delay per capita – are summarized in Table A.9 in Appendix A. Across these specifications, the short-run substitution effect is negative, the medium-run equilibrium effect is statistically insignificant, and the long-run equilibrium effect is positive. We are not overly concerned with congestion measurement error, since in a linear regression model, measurement errors in the dependent variable inflate the standard errors of the regression parameters but do not lead to inconsistency of the estimator (Cameron and Trivedi, 2005).

Additionally, if we instrument for both transit capacity and auto capacity using different combinations of lagged values for the instrument, our estimates of the elasticity of auto travel with respect to transit capacity do not change qualitatively, though the estimates are less precise due to our instruments being weak estimators of auto capacity. We also try instrumenting for auto price and transit price using lagged auto price and lagged transit price, in addition to instrumenting for transit capacity, and our results are again robust. Finally, we also use various weights for the different heterogeneity characteristics outlined above; our results are robust to the various weighting schemes employed.

6 Conclusion

Traffic congestion has increased significantly in the U.S. over the last 30 years. For 96 of the largest urban areas, traffic volumes in 1982 caused an average trip to take 10% longer than it would in uncongested conditions; by 2011, this congestion delay penalty increased to 23%. The issue of congestion is attracting heightened awareness and a greater sense of urgency for policymakers as we strive for an economically and environmentally sustainable transportation sector. This paper empirically examines the effect of past public transit investment on the demand for automobile transportation.

Our empirical results show that, owing to the countervailing effects of substitution and induced demand, the effects of increases in public transit supply on auto travel depend on the time horizon. In the short run, when accounting for the substitution effect only, we find that on average a 10% increase in transit capacity leads to a 0.7% reduction in auto travel. However, transit has no effect on auto travel in the medium run, as latent and induced demand offset the substitution effect. In the long run, when accounting for both substitution and induced demand, we find that on average a 10% increase in transit capacity is associated with a 0.4% increase in auto travel. We also find that public transit supply does not have a significant effect on auto travel when traffic congestion is below a threshold level.

Additionally, we find that there is substantial heterogeneity across urban areas. When accounting for the substitution effect only, the magnitude of the elasticity of auto travel with respect to transit capacity varies from approximately -0.008 in smaller, less densely populated regions with less-developed public transit networks; to approximately -0.215 in larger, more densely populated regions with more extensive public transit networks. When accounting for both the substitution effect and the induced demand effect in the long run, the elasticity of auto travel with respect to transit capacity varies from approximately 0.005 in smaller, less densely populated regions with less-developed public transit networks; to approximately 0.129 in larger, more densely populated regions with more extensive public transit networks.

The Federal Highway Administration (2012) suggests that the elasticity of auto travel with respect to transit fares ranges from 0.03 to 0.1 in the short run, and our estimate is in line with this value. While there is a general belief that commuters are more responsive to changes in the time components of transit travel, there does not appear to be a widely used estimate of the elasticity of auto travel with respect to transit capacity. McFadden (1974) uses a disaggregate discrete choice approach and estimates that the elasticity of auto travel with respect to waiting and travel time for bus and rail ranges from 0.02 to 0.15; again, our estimate is of a commensurate order of magnitude.

Our results highlighting the importance of accounting for regional heterogeneity and of distinguishing between the substitution effect and the equilibrium effect when evaluating the impacts of transit on congestion help reconcile the apparent mixed evidence of the existing empirical studies discussed in Section 2. While it is not possible to directly compare results across studies due to differences in the types of analysis undertaken, the data used, and how variables are measured, there are some unifying results.

Winston and Langer (2006) report that the type of transit service has a differential effect on congestion; our results are consistent with this conclusion, though we are not able to ascertain whether this is directly due to the transit technology, or whether rail happens to be located in the largest and most dense regions where public transit is best positioned to reduce congestion. Winston and Maheshri (2007) discuss the importance of the transit network configuration in regards to the efficiency of its operations, and our results comparing the effects of transit investment with and without taking regional fixed effects into account (such as transit and road network configuration) suggest a similar interpretation. Anderson (2014) emphasizes the importance of accounting for *intra*-city heterogeneity across commuters when estimating the effect of transit supply on congestion, whereas our results focus on the importance of *inter*-city heterogeneity.

Overall, our results are broadly consistent with those of Duranton and Turner (2011) and suggest that induced demand is a significant factor. If we only include mixed traffic transit modes and exclude rail service, then transit has a negligible effect on congestion in our model as well.[28] While we also find that transit does not reduce auto travel in the medium run or the long run, we do find that transit can reduce auto congestion for certain transportation networks in the short run.

While our results suggest that fixed guideway transit investments in dense regions yield higher congestion-reduction benefits than do mixed transit modes in the short run, this should not be construed as advocating for fixed guideway modes over mixed transit modes *per se*. In the analysis, we have only considered the benefits in the auto market due to transit investment, and have not considered the costs of the various transit modes. Both construction and operating costs of transit vary widely by region and type of transit.[29] Further, proponents of public transit may argue that investment in public transit today is necessary to develop transit ridership in the future and to influence land-use patterns in order to sow the roots for a more efficient public transit system in the future. Overall, the magnitude of this benefit is subject to considerable variability, and is dependent upon the characteristics of the existing transportation network, the technology of the proposed transit system, and the socioeconomic and geographic attributes of the region. The implication is that transit cost-benefit analyses must be carried out on a case-by-case basis and there may be limited scope for the external validity of regional studies, as past experiences in one city may not generalize to potential new transit investments in another.

Our results when accounting for both substitution and induced demand cast doubt on the benefi-

[28] Their study includes counts of large buses in peak service as the measure of transit capacity, whereas we include all types of transit and a more accurate measure of transit supply in the form of vehicle-miles supplied.

[29] Estimates of the construction costs of different transit modes are provided in Table 3.5 of Small and Verhoef (2007).

cial effects of public transport on congestion in the medium and long run. By reducing congestion, increasing accessibility, increasing economic activity, and/or attracting additional residents and workers to the area, transit investment may generate additional automobile trips that were previously not undertaken, and we find that on average this induced demand may offset the substitution effect in the medium run and outweigh the substitution effect in the long run. However if additional residents and workers are attracted to the area in the medium and long run as a result of transit investment, this migration may possibly reduce congestion in the areas that the migrants leave behind. Although a rigorous analysis of the subsequent induced demand and any effects of the 'fundamental law of traffic congestion' that may subsequently arise as a result of the reduction in congestion in the areas that the migrants leave behind is beyond the scope of this paper, the reduction in congestion in areas that migrants leave behind may yield benefits to these areas, at least initially. Thus, if we account for the general equilibrium effects of public transit investment across a broader geographical scope beyond the urban area where the public transit investment takes place, it is possible that public transit investment remains beneficial not only in the short run, but in the medium and long run as well. In future work we hope to more rigorously explore the broader, more geographically expansive effects of public transit.

In addition, there are two factors that suggest that public transit could have a more beneficial impact on road congestion in the future. First, the estimated effects have been generated via the existing public transit networks, which Winston and Maheshri (2007) emphasize are not presently optimally configured and should not be assumed to be in long-run equilibrium, due to regulatory, political, and physical constraints. Second, these results are also in the context of inadequate road pricing. Small (2005) discusses the potential complementarity of road pricing and public transit provision; the ability of public transit to reduce congestion could be greatly enhanced if individuals were required to pay the full marginal social cost of auto travel, which would increase the substitution effect. Additionally, auto travel is averaged over the entire day in our data; in practice, transit capacity varies according to peak/off-peak travel periods. With more detailed data disaggregated over time, it would be possible to generate peak and off-peak elasticities of auto travel with respect to transit capacity, which would further aid transit investment decisions.

Our finding that there can considerable heterogeneity and sizable differences across regions in the elasticity of auto travel with respect to transit capacity implies that the observed effects of transit investment in one region may not generalize to another region, so comparison groups should be considered carefully when forecasting future effects of potential transit investments. The potential for regional heterogeneity also has implications for the external validity of our results. Our estimates of the average elasticities are based on the characteristics of US urban areas and on the observed travel behavior in relation to existing US policies; the *average* effect of transit on auto travel in the US may not necessarily apply to other countries in Europe, South America, etc. In addition, mobility may be lower in other countries than in the U.S., perhaps owing in part to unobservable factors such as culture, which may mitigate the induced demand effect in other countries. We hope to examine such cross-country differences in future work.

This paper contributes to the literature by separately estimating the substitution and equilibrium effects following public transit investment; by accounting for regional heterogeneity in the effect of transit supply on auto use; by using a wider and longer time series of data; by distinguishing between the substitution effect and the equilibrium effect; and by being cognizant of the potential endogeneity inherent in evaluating the effect of past investments in transit on traffic congestion. While there is modest evidence that public transit may be able to reduce congestion levels in the short run, these benefits may be offset by induced demand. Our results also reaffirm the theoretical and empirical argument that traffic congestion can only be fully addressed in the long run by devising economically and politically accepted approaches to efficiently pricing auto travel across the U.S.

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Appendix A: Supplementary Tables

Table A.1: Summary statistics

	Obs	Mean	Std. Dev.	Min	Max	Source
Traffic Congestion						
Travel time index	2,016	1.18	0.08	1.02	1.43	UMR
Total annual hours of delay	2,016	41,954	78,991	289	632,212	UMR
Roadway congestion index	2,016	0.97	0.19	0.50	1.58	UMR
% of peak vehicle-miles traveled under congested conditions	2,016	40.7	20.2	5	96	UMR
Annual delay hours per capita	2,016	21.1	8.9	1.8	58.1	UMR
Daily auto vehicle-mile traveled per lane-mile (000s)	2,016	7.1	1.5	3.0	11.5	UMR
Auto Network						
Freeway lane-miles	2,016	909	1,048	30	7,600	UMR
Arterial street lane-miles	2,016	2,618	3,200	190	20,900	UMR
Freeway auto vehicle-miles traveled (daily, 000s)	2,016	13,714	19,304	205	139,275	UMR
Arterial streets auto vehicle-miles traveled (daily, 000s)	2,016	13,461	17,545	600	126,010	UMR
Fuel price per vehicle-mile traveled (2011 dollars)	2,016	0.107	0.023	0.060	0.241	UMR, FHWA
Transit Funding						
Transit fare per passenger-mile traveled (2011 dollars)	1,997	0.215	0.093	0.009	2.121	NTD
Annual total Federal funding	2,002	73,136,182	216,742,246	0	2,999,359,744	NTD
Federal funding per capita	2,002	27,902	27,734	0	245,834	NTD
% of capital funds from Federal sources	1,977	0.666	0.228	0	1	NTD
% of operating funds from Federal sources	2,002	0.135	0.106	0	0.662	NTD
Transit Network Size: Directional Route-Miles						
Commuter rail	2,002	69.9	282.6	0	2,368	NTD
Light rail	2,002	10.1	24.3	0	152	NTD
Heavy rail	2,002	26.2	116.8	0	958	NTD
Hybrid rail	2,002	0.04	1.56	0	70	NTD
Monorail and automated guideway	2,002	0.18	1.01	0	9	NTD
Bus rapid transit	2,002	0.04	1.15	0	42	NTD
Bus	2,002	1,666	2,237	82	20,520	NTD
Trolleybus	2,002	4.7	23.3	0	173	NTD
Fixed guideway	2,002	106	327	0	2,956	NTD
Mixed traffic	2,002	1,670	2,331	82	20,520	NTD
All transit	2,002	1,777	2,632	82	23,371	NTD
Transit Capacity: Annual Vehicle Revenue-Miles						
Commuter rail	2,002	2,677,667	16,637,135	0	186,000,000	NTD
Light rail	1,997	594,859	1,556,640	0	10,154,573	NTD
Heavy rail	2,002	6,113,300	35,689,201	0	367,000,000	NTD
Hybrid rail	2,002	609	27,254	0	1,219,426	NTD
Monorail and automated guideway	2,002	17,811	106,417	0	1,120,647	NTD
Bus rapid transit	2,002	818	22,039	0	874,385	NTD
Bus	2,002	16,294,348	32,901,483	118,378	289,000,000	NTD
Trolleybus	2,002	138,270	832,751	0	7,915,843	NTD
Fixed guideway	1,997	9,427,123	52,303,899	0	554,976,384	NTD
Mixed traffic	2,001	16,410,332	33,028,658	118,378	289,000,000	NTD
All transit	1,996	25,847,205	82,595,975	118,378	843,976,384	NTD
Transit Ridership: Annual Passenger-Miles Traveled						
Commuter rail	2,002	97,201,568	604,396,641	0	6,690,000,000	NTD
Light rail	1,997	14,758,379	41,874,325	0	338,000,000	NTD
Heavy rail	2,002	141,634,084	874,646,063	0	10,700,000,000	NTD
Hybrid rail	2,002	20,263	906,638	0	40,566,372	NTD
Monorail and automated guideway	2,002	115,772	760,162	0	10,039,936	NTD
Bus rapid transit	2,002	11,020	314,982	0	12,238,706	NTD
Bus	2,002	184,657,374	485,064,038	230,832	4,790,000,000	NTD
Trolleybus	2,002	1,979,391	13,120,112	0	134,000,000	NTD
Fixed guideway modes	1,997	254,339,441	1,474,259,227	0	17,487,702,016	NTD
Mixed traffic modes	2,002	186,636,765	486,890,379	230,832	4,790,000,128	NTD
All transit modes	1,997	440,954,265	1,921,938,252	230,832	22,099,701,760	NTD
Avg trip length (passenger-miles per trip), fixed guideway	622	7.8	10.1	0	182.3	NTD
Avg trip length (passenger-miles per trip), mixed traffic	2,002	4.2	1.5	1.0	18.8	NTD
Avg trip length (passenger-miles per trip), all transit	1,997	4.5	1.7	1.0	19.5	NTD
Geographic and Socioeconomic						
Population (000s)	2,016	1,568	2,386	120	18,946	UMR
Area (square-miles)	2,016	501	522	43	3,353	NTD
Population density (000s per square-mile)	2,016	2.9	1.3	0.8	9.3	UMR, NTD
Proportion of population employed	2,016	0.58	0.07	0.33	0.80	BEA
Per capita income (2011 dollars, 000s)	2,016	38.6	7.6	16.1	71.5	BEA

Data Sources (see Section 4 for details): BEA - Bureau of Economic Analysis; FHWA - Federal Highway Administration; NTD - National Transit Database; UMR - Texas Transportation Institute's Urban Mobility Report

Table A.2: Overview of regions included in the analysis

Urban Area (UZA)	Population			Travel Time Index		Delay Hrs	Freeways (Auto)		Transit			Mode Split	Rail
	000s	%Δ	per sq mi	1991	2011	(per cap)	%Δlane-mi	%ΔVMT	%ΔDRM	%ΔVRM	%ΔPMT	(VMT/PMT)	(Y = 1)
Akron, OH	619	19.0%	2,010	1.10	1.12	15.8	17.3%	38.4%	31.7%	11.0%	11.6%	116.7	No
Albany, NY	616	25.7%	2,169	1.08	1.16	21.3	41.1%	68.4%	58.5%	11.4%	-26.8%	70.7	No
Albuquerque, NM	630	21.2%	2,813	1.11	1.10	19.8	70.9%	120.5%	0.5%	75.2%	115.4%	34.1	Yes
Allentown, PA-NJ	635	22.1%	2,190	1.12	1.17	20.9	65.9%	105.5%	-3.5%	49.6%	8.2%	167.4	No
Anchorage, AK	307	30.6%	3,886	1.18	1.18	11.8	15.2%	28.4%	-35.8%	8.5%	37.8%	39.3	Yes
Atlanta, GA	4,360	50.3%	2,221	1.14	1.24	32.6	52.7%	90.6%	7.1%	16.8%	32.0%	28.5	Yes
Austin, TX	1,345	94.9%	4,230	1.17	1.32	28.5	102.8%	117.0%	60.7%	50.7%	50.6%	43.5	Yes
Bakersfield, CA	544	72.7%	4,945	1.03	1.11	8.7	20.6%	42.0%	41.0%	65.2%	23.3%	76.4	No
Baltimore, MD	2,523	24.9%	3,694	1.14	1.23	27.8	24.9%	67.1%	-9.6%	36.7%	45.9%	16.5	Yes
Baton Rouge, LA	610	64.9%	2,171	1.11	1.22	28.1	61.7%	105.4%	7.8%	2.2%	9.8%	217.7	No
Beaumont, TX	243	15.7%	3,000	1.04	1.10	17.3	27.0%	67.7%	14.6%	40.6%	-51.0%	775.4	No
Birmingham, AL	861	35.6%	2,196	1.08	1.19	24.3	30.6%	67.0%	62.9%	-19.1%	-47.9%	342.2	No
Boise, ID	319	87.6%	2,927	1.04	1.06	11.4	137.1%	131.0%	-10.3%	111.1%	181.5%	147.5	No
Boston, MA-NH-RI	4,320	19.3%	2,488	1.27	1.28	31.7	44.8%	44.4%	29.9%	19.6%	54.1%	10.6	Yes
Bridgeport, CT-NY	938	31.2%	2,017	1.13	1.27	28.3	31.9%	52.1%	65.6%	53.3%	42.9%	126.0	No
Brownsville, TX	214	78.3%	3,754	1.13	1.18	17.3	170.0%	266.1%	72.3%	32.3%	-32.9%	62.1	No
Buffalo, NY	1,048	-1.6%	2,856	1.10	1.17	20.6	24.4%	31.6%	-24.3%	4.3%	4.8%	46.1	Yes
Cape Coral, FL	473	93.1%	2,464	1.13	1.15	21.1	285.0%	507.8%	12.0%	129.4%	104.4%	109.8	No
Charleston, SC	535	33.8%	2,316	1.13	1.15	20.3	44.9%	92.5%	90.0%	79.8%	21.0%	155.5	No
Charlotte, NC-SC	1,070	91.1%	2,460	1.14	1.20	27.1	344.5%	357.0%	40.9%	181.6%	207.7%	48.0	Yes
Chicago, IL-IN	8,605	14.5%	4,053	1.17	1.25	31.6	52.2%	66.6%	23.6%	1.9%	17.1%	7.3	Yes
Cincinnati, OH-KY-IN	1,717	43.1%	2,555	1.14	1.20	24.9	52.6%	70.5%	3.8%	-2.8%	-21.6%	73.3	No
Cleveland, OH	1,700	-3.4%	2,628	1.14	1.16	20.6	33.9%	35.0%	7.5%	-38.6%	-27.9%	39.5	Yes
Colorado Springs, CO	557	68.8%	2,827	1.04	1.13	17.8	77.0%	157.6%	65.9%	20.5%	9.7%	145.9	No
Columbia, SC	490	46.3%	1,822	1.05	1.11	20.6	57.1%	122.8%	23.9%	-20.4%	-16.4%	335.1	No
Columbus, OH	1,289	40.1%	3,239	1.08	1.18	27.7	42.5%	79.0%	22.5%	20.2%	-19.3%	100.5	No
Corpus Christi, TX	337	18.2%	3,064	1.02	1.04	9.4	33.3%	40.1%	-10.5%	3.6%	28.3%	62.6	No
Dallas, TX	5,260	59.9%	3,738	1.13	1.26	31.9	39.6%	72.9%	-16.9%	24.6%	32.8%	65.6	Yes
Dayton, OH	745	24.2%	2,299	1.13	1.11	16.7	62.1%	74.4%	-15.3%	-18.4%	-35.1%	93.2	No
Denver-Aurora, CO	2,348	48.6%	4,705	1.14	1.27	32.4	65.3%	94.4%	91.2%	86.3%	143.5%	20.3	Yes
Detroit, MI	3,869	-2.9%	3,066	1.19	1.18	27.5	22.5%	19.6%	-11.4%	-12.2%	-45.5%	91.8	No
El Paso, TX-NM	739	32.0%	3,374	1.09	1.21	21.6	102.4%	100.8%	43.9%	63.7%	4.0%	40.5	No
Eugene, OR	256	31.3%	3,765	1.08	1.08	8.9	49.1%	94.8%	25.2%	4.2%	63.0%	22.1	No
Fresno, CA	686	44.4%	4,935	1.07	1.08	10.8	82.6%	137.4%	28.7%	31.8%	26.6%	73.6	No
Grand Rapids, MI	612	37.5%	2,381	1.05	1.09	16.4	81.7%	100.9%	97.6%	113.8%	144.8%	94.5	No
Greensboro, NC	351	59.5%	2,600	1.03	1.10	18.9	71.6%	122.5%	612.1%	326.0%	621.1%	67.0	No
Hartford, CT	905	9.0%	1,930	1.11	1.18	25.4	29.3%	52.3%	19.2%	27.7%	-5.8%	68.5	Yes
Honolulu, HI	719	7.3%	4,669	1.30	1.36	29.0	28.2%	16.8%	12.0%	20.0%	19.9%	6.1	No
Houston, TX	4,129	41.2%	3,188	1.19	1.26	35.3	59.2%	73.1%	77.6%	29.2%	-0.6%	54.7	Yes
Indianapolis, IN	1,234	29.9%	2,231	1.10	1.17	28.5	56.8%	75.4%	-11.6%	12.1%	-25.6%	202.1	No
Jackson, MS	426	25.3%	2,646	1.05	1.10	17.7	31.9%	64.5%	-7.9%	-2.2%	-38.4%	1469.2	No
Jacksonville, FL	1,083	44.4%	2,635	1.18	1.14	20.9	102.8%	123.5%	-12.7%	53.4%	52.8%	80.4	No
Kansas City, MO-KS	1,585	36.6%	2,714	1.09	1.13	18.6	37.9%	73.3%	37.5%	10.8%	-2.4%	130.7	No
Knoxville, TN	508	58.8%	1,499	1.21	1.16	26.1	49.2%	72.6%	-16.0%	48.6%	14.1%	325.1	No
Laredo, TX	235	88.0%	5,465	1.06	1.14	13.1	156.7%	185.9%	125.7%	110.0%	20.7%	65.0	No
Las Vegas, NV	1,443	92.4%	5,045	1.15	1.20	31.5	212.5%	241.8%	27.7%	121.6%	477.7%	35.8	No
Little Rock, AR	464	49.7%	2,252	1.02	1.07	17.5	74.5%	103.5%	1.0%	40.9%	42.1%	227.5	Yes
Los Angeles, CA	13,229	12.5%	7,931	1.40	1.37	37.9	22.7%	25.0%	25.1%	34.8%	40.8%	21.3	Yes
Louisville, KY-IN	1,084	33.8%	2,772	1.13	1.18	24.2	46.4%	86.7%	22.3%	-18.0%	-32.2%	103.9	No
Madison, WI	403	30.0%	3,535	1.05	1.11	13.3	65.1%	59.0%	34.3%	30.7%	50.5%	31.2	No
McAllen, TX	578	122.3%	1,841	1.02	1.16	19.8	96.4%	159.5%	12.8%	389.0%	50.5%	1982.4	No
Memphis, TN-MS-AR	1,058	22.3%	2,645	1.16	1.18	27.1	58.8%	80.8%	18.3%	1.9%	-19.6%	109.6	No
Miami, FL	5,482	38.3%	4,912	1.19	1.25	31.9	35.2%	91.6%	77.1%	55.7%	79.6%	26.9	Yes
Milwaukee, WI	1,496	22.1%	3,072	1.11	1.15	18.6	46.6%	47.3%	5.4%	-5.2%	-8.2%	46.9	No
Minneapolis-St. Paul, MN	2,757	34.2%	3,084	1.12	1.21	22.0	37.4%	63.3%	51.1%	51.8%	74.2%	31.9	Yes
Nashville, TN	1,145	99.1%	2,657	1.15	1.23	31.2	82.5%	126.9%	35.4%	35.7%	73.4%	134.1	Yes
New Haven, CT	616	35.4%	2,161	1.10	1.17	23.6	57.1%	83.4%	-23.8%	21.3%	-8.6%	116.2	No
New Orleans, LA	1,065	0.5%	5,379	1.22	1.20	18.0	-2.6%	-2.8%	-4.8%	-53.1%	-59.6%	42.6	No
New York, NY-NJ-CT	18,946	18.6%	5,650	1.22	1.33	28.7	24.6%	44.0%	20.2%	18.3%	50.5%	2.7	Yes
Oklahoma City, OK	983	39.4%	3,053	1.04	1.15	25.6	32.0%	49.4%	22.3%	4.5%	30.4%	370.2	No
Omaha, NE-IA	646	20.7%	2,858	1.06	1.11	16.6	88.1%	144.3%	-2.8%	-0.1%	-28.7%	190.9	No

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Table A.2 – continued from previous page

Urban Area (UZA)	Population			Travel Time Index		Delay Hrs	Freeways (Auto)		Transit			Mode Split	Rail
	000s	%Δ	per sq mi	1991	2011	(per cap)	%Δlane-mi	%ΔVMT	%ΔDRM	%ΔVRM	%ΔPMT	(VMT/PMT)	(Y = 1)
Orlando, FL	1,475	62.1%	3,256	1.21	1.20	31.6	99.2%	130.2%	142.9%	204.6%	275.5%	56.2	No
Oxnard, CA	428	43.4%	5,632	1.02	1.10	17.5	12.0%	34.9%	79.1%	162.0%	143.0%	137.2	No
Pensacola, FL-AL	361	36.2%	1,648	1.07	1.11	15.7	96.8%	84.3%	106.6%	60.7%	31.9%	240.1	No
Philadelphia, PA-NJ-MD	5,381	17.2%	2,989	1.16	1.26	29.0	45.8%	55.1%	40.1%	28.8%	26.3%	11.5	Yes
Phoenix-Mesa, AZ	3,679	90.6%	4,605	1.09	1.18	22.4	162.3%	229.0%	116.7%	174.9%	101.9%	56.5	Yes
Pittsburgh, PA	1,761	-0.8%	2,067	1.29	1.24	26.5	26.2%	32.9%	-0.5%	-18.1%	-37.3%	29.0	Yes
Portland, OR-WA	1,925	57.8%	4,061	1.14	1.28	27.0	53.5%	67.6%	3.6%	41.2%	103.9%	15.9	Yes
Poughkeepsie, NY	550	59.4%	2,075	1.12	1.12	17.8	75.9%	56.2%	90.7%	56.7%	231.1%	92.2	No
Providence, RI-MA	1,236	12.4%	2,452	1.09	1.16	19.9	39.7%	62.7%	140.2%	39.7%	20.7%	67.0	No
Raleigh-Durham, NC	1,142	119.6%	3,569	1.08	1.14	15.7	150.0%	176.9%	10.5%	131.0%	80.2%	244.7	No
Richmond, VA	974	42.2%	2,229	1.09	1.11	20.0	81.5%	76.8%	29.6%	1.1%	-27.4%	165.1	No
Riverside, CA	2,025	50.0%	4,613	1.13	1.23	25.3	35.9%	65.7%	36.2%	109.9%	78.6%	77.4	No
Rochester, NY	749	21.8%	2,539	1.13	1.13	19.8	27.7%	40.7%	51.5%	-25.1%	25.2%	59.2	No
Sacramento, CA	1,895	62.7%	5,136	1.16	1.20	20.7	24.6%	61.4%	94.7%	59.6%	51.6%	48.5	Yes
Salem, OR	246	44.7%	3,565	1.11	1.14	18.7	68.9%	73.9%	-18.9%	32.0%	55.1%	70.0	No
Salt Lake City, UT	1,027	27.6%	4,446	1.14	1.14	21.3	28.8%	48.5%	72.8%	47.7%	107.6%	18.5	Yes
San Antonio, TX	1,558	32.0%	3,819	1.06	1.19	25.7	31.4%	97.1%	49.6%	14.6%	13.4%	45.4	No
San Diego, CA	3,121	27.6%	3,991	1.12	1.18	23.2	22.8%	37.2%	4.9%	12.3%	22.8%	32.2	Yes
San Francisco, CA	4,101	10.1%	7,782	1.23	1.22	37.8	15.7%	27.7%	12.1%	27.5%	23.5%	8.5	Yes
San Jose, CA	1,838	22.5%	7,069	1.23	1.24	25.8	-5.7%	3.8%	-3.6%	-16.6%	-1.8%	43.2	Yes
Sarasota, FL	688	51.2%	2,548	1.11	1.12	15.3	260.0%	619.1%	93.4%	168.6%	205.1%	103.0	No
Seattle, WA	3,286	39.8%	3,444	1.27	1.26	30.7	52.9%	44.3%	-9.4%	73.1%	82.3%	16.5	Yes
Spokane, WA-ID	383	29.8%	2,678	1.12	1.12	15.9	104.0%	138.1%	-6.8%	15.0%	27.7%	40.1	No
Springfield, MA-CT	628	9.2%	2,032	1.11	1.13	19.2	36.3%	68.6%	26.4%	5.6%	-4.7%	92.8	No
St. Louis, MO-IL	2,343	19.2%	2,826	1.14	1.14	21.2	74.1%	72.6%	12.5%	50.7%	56.8%	44.8	Yes
Stockton, CA	409	43.5%	5,527	1.10	1.10	8.6	37.5%	99.5%	233.8%	112.4%	292.5%	29.5	Yes
Tampa, FL	2,393	38.7%	2,984	1.22	1.20	26.3	139.1%	145.5%	-30.7%	54.8%	55.7%	73.2	Yes
Toledo, OH-MI	516	5.3%	2,554	1.05	1.13	17.8	21.9%	44.9%	-53.3%	-42.0%	-54.3%	162.3	No
Tucson, AZ	718	30.5%	2,467	1.13	1.16	26.6	145.7%	203.4%	141.2%	36.5%	15.1%	54.0	No
Tulsa, OK	717	12.9%	2,747	1.06	1.12	21.6	96.0%	72.3%	52.4%	-4.1%	-21.8%	295.9	No
Virginia Beach, VA	1,555	14.8%	2,951	1.18	1.20	29.7	27.6%	51.5%	38.2%	45.7%	76.6%	81.4	No
Washington, DC-VA-MD	4,613	41.9%	3,987	1.25	1.32	38.9	27.0%	54.2%	172.0%	67.4%	50.5%	9.4	Yes
Wichita, KS	510	39.7%	2,849	1.06	1.09	13.5	83.2%	134.9%	-20.5%	-20.1%	1.7%	226.0	No
Winston-Salem, NC	388	68.7%	1,546	1.04	1.11	13.9	64.3%	70.6%	-11.4%	14.6%	-20.6%	258.6	No
Worcester, MA-CT	447	17.6%	1,788	1.11	1.13	22.7	45.6%	47.4%	-19.9%	-27.7%	-17.0%	264.7	No
Mean	1,761	39.4%	3,272	1.12	1.17	22.48	66.4%	96.5%	0.39	0.45	48.3%	136.6	0.354
Median	956	34.8%	2,857	1.12	1.17	21.29	50.7%	72.8%	0.23	0.30	25.8%	69.2	0
Min	214	-3.4%	1,499	1.02	1.04	8.60	-5.7%	-2.8%	-0.53	-0.53	-59.6%	2.7	0
Max	18,946	122.3%	7,931	1.40	1.37	38.88	344.5%	619.1%	6.12	3.89	621.1%	1982.4	1

Abbreviations: VMT - vehicle-miles traveled; DRM - directional route-miles; VRM - vehicle revenue-miles; PMT - passenger-miles traveled
Note: Throughout the table, values for each urban area (UZA) are measured in 2011 (unless specified otherwise), and growth rates reflect the cumulative growth of 2011 values relative to 1991 values.

Table A.3: Correlation between various measures of congestion for the 96 urban areas (UZAs)

	V/C ratio (freeways)	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita
Volume-to-capacity (V/C) ratio, freeways	1.000	-	-	-	-
Travel Time Index	0.601	1.000	-	-	-
Roadway Congestion Index	0.933	0.620	1.000	-	-
% peak VMT in congested conditions	0.858	0.677	0.911	1.000	-
Annual delay hours per capita	0.653	0.792	0.677	0.720	1.000

Notes: Table shows the pairwise correlations between each pair of the following measures of congestion: the volume-to-capacity ratio on freeways; the Travel Time Index; the Roadway Congestion Index; the percentage of peak vehicle-miles traveled in congested conditions; and the annual hours of delay per capita.

Table A.4: Average congestion levels by urban area (UZA), 1991-2011

Urban Area (UZA)	Roadway Congestion Index	Annual Delay Hours per Capita	Urban Area (UZA)	Roadway Congestion Index	Annual Delay Hours per Capita
Los Angeles, CA	1.543	43.7	Nashville, TN	0.950	31.1
San Francisco, CA	1.354	44.4	St. Louis, MO-IL	0.946	24.2
Riverside, CA	1.317	20.3	Milwaukee, WI	0.936	19.1
San Diego, CA	1.301	21.3	New Orleans, LA	0.927	15.1
San Jose, CA	1.282	33.1	Allentown, PA-NJ	0.920	20.8
Washington, DC-VA-MD	1.270	39.3	New Haven, CT	0.912	23.9
Miami, FL	1.260	27.8	Birmingham, AL	0.907	22.0
Atlanta, GA	1.248	32.8	Memphis, TN-MS-AR	0.900	25.7
Sacramento, CA	1.227	22.6	Fresno, CA	0.897	11.7
Oxnard, CA	1.213	14.5	Boise, ID	0.895	10.6
Tampa, FL	1.192	23.1	Cleveland, OH	0.889	18.0
Phoenix-Mesa, AZ	1.168	20.0	Dayton, OH	0.877	19.3
Detroit, MI	1.163	29.7	Hartford, CT	0.872	22.1
Las Vegas, NV	1.162	27.8	Omaha, NE-IA	0.868	12.2
Chicago, IL-IN	1.140	25.9	Poughkeepsie, NY	0.863	14.8
Portland, OR-WA	1.134	26.1	Salem, OR	0.858	22.2
Seattle, WA	1.134	33.2	El Paso, TX-NM	0.852	18.6
Houston, TX	1.123	26.3	Columbia, SC	0.846	14.5
Indianapolis, IN	1.113	31.7	Eugene, OR	0.844	10.7
Cape Coral, FL	1.112	21.3	Oklahoma City, OK	0.844	21.5
Orlando, FL	1.112	32.9	Grand Rapids, MI	0.842	14.1
Baltimore, MD	1.105	23.7	Madison, WI	0.838	7.8
Dallas, TX	1.091	25.8	Providence, RI-MA	0.838	18.7
Denver-Aurora, CO	1.090	27.3	Akron, OH	0.831	19.5
Sarasota, FL	1.087	15.1	Little Rock, AR	0.820	12.6
Minneapolis-St. Paul, MN	1.080	20.6	Toledo, OH-MI	0.818	20.0
Boston, MA-NH-RI	1.073	30.6	Jackson, MS	0.814	13.7
Bridgeport, CT-NY	1.073	29.4	Worcester, MA-CT	0.810	24.8
Charleston, SC	1.056	19.0	Winston-Salem, NC	0.806	11.6
Louisville, KY-IN	1.055	23.3	Richmond, VA	0.803	15.4
Knoxville, TN	1.051	27.9	Kansas City, MO-KS	0.792	21.7
Honolulu, HI	1.051	25.1	McAllen, TX	0.789	13.6
New York, NY-NJ-CT	1.049	24.0	Tulsa, OK	0.780	16.4
Tucson, AZ	1.044	22.0	Springfield, MA-CT	0.779	17.4
Baton Rouge, LA	1.030	22.2	Colorado Springs, CO	0.776	18.5
Stockton, CA	1.030	7.3	Bakersfield, CA	0.766	4.5
Jacksonville, FL	1.027	23.1	Brownsville, TX	0.759	8.8
Columbus, OH	1.027	23.8	Pittsburgh, PA	0.757	26.5
Salt Lake City, UT	1.020	19.4	Beaumont, TX	0.757	12.8
Philadelphia, PA-NJ-MD	1.019	24.4	Spokane, WA-ID	0.728	19.5
Charlotte, NC-SC	1.012	19.8	Albany, NY	0.727	17.1
Cincinnati, OH-KY-IN	1.008	30.4	Anchorage, AK	0.725	17.5
San Antonio, TX	0.997	19.5	Rochester, NY	0.725	17.6
Austin, TX	0.989	26.1	Corpus Christi, TX	0.686	8.2
Pensacola, FL-AL	0.987	13.6	Laredo, TX	0.686	7.6
Albuquerque, NM	0.982	22.4	Buffalo, NY	0.666	18.0
Virginia Beach, VA	0.964	30.1	Greensboro, NC	0.655	19.8
Raleigh-Durham, NC	0.951	15.0	Wichita, KS	0.554	12.8
			Mean	**0.965**	**21.1**

Table A.5: First-stage regression results: transit capacity (Substitution Effect)

Dependent variable is Transit Capacity in total vehicle revenue-miles (millions)		
	Coefficient	**(Std. Err)**
Instrument		
Federal Capital Funding, Two Years Prior (2011$)	2.70e-08***	(7.19e-09)
Controls		
Auto capacity: freeways (total lane-miles)	-0.008	(0.006)
Auto capacity: arterials (total lane-miles)	0.002	(0.004)
Fuel price ($ per vehicle-mile)	36.204	(31.988)
Transit fare ($ per unlinked trip)	-0.445	(0.274)
Employment rate (total employed per capita)	11.972	(19.429)
Income (real per capita income)	0.268	(0.214)
Population (millions)	27.442*	(10.764)
Year fixed effects	Yes	
UZA fixed effects	Yes	
N	1802	
R^2	0.671	
p-val. (Prob > F)	0.000	
First-stage F-statistic		
First-stage AP F-stat	14.12	
Weak-instrument-robust inference		
Anderson-Rubin Wald F test: p-val.	0.027	
Anderson-Rubin Wald χ^2 test: p-val.	0.023	

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses.

(Significance levels: $* : p < 0.05$ $** : p < 0.01$ $*** : p < 0.001$)

Table A.6: First-stage regression results: transit capacity (Medium-Run Equilibrium Effect)

Dependent variable is Transit Capacity in total vehicle revenue-miles (millions)		
	Coefficient	**(Std. Err)**
Instrument		
Federal Capital Funding, Two Years Prior (2011$)	2.33e-08***	(6.69e-09)
Controls		
Auto capacity: freeways (total lane-miles)	-0.007	(0.007)
Auto capacity: arterials (total lane-miles)	0.004	(0.004)
Fuel price ($ per vehicle-mile)	31.589	(26.273)
Transit fare ($ per unlinked trip)	-0.257	(0.233)
Employment rate, 5-year lag (total employed per capita)	-37.424	(21.337)
Income, 5-year lag (real per capita income)	0.155	(0.228)
Population, 5-year lag (millions)	21.279*	(8.373)
Year fixed effects	Yes	
UZA fixed effects	Yes	
N	1521	
R^2	0.551	
p-val. (Prob > F)	0.000	
First-stage F-statistic		
First-stage AP F-stat	12.15	
Weak-instrument-robust inference		
Anderson-Rubin Wald F test: p-val.	0.327	
Anderson-Rubin Wald χ^2 test: p-val.	0.318	

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses.

(Significance levels: $*: p < 0.05$ $**: p < 0.01$ $***: p < 0.001$)

Table A.7: First-stage regression results: transit capacity (Long-Run Equilibrium Effect)

Dependent variable is Transit Capacity in total vehicle revenue-miles (millions)

	Coefficient	**(Std. Err)**
Instrument		
Federal Capital Funding, Two Years Prior (2011$)	4.53e-08***	(1.09e-08)
Controls		
Auto capacity: freeways (total lane-miles)	0.004	(0.007)
Auto capacity: arterials (total lane-miles)	0.009**	(0.003)
Fuel price ($ per vehicle-mile)	63.176	(38.300)
Transit fare ($ per unlinked trip)	-0.577	(0.420)
Year fixed effects	Yes	
UZA fixed effects	Yes	
N	1802	
R^2	0.518	
p-val. (Prob > F)	0.000	
First-stage F-statistic		
First-stage AP F-stat	17.17	
Weak-instrument-robust inference		
Anderson-Rubin Wald F test: p-val.	0.044	
Anderson-Rubin Wald χ^2 test: p-val.	0.039	

Notes: Robust standard errors clustered by urban area (UZA) are in parentheses.

(Significance levels: $* : p < 0.05$ $** : p < 0.01$ $*** : p < 0.001$)

Table A.8: Elasticity of auto travel with respect to transit capacity for 2 alternative specifications

	(1) base case	**(2)** census division-year fixed effects	**(3)** lagged dependent variable
Substitution Effect	-0.066*	-0.054†	-0.016*
Medium-Run Equilibrium Effect	-0.037	-0.005	0.002
Long-Run Equilibrium Effect	0.037*	0.050**	0.016**

Notes: Table compares elasticities of auto travel with respect to transit capacity in (1) the base case, with those obtained with regressions that also include (2) census division-year fixed effects, and (3) a lagged dependent variable. Robust standard errors are clustered by urban area (UZA). Transit capacity is instrumented by Federal transit funding in UZA, lagged two periods. Significance levels: † : $p < 0.10$ $*$: $p < 0.05$ $**$: $p < 0.01$ $***$: $p < 0.001$.

Table A.9: Elasticity of auto travel with respect to transit capacity for 6 alternative dependent variables

	(1) log of V/C ratio	**(2)** V/C ratio: freeways & arterials	**(3)** Travel Time Index	**(4)** Roadway Congestion Index	**(5)** % peak VMT in congested conditions	**(6)** Annual delay hrs per capita
Substitution Effect	-0.022*	-0.042*	-0.020*	-0.053***	-0.089**	0.001
Medium-Run Equilibrium Effect	-0.014	-0.009	-0.013	-0.023	-0.061	0.034
Long-Run Equilibrium Effect	0.015**	-	0.013**	0.045***	0.076**	0.059**

Notes: Table shows elasticities of auto travel with respect to transit capacity that result from using the following alternative measures of congestion, respectively: (1) the log of the volume-to-capacity ratio on freeways; (2) the volume-to-capacity ratio combining travel on freeway and arterial roads; (3) the Travel Time Index; (4) the Roadway Congestion Index; (5) the percentage of peak vehicle-miles traveled in congested conditions; and (6) the annual hours of delay per capita. Robust standard errors are clustered by urban area (UZA). Transit capacity is instrumented by Federal transit funding in UZA, lagged two periods. Significance levels: $*: p < 0.05$ $**: p < 0.01$ $***: p < 0.001$.

Appendix B: Detailed Analysis of Regional Heterogeneity

In this Appendix we provide additional analysis regarding the heterogeneity of the effects of public transit supply on auto travel across regional characteristics, as outlined in Section 5.2. For each characteristic, the urban areas (UZAs) are stratified using each UZA's mean value of that characteristic over the panel duration; as a result, the decile each UZA is in for a particular characteristic is held fixed over time.

Population size

As population increases, the number of commuters for whom transit is the most desirable (or only) mode of travel is also likely to increase. In large cities, the marginal external effect of the mode choice of an individual traveler is also higher, given the convexity of the congestion externality. Taken together, it is predicted that public transit will lead to a more significant effect on congestion as the city size increases.

There is significant variation in population across the UZAs: in 2011, the mean population was 1.76 million, ranging from a low of 0.21 million in Brownsville, TX to a high of 18.95 million in New York-Newark, NY-NJ-CT. Table B.1 summarizes the relationship between various congestion measures and the population of the UZA, indicating that congestion is most prevalent in the largest regions, as expected.

Table B.1: Congestion versus population size (means)

Population Quintile	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita	VMT per freeway lane-mile ('000s/day)
Very Low	1.115	0.809	20.07	12.85	10.32
Low	1.137	0.889	30.03	17.99	11.94
Medium	1.173	0.944	40.16	21.39	12.82
High	1.201	1.006	47.54	24.20	13.84
Very High	1.247	1.175	65.26	28.78	16.72

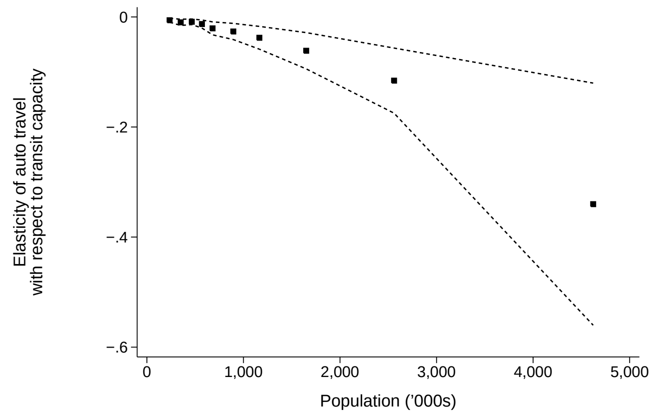
Figure B.1 plots our estimates of the elasticity of auto travel with respect to transit capacity when the models in equations (1) - (3) are stratified according to population deciles. The results indicate that transit is likely to have a minimal impact on congestion at lower population levels, but has a sizable impact for the most populous UZAs, suggesting that a threshold UZA size is required for transit to have a significant effect in the auto market. The magnitude of the elasticity of demand for automobile travel with respect to transit capacity increases (becoming more negative for the substitution effect and more positive for the long-run equilibrium effect) and the precision of the estimate decreases with population.

Population density

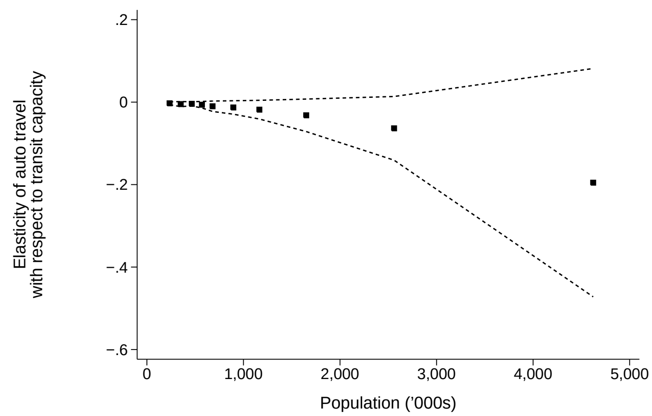
The population density of the UZA is expected to have an effect similar to the scale of the population. The average UZA in the sample had a population density of 3,311 people per square mile in 2011, with Knoxville, TN having the lowest density at 1,499 and Los Angeles, CA having the highest at 7,931.[30] Table B.2 shows that congestion increases with population density, but the

[30] For the population density stratification, we have excluded Oxnard, CA, which appears to be an outlier along this dimension with a population density of 9,342. The results of the population density stratification are robust to

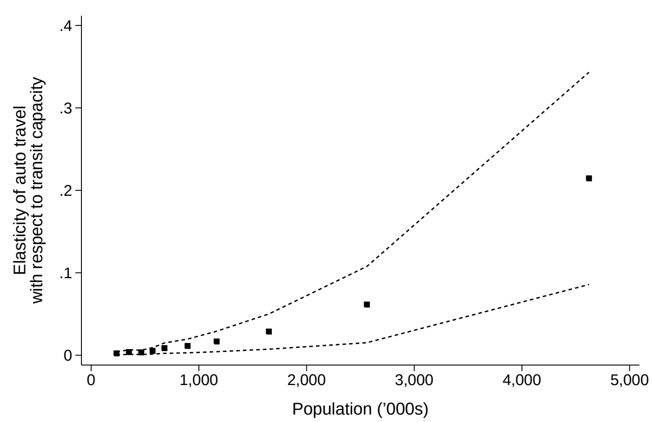
Figure B.1: Elasticity of auto travel with respect to transit capacity vs. population size



(a) Substitution Effect



(b) Medium-Run Equilibrium Effect



(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of population across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.

Table B.2: Congestion versus population density (means)

Density Quintile	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita	VMT per freeway lane-mile ('000s/day)
Very Low	1.137	0.897	29.61	18.45	11.73
Low	1.172	0.913	35.95	21.10	12.17
Medium	1.165	0.914	36.35	20.77	12.50
High	1.178	0.967	42.84	20.93	13.34
Very High	1.222	1.136	58.77	24.13	15.95

dispersion between low- and high-density regions is somewhat less than is the case for low- and high-population regions. Figure B.2 plots our estimates of the elasticity of auto travel with respect to transit capacity when the models in equations (1) - (3) are stratified according to population density deciles. The relationship follows a similar pattern to that above for total population size.

Rail service

Regions with rail service are expected to experience a larger effect of transit supply on congestion, as fixed guideway modes may be more competitive with auto travel for a larger subset of commuters than are mixed traffic modes. Over the study period, 28.7% of observations relate to UZAs with rail service in that year. 20 of the 96 UZAs had rail throughout the entire period, while 16 UZAs initiated rail service between 1991-2011, implying that 36 UZAs had rail in 2011. Accordingly, 60 UZAs have not had rail service at any point in time. Table B.3 shows that rail systems tend to be located in the more congested regions. Separating the regions according to whether they had rail service prior to 1991 yields very similar results. According to our results in Table 5, on average the magnitude of the elasticity of auto travel with respect to transit capacity is nearly 10 times higher in regions with rail service than in regions without.

Table B.3: Congestion versus rail service (means)

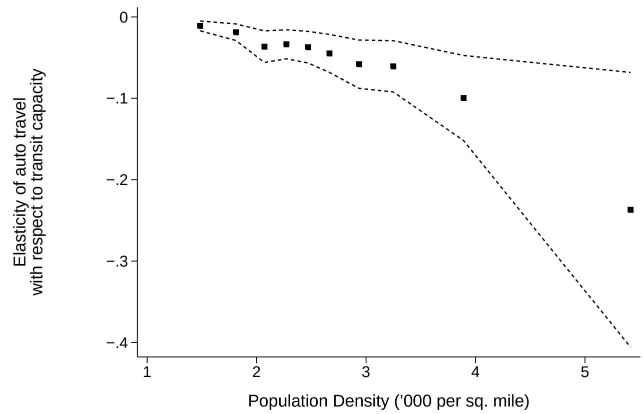
Rail Service?	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita	VMT per freeway lane-mile ('000s/day)
No	1.150	0.916	34.64	18.89	12.29
Yes	1.239	1.091	56.31	26.84	15.31

Transit type

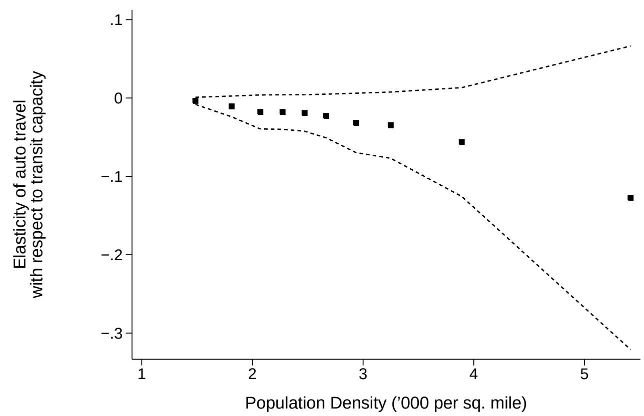
Similarly, we differentiate regions according to the proportion of total transit capacity supplied by fixed guideway modes. In 2011, 8.5% of total vehicle-revenue miles was provided by fixed guideway modes; 57 UZAs had no fixed guideway service, while the New York UZA had the highest percentage of fixed guideway transit at 66.1%. Table B.4 shows that fixed guideway transit occurs most prominently in higher-congested regions. It is possible that fixed guideway modes – that may have a greater effect on modal demand substitution and do not interact with auto traffic – can be expected to reduce traffic congestion, while mixed traffic modes may not. According to our results in Table 5, regions with a high proportion of fixed guideway transit have a magnitude of the elasticity of auto travel with respect to transit capacity approximately 8-9 times as large as those regions with a low proportion of fixed guideway transit.

whether Oxnard, CA is excluded.

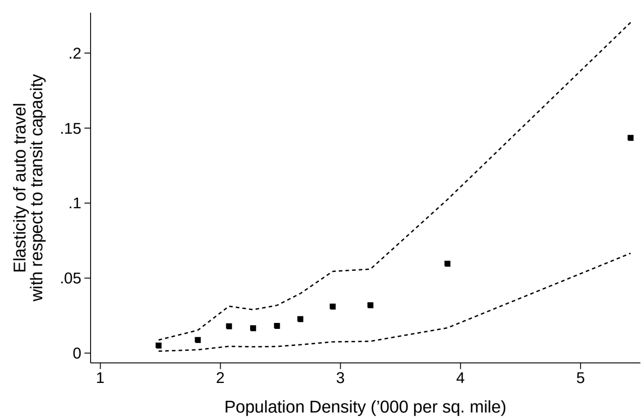
Figure B.2: Elasticity of auto travel with respect to transit capacity vs. population density



(a) Substitution Effect



(b) Medium-Run Equilibrium Effect



(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of population density across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.

Table B.4: Congestion versus % of fixed guideway transit (means)

% of FG transit service	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita	VMT per freeway lane-mile ('000s/day)
Low	1.159	0.925	35.90	19.64	12.44
High	1.241	1.133	60.66	27.29	16.03

Transit accessibility

Transit accessibility represents the extent to which the transit system has developed in a region, and is measured here by the directional-route miles of service provided per square mile. In 2011, the average UZA had 4.1 directional-route miles per square mile, ranging from a low of 0.7 in Winston-Salem, NC to a high of 34.2 in Stockton, CA. Greater transit accessibility is expected to lead to a higher likelihood of modal substitution when an increase in transit supply lowers the generalized cost of transit travel. Table B.5 shows that the accessibility of public transit is highest in the most congested regions.

Table B.5: Congestion versus transit accessibility (means)

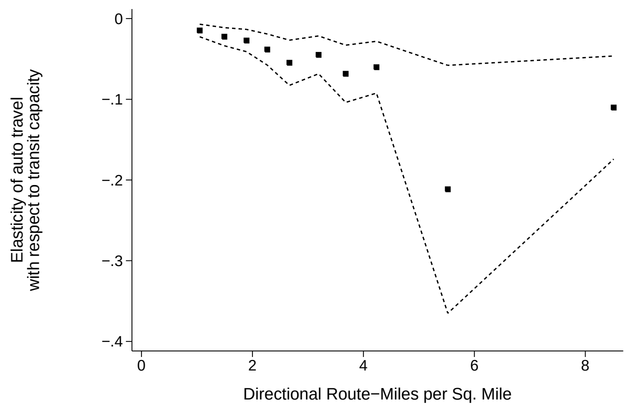
Transit Access quintile	Travel Time Index	Roadway Congestion Index	% peak VMT in congested conditions	Annual delay hours per capita	VMT per freeway lane-mile ('000s/day)
Very Low	1.137	0.909	32.41	19.26	12.07
Low	1.165	0.942	37.31	21.14	12.57
Medium	1.172	0.939	40.41	20.16	12.89
High	1.190	0.966	42.71	21.53	13.45
Very High	1.213	1.075	51.34	23.64	14.79

According to our results in Figure B.3, the magnitude of the elasticity of demand for automobile travel with respect to transit capacity increases (becoming more negative for the substitution effect and more positive for the long-run equilibrium effect) and the precision of the estimate decreases with transit accessibility. In the long run, the relationship between transit accessibility and the elasticity of demand for automobile travel with respect to transit capacity appears somewhat non-monotonic, with the elasticity decreasing slightly at high levels of transit accessibility. Thus, at high levels of transit accessibility, increases in transit accessibility are associated with a decrease in the elasticity of demand for automobile travel with respect to transit capacity. A possible explanation is that when transit is already extremely accessible, auto demand does not increase as much in the long run in response to changes in transit capacity, perhaps because transit capacity is not as binding in areas where transit is already extremely accessible.

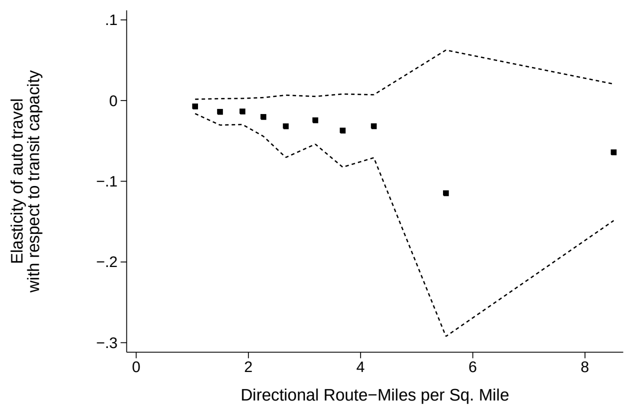
Transit capacity

We measure transit capacity by the per capita vehicle-revenue miles of transit service provided, which is another indication of the degree of transit network development. In 2011, the average value across UZAs was 9.4 vehicle-revenue miles per capita, ranging from a low of 1.7 in McAllen, TX to a high of 43.4 in New York. Table B.6 indicates that the highest public transit service frequency occurs in the most congested regions. As was the case with transit accessibility, Figure B.4 illustrates that additional transit service capacity has the greatest impact in regions that have a high pre-existing supply of public transit.

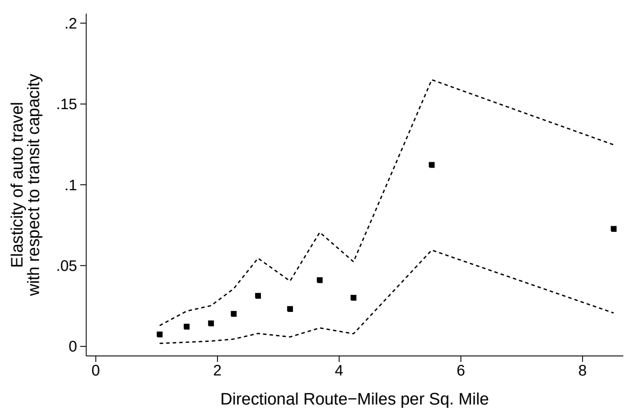
Figure B.3: Elasticity of auto travel with respect to transit capacity vs. transit accessibility



(a) Substitution Effect



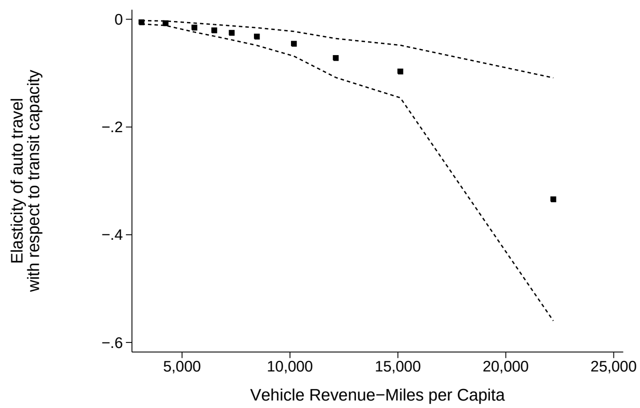
(b) Medium-Run Equilibrium Effect



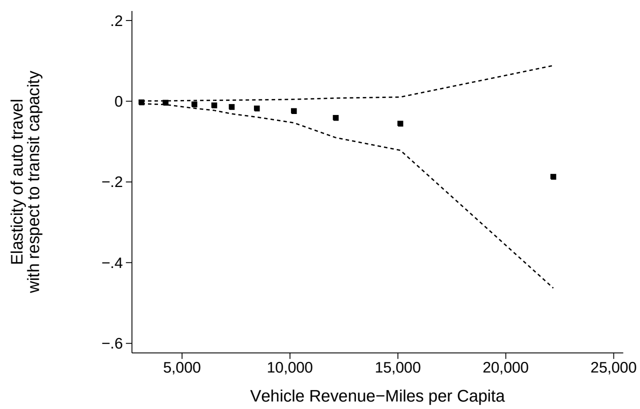
(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of the level of transit accessibility (as measured by directional-route miles of service provided per square mile) across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.

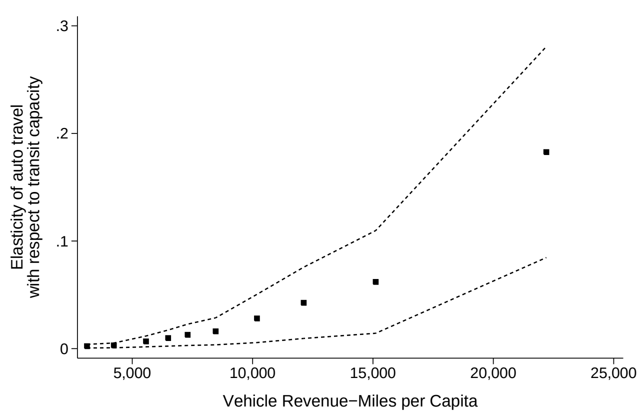
Figure B.4: Elasticity of auto travel with respect to transit capacity vs. transit capacity



(a) Substitution Effect



(b) Medium-Run Equilibrium Effect



(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of the level of transit capacity (as measured by per capita vehicle-revenue miles of transit service) across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.

Table B.6: Congestion versus transit capacity (means)

Transit Capacity quintile	**Travel Time Index**	**Roadway Congestion Index**	**% peak VMT in congested conditions**	**Annual delay hours per capita**	**VMT per freeway lane-mile ('000s/day)**
Very Low	1.124	0.881	28.11	16.89	11.61
Low	1.153	0.927	36.00	20.27	12.46
Medium	1.163	0.931	38.00	19.31	12.60
High	1.197	1.035	48.40	23.16	14.30
Very High	1.240	1.057	53.76	26.23	14.82

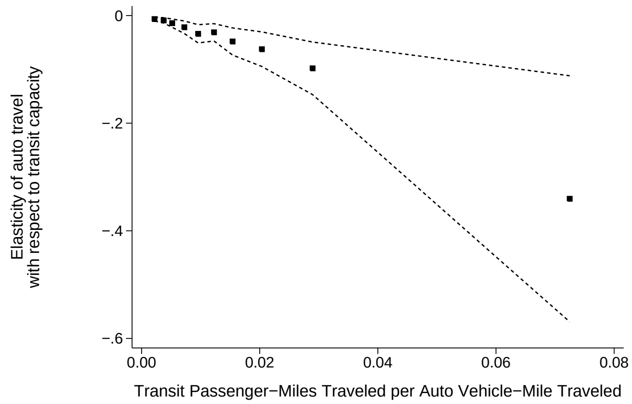
Transit usage

Lastly, we consider how the existing rate of transit ridership influences the effect of transit supply on congestion. The relative transit usage of a region is measured by the ratio of transit passenger-miles traveled to auto vehicle-miles traveled. Table B.7 indicates that the modal travel share of transit is positively correlated with the level of congestion. According to our results in Figure B.5, the magnitude of the elasticity of demand for automobile travel with respect to transit capacity increases (becoming more negative for the substitution effect and more positive for the long-run equilibrium effect) and the precision of the estimate decreases with the degree of existing transit usage.

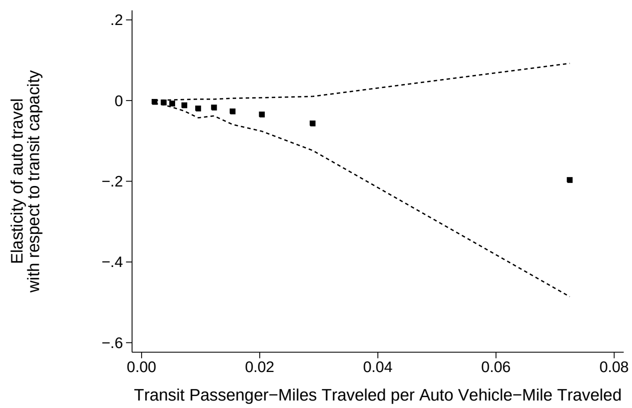
Table B.7: Congestion versus transit use (means)

Transit Usage quintile	**Travel Time Index**	**Roadway Congestion Index**	**% peak VMT in congested conditions**	**Annual delay hours per capita**	**VMT per freeway lane-mile ('000s/day)**
Very Low	1.121	0.879	27.41	17.96	11.66
Low	1.158	0.953	38.35	21.08	12.70
Medium	1.169	0.945	39.89	20.63	12.79
High	1.184	0.980	43.78	20.61	13.59
Very High	1.245	1.075	54.83	25.58	15.03

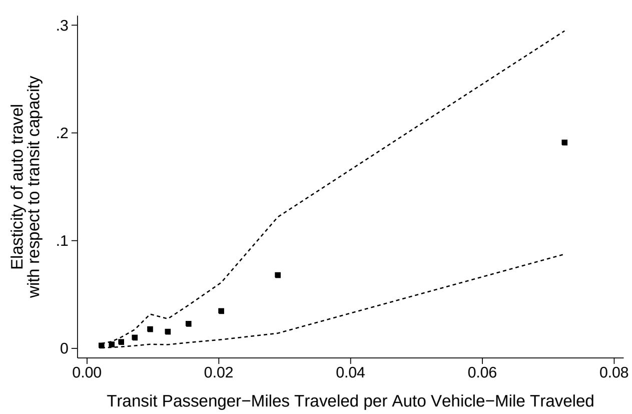
Figure B.5: Elasticity of auto travel with respect to transit capacity vs. transit use



(a) Substitution Effect



(b) Medium-Run Equilibrium Effect



(c) Long-Run Equilibrium Effect

Notes: Graphs show the elasticities of auto travel with respect to transit capacity that result when the models in equations (1) - (3) are stratified according to deciles of the level of transit use (as measured by the ratio of transit passenger- miles traveled to auto vehicle-miles traveled) across the 96 urban areas (UZAs). Dotted lines indicate 95% confidence interval.