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High Occupancy Vehicle (HOV) lanes (or carpool lanes) can carry more people in less space than general purpose lanes but their impact on congestion, air quality, fuel consumption and economic welfare is unknown. Despite this, U.S. transportation and environmental policies treat HOV lanes as a traffic management tool, making HOV lanes exempt from the standard of review required for new general purpose lanes in areas that exceed federal air quality standards. This paper finds the theoretical impacts of HOV lanes on vehicle miles traveled (VMT) depend upon local conditions and that empirically the impacts of HOV lanes are ambiguous suggesting they should be subject to the same review as general purpose lanes.

The United States has invested heavily in High Occupancy Vehicle (HOV) lanes despite very little evidence showing HOV lanes deliver on their promise to reduce vehicle miles traveled (VMT) and improve air quality. Theoretically, HOV lanes move more people in less space by convincing solo drivers to carpool, lowering congestion and overall travel times. However, lower travel times encourages more people to drive, a phenomenon known as induced demand. Furthermore, HOV violation rates exceed 90% in some areas of the U.S. (Walters, 2014) suggesting HOV lanes may be a way for local traffic managers to build an additional lane when air quality violations would otherwise prohibit a highway expansion.

Areas that exceed federal air quality standards are required by the U.S. Clean Air Act to obtain special approval to expand their highways, unless the expansion is from a list of travel demand management tools. HOV lanes are on this list, but the efficacy of HOV lanes in reducing VMT is not supported by high quality research. Most of the research on HOV lanes contains one of the following flaws: metrics used are not tied to welfare or environmental concerns (a common metric is average vehicle occupancy), researchers use overly simplistic assumptions about carpooling behavior, and most studies ignore induced demand. There are very few empirical studies on carpooling behavior and most focus on individual cities or one road. This is the first to use nationwide data to study the impacts of HOV lanes on VMT.

The U.S. has built over 2,500 lane-miles of HOV lanes, spending hundreds of billions of dollars.[1] The efficacy of HOV lanes is so understudied that for this study, researchers

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[1]The 2,500 lane-miles statistic comes from the author's HOV lane inventory. Building 10 miles of HOV lanes on 405 in Los Angeles was estimated to cost $1 billion. If the cost of building HOV lanes in Los Angeles is ten times the nationwide average, the cost of building 2,500 lane-miles is still $250 billion. While the average freeway

had to comb state transportation reports, speak with traffic managers and physically visit HOV facilities to find out when and where HOV lanes were built. This paper first provides background on HOV lanes, next develops a theoretical model to understand how HOV lanes can impact VMT, then focuses on areawide measures to estimate the effect of a new HOV lane on an area's VMT. Theoretical results show that HOV lanes may be able to reduce VMT and commuting costs in some situations. Regression results show that on average HOV lanes have ambiguous impacts on VMT, suggesting the U.S. Clean Air Act should only allow HOV lanes to be used as a travel demand management program when they have demonstrated negative impacts on VMT.

I. Background on HOV Lanes

HOV lanes are separate lanes that require two (but sometimes three or more) occupants per vehicle. Most HOV lanes are adjacent to general purpose lanes, but some HOV lanes are separated with physical barriers and have limited entry and exit points. Some roads have HOV restrictions only during certain hours and provide exemptions for energy efficient cars, two-seater cars, and motorcycles. Bridges and toll roads may have reduced rates for HOVs.

An efficient transportation system would balance the private benefits of travel with each vehicle's external costs, including excessive congestion, pollution, and accidents. Price based policies are the first best method of reducing externalities from automobiles and have been shown to reduce congestion and improve air quality (Gibson and Carnovale, 2015; Small and Verhoef, 2007; Vickrey, 1969). Second best policies, such as public transit subsidies can also reduce congestion, air pollution or both (Anderson, 2014; Chen and Whalley, 2012; Lalive, Luechinger, and Schmutzler, 2017), although the long-run impacts are unclear (Beaudoin and Lin Lawell, 2018). HOV lanes fall into other non-price policies such as alternate day driving, which has been shown to potentially worsen air quality by allowing for substitution into other forms of driving (Zhang, Lin Lawell, and Umanskaya, 2017; Davis, 2008). While there is a transportation literature on HOV lanes, many papers focus on performance metrics, such as increasing average vehicle occupancy, that have little to do with economic welfare or improvements in environmental quality. Other papers make unrealistic simplifying assumptions about how carpools are formed or ignore induced demand.

The most commonly cited reason for building an HOV lane is to "maximize person throughput" (Chang et al., 2008b), often measured as changes in average vehicle occupancy. Maximizing person throughput can decrease economic welfare if the additional travelers have a low value of travel and crowd out higher value users by exacerbating congestion. Average vehicle occupancy is a poor performance metric since while it may indicate higher carpooling rates, those carpools could be drawing commuters who would have otherwise taken transit or not traveled. In the San Francisco Bay Area, vehicles wishing to avoid tolls on the Bay Bridge pick up transit riders in order to use the HOV lane. Similar stories about casual carpooling or "slugging" exist for I-66 in Arlington, Virginia. In Jakarta, Indonesia, professional passengers charge $1.20 per ride to drivers

in Los Angeles is likely more expensive than the average freeway nationwide, HOV lanes are built in urban areas with expensive real estate.

wanting to use HOV3 lanes (Hanna, Kriendler, and Olken, 2017). All of these measures increase average vehicle occupancy, but they do this by adding travelers who otherwise would have used transit or may even have a negative value of travel. Shewmake (2012) provides an extensive discussion of the faulty metrics used to evaluate HOV lanes.

Most simulations that evaluate HOV lanes ignore the endogeneity of carpool formation. For example, Mannering and Hamed (1990) assume that building an HOV lane will increase carpooling rates from 17% to 20-30%. A free-flowing HOV lane next to a congested general purpose route can be a powerful incentive to carpool, but as more drivers join the HOV lane, congestion on the HOV lane reduces the incentive to carpool. Carpooling is an economic decision that balances time and inconvenience in assembling the carpool with monetary savings and added convenience from using an HOV lane or splitting the task of driving (DeLoach and Tiemann, 2012). Bento, Hughes, and Kaffine (2013) find carpooling is responsive to gasoline prices, while others find drivers are willing to pay substantial sums for the privilege of using the HOV lanes (Bento et al., 2014; Shewmake and Jarvis, 2014). Any model that attempts to evaluate HOV lanes needs to make carpools endogenous.

When a new HOV lane draws vehicles away from the congested general purpose lanes, it temporarily relieves congestion. However, as motorists adjust, those who were constrained by congestion start taking more trips. Duranton and Turner (2011) find the elasticity of VMT to road capacity is close to 1, suggesting it is futile to try to "build our way out of congestion." Furthermore, any analysis of HOV lanes that ignores induced demand is systematically biased toward finding HOV lanes reduce VMT.

Of the one empirical paper and three simulation models that use relevant metrics (usually welfare or VMT), allow for endogenous carpool formation, and induced demand, two papers find HOV lanes decrease traffic volume (Brownstone and Golob, 1992; Hanna, Kriendler, and Olken, 2017) and the other two related studies find HOV lanes increase traffic volume and decrease welfare (Johnston and Ceerla, 1996; Rodier and Johnston, 1997). Hanna, Kriendler, and Olken (2017) find HOV restrictions in Jakarta can improve traffic conditions. This finding is important, but of questionable relevance to U.S. HOV policy. Jakarta's HOV3 restrictions are applied to all streets in Jakarta's Central Business District, whereas most U.S. HOV lanes run parallel to general purpose lanes[2] and are found on line-haul routes into and between congested areas. Furthermore, a solo driver in Jakarta can hire two professional passengers for \$1.20 each, or \$2.40 per ride, making the system work much more like an inconvenient congestion charge. Furthermore, the fine for violating the HOV restriction is \$37.50, or about twice the London Congestion Charge.[3] Fines for violating H.O.V. lanes in the U.S. are typically over \$100, although enforcement rates vary considerably across cities.

The next section describes a theoretical model of carpooling and HOV lanes that uses a cost minimization framework which allows for both endogenous carpools and induced demand. The theoretical model finds the impacts of HOV lanes depend on the initial

[2]There are some exceptions such as I-66 in Arlington, VA.

[3]The differences in HOV lanes in the U.S. and Indonesia has not stopped popular press articles from drawing inferences, "Lessons from the fast lane: does this study prove car-pooling works?" at *The Guardian*, https://www.theguardian.com/cities/2017/aug/01/lessons-fast-lane-study-car-pooling-works-jakarta-google and "A city scraps its HOV lanes: Disaster ensues" from CNN http://money.cnn.com/2017/07/06/technology/culture/jakarta-hov-lanes/index.html.

parameters, similar to the finding by Konishi and Mun (2010). This model is then tested using data from ninety-eight Metropolitan Statistical Areas (MSAs) across the United States.

II. Theoretical Model

Following Vickrey (1969), Arnott, De Palma, and Lindsey (1993), Yang and Huang (1999), and de Palma, Kilani, and Lindsey (2008), commuters choose between three methods of travel or modes: driving alone, carpooling, transit/not driving based on the generalized cost of travel which includes the time and monetary cost of each mode. The sum of individual decisions results in a level of congestion, which influences the time cost of each lane, which then feeds back into the original mode decision. Each stage of this decision can be seen in Figure 1. Consumer preferences, fuel prices, carpool/transit incentives, assembly costs, and endogenous travel times influence the consumer's decision to drive alone, carpool, or not drive. The time it takes to drive on HOV and general purpose lanes is a function of the traffic volume, which is equal to the sum of commuters that drive alone and half of the commuters that carpool. These travel times then feed back into the original mode decision.

Commuters carpool if the cost of carpooling, C_y, is less than both the cost of driving alone, C_z, and not driving, C_x. The cost of commuting is composed of monetary costs such as fuel, insurance, depreciation of the car, parking, and tolls, and time costs in the line haul and assembly portions of the trip.

Those who take transit or do not drive have zero monetary costs but a high time cost (V) that does not vary with congestion or agent.[4] This time cost can be interpreted as the time cost of taking public transit, time cost of walking or biking or the lost productivity of telecommuting.[5] The time cost is then multiplied by a value of time β_i which varies by agent. For those who take transit, the total cost is $C_x = \beta_i V$. Driving alone takes time $t(v_z)$ which is the time to get from point A to point B and is a function of traffic volume on roads available to solo drivers, v_z. The monetary cost of driving alone is M and the total cost of driving alone is $C_z = \beta_i t(v_z) + M$.[6]

The monetary cost of commuting is halved for carpoolers. Carpoolers face a time cost of getting from point A to point B, $t()$ which is a function of the volume on lanes available to carpoolers, v_y. They face an additional assembly cost which varies by agent. The assembly cost captures not just the amount of time it takes to drive to a carpool partner's house but also the utility/disutility of sharing a vehicle and schedule inflexibility. Unlike Huang and Yan's model, β and a are allowed to vary over individuals thus introducing heterogeneity into a model of carpool behavior. In summary, the costs of carpooling, driving alone, and not driving are:

[4]It is possible to vary V as well as assembly costs and value of time, but since each user must choose a transportation option, it is the relative cost of each option that is important. Having V be a constant allows the model to have one less distribution.

[5]Many of these modes may have monetary costs, however they are likely less than the monetary costs of carpooling and driving alone.

[6]In practice, the monetary cost of driving is composed of long-term costs such as the purchase and maintenance of a vehicle and short-term costs such as fuel, tolls, and depreciation due to wear and tear. Over 90% of American households own at least one vehicle, so this paper focuses on the intensive margin–how much to use the vehicle. Thus the M parameter is directly related to tolls plus mileage reimbursement rates.

$$
\text{(II.1)} \qquad \begin{aligned} C_y = &\quad \beta_i t(v_y) + \beta_i a_i + M/2 \\ C_z = &\quad \beta_i t(v_z) + M \\ C_x = &\quad \beta_i V. \end{aligned}
$$

If there are no HOV lanes, $v_y = v_z = v$ for all commuters however if HOV lanes are present $v_y = v_{HOV}$ for carpoolers and $v_z = v_{GP}$ for solo drivers. Monetary assembly costs are assumed to be negligible or correlated with the value of time. By allowing a portion of the population to take transit or other, it is possible to take into account demand responses to changing congestion levels.

Driving alone has the highest monetary costs but takes the least amount of time (without HOV lanes). Carpooling costs less than driving alone since users share the vehicle, tolls, and fuel, but carpooling comes with a higher time cost (without HOV lanes) because carpoolers face assembly costs. When HOV lanes are present, carpooling may take less time than driving alone for commuters with small assembly costs. The third option is not driving. Interesting parametrizations require transit to take more time than carpooling ($V > t(v) + a_i$) for at least some values of a_i. The option to avoid the line haul time costs and the monetary costs of driving is what allows for induced demand in this model.[7]

To assign each commuter to their lowest cost mode, set the expressions in Equation II.1 equal to each other and solve for the critical values of time, β^*, and assembly costs, a^*, where commuters are indifferent between driving alone and transit ($C_x = C_y$), carpooling and driving alone ($C_y = C_z$), and taking transit and carpooling ($C_x = C_z$). These critical values then map the a_i and β_i parameter space into commuters who choose each mode for a given t_z and t_y. This is graphically presented in Figure 2 for the case with and without HOV lanes. When there are no HOV lanes, there is only one line haul time, t whereas when there are HOV lanes there is a time for both the general purpose (t_{GP}) and the HOV lane (t_{HOV}). For Figure 2, assume $t_{GP} = t > t_{HOV}$.

Without HOV lanes, commuters with assembly costs greater than $\tilde{a}_h = (V - t)/2$ never carpool. These commuters switch between driving alone and taking transit, depending on whether their value of time is greater or less than $\tilde{\beta}_m = M/(V - t)$. Lower assembly costs encourage carpooling and commuters with assembly costs less than $\tilde{a}_h$ and an intermediate value of time ($\beta_1^*(a_i) > \beta_i > \beta_2^*(a_i)$) carpool. Commuters with assembly costs less than $\tilde{a}_h$ may still drive alone if they have a value of time that is greater than $\beta_2^*(a_i) = M/(2a_i)$. Commuters with assembly costs less than $\tilde{a}_h$ and a value of time less than $\beta_1^*(a_i) = \frac{M}{2(V-t-a_i)}$ take transit.

The areas in Figure 2 represent the values of a_i and β_i that leads commuters to choose each mode for a given line haul distance t (or t_{HOV} and t_{GP}). The model is solved by integrating over these spaces to calculate the proportion of the population that chooses carpooling (y), driving alone (z), and transit (x). Thus the total volume on the road is

[7]Helicopters between congested areas, high speed commuter trains, and limousine services that allow the commuter to work while driving constitute a fourth mode of travel with a very high monetary costs and lower time costs. This mode is rare and including it would be another source of induced demand. Excluding this additional source of induced demand biases our model toward finding HOV lanes decrease VMT and improve welfare.

the number of solo drivers plus half the number of carpoolers, $v = \frac{y}{2} + z$. To calculate the line haul travel time, the model uses a linear function to relate traffic volume and line-haul travel time:

$$t(v) = t_f + \frac{\alpha}{L} v \tag{II.2}$$

which allows for analytical solutions in the case without HOV lanes and simpler functions with HOV lanes.[8] The parameter L is the number of lanes and α can be interpreted as the time cost of an additional vehicle.

When HOV lanes are present, the areas in Figure 2 where commuters carpools expand. The highest assembly costs at which carpooling is observed shifts from $\tilde{a}_h$ to $\tilde{a}'_h$ which expands the set of potential carpoolers. The minimum value of time for which anyone drives, $\tilde{\beta}'_l$, shifts down carpooling now takes less time but has the same monetary cost. The maximum value of time for which anyone takes transit, $\tilde{\beta}'_m$, does not change since $t_{GP} = t$.[9] The expressions $\beta_1^{*'}(a_i)$ and $\beta_2^{*'}(a_i)$ are modified to incorporate the difference in travel time between the general purpose and HOV lanes. Because the HOV lane is faster than the general purpose lanes, commuters with assembly costs less than $\tilde{a}'_l = t_{HOV} - t_{GP}$ will carpool even as their value of time approaches infinity.

To solve the model with HOV lanes use a similar method, but now there is a volume for both the HOV and the general purpose lane:

$$\begin{aligned} v_{HOV} &= y/2 \\ v_{GP} &= z. \end{aligned} \tag{II.3}$$

In situations with more carpoolers per HOV lane than SOVs per general purpose lane, come carpoolers use the general purpose lane until the times are equalized $t_{HOV} = t_{GP} = t(v)$. Otherwise $t_{HOV} \leq t_{GP}$.

The impact of HOV lanes on total commuting costs and traffic volume depends upon the simulation parameters. In figures 3 and 4, α, the parameter governing how much each additional vehicle contributes delay, is varied to illustrate this point. Figure 3 shows three theoretical highways: a highway with two general purpose lanes only (no HOV), a highway with a converted HOV lane (one general purpose lane, one HOV lane) and a highway with an additional HOV lane (two general purpose lanes, one HOV lane). The additional HOV lane decreases commuting costs for all values of α, however this scenario has three lanes instead of two like the others. To really determine whether an additional HOV lane improves welfare, its benefits would need to be balanced with the capital expense of building that additional lane and potential increases in externalities due to pollution and accidents. Conversion of a general purpose lane to an HOV lane has an ambiguous impact on total social costs–for low values of α the conversion of a general purpose lane can reduce commuting costs but not for larger values of α.

Figure 4 compares the total traffic volume that results from two general purpose lanes versus two general purpose lanes plus an additional HOV lane. For low values of α,

[8] Another option would be to use the Bureau of Public Roads function, $t(v) = t_f(1 + 0.15(v/v_K)^4)$ where t_f is the time it takes to travel the road without congestion and v_K is the capacity of the road.

[9] If HOV lanes slow down the general purpose lanes, $t_{GP} > t$, then $\tilde{\beta}'_m$ shifts up and increases the number of transit riders with high assembly costs.

the additional HOV lane lowers total traffic volume, but for higher values of α, the HOV lane increases total traffic volume. The actual distribution for the value of time travel reductions is explored in Small, Winston, and Yan (2005) but the authors provide no guidance for the particular form of how the value of time is distributed, simply that heterogeneity exists. Additional simulations for how parameter values impact total social cost and total traffic volume are available from the author, but the larger point is that the theoretical impact of HOV lanes on congestion and VMT depend on context. The next section examines how HOV lanes have impacted VMT on U.S. cities on average.

III. Empirical Strategy

Following Duranton and Turner (2011), the demand for VMT in city i at time t is a function of the number of HOV lanes, HOV_{it}, observed city characteristics, X_{it}, and unobserved contributors to driving, ϵ_{it}:

$$VMT_{it} = A_0 + \beta HOV_{it} + X_{it}A_1 + \epsilon_{it}. \tag{III.1}$$

Equation III.1 gives a consistent estimate for β when $cov(HOV, \epsilon|X) = 0$ and $cov(X, \epsilon) = 0$. However, traffic managers may believe HOV lanes reduce congestion and thus they may place these lanes in areas that are expected to increase in traffic. If a shock occurs to an MSA that is unobserved to the econometrician but observed by the traffic manager, then this shock will impact decisions made by the traffic manager and traffic volume. This implies a positive covariance between ϵ_{it} and HOV_{it}, resulting in a biased estimate of β. Duranton and Turner (2011) found only small differences between OLS and IV estimates for the impact of roads on traffic. Their work found traffic managers place roads in areas expected to have a negative productivity shock, thus OLS underestimates the true impact of roads on traffic. For this reason the endogeneity of regular road placements is ignored in order to concentrate on identifying the impact of HOV lanes. To identify the impact of HOV lanes on a city's VMT, Equation III.1 is estimated as a first difference equivalent:

$$\Delta VMT_{it} = \beta \Delta HOV_{it} + \Delta X_{it}A_1 + \Delta\epsilon_{it}. \tag{III.2}$$

and then using an instrumental variable technique. Equation III.2 will provide a consistent estimate of β if HOV lanes are assigned to cities on the basis of an unobserved but constant feature. If HOV lanes are assigned to cities after they receive an unobserved traffic shock, then Equation III.2 will result in inconsistent estimates of β.

The instrumental variables approach can theoretically adjust for unobserved shocks that are correlated with HOV lane placement. This approach uses two equations, one to predict when and where HOV lanes will be built and another to describe the impact of HOV lanes on traffic. Because of the structure of the Clean Air Act, attainment status can predict where HOV lanes will be built but does not have a direct impact on traffic volume. Thus a measure of non-attainment status can predict HOV lane miles, HOV_{it}, and then examine the impact of new HOV lanes on VMT. Because HOV lanes and state implementation plans take time to design and implement, five-year lag between non-attainment and HOV lane placement are used. Thus, the first equation predicts which

MSAs will build HOV lanes in five years, while the second equation relates HOV lane miles to VMT:

$$\text{(III.3)} \qquad \begin{aligned} HOV_{it} = &\quad B_0 + B_1 Z_{i,t-5} + X_{it} B_2 + \mu_{it} \\ VMT_{it} = &\quad A_0 + \beta \widehat{HOV}_{it} + X_{it} A_1 + \epsilon_{it}. \end{aligned}$$

The variable $Z_{i,t-5}$ is an instrument for HOV_{it}, meaning $Z_{i,t-5}$ can predict how many HOV lanes will be built, but is not directly related to traffic volume. To be a valid instrument, it must be the case that $cov(Z_{i,t-5}, HOV_{it}|X_{it}) \neq 0$ and $cov(Z_{it-5}, \epsilon_{it}|X_{it}) = 0$. In other words, the instrument must be associated with the miles of HOV lanes but unrelated to shocks in traffic. This paper argues that lagged Clean Air Act attainment status predicts the building of HOV lanes and other traffic control management techniques but does not otherwise influence traffic. To the extent that traffic managers increase other traffic control management measures, the measured impact of HOV lanes as predicted by attainment status will be biased against finding HOV lanes increase traffic. This instrument however is weak, which may introduce additional bias. Thus this paper relies on evidence from cross section regressions with fixed effects and IV to estimate the impact of HOV lanes on traffic volume.

Chay and Greenstone (2005) instrumented for changes in air quality to estimate the impact of air quality on housing prices. Instead of instrumenting for air quality, this paper instruments for HOV lanes. The 1990 Clean Air Act Amendments encourage non-attainment areas to build HOV lanes as part of their air quality implementation plan. Formally, the 1990 Clean Air Act Amendments require the Environmental Protection Agency (EPA) to establish National Ambient Air Quality Standards (NAAQS), which apply to six criteria pollutants: ozone, carbon monoxide (CO), lead, nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM). When an area's ambient pollution exceeds these federal standards, the area is designated as non-attainment for that particular pollutant. Non-attainment areas face various restrictions and are often required to use traffic control measures to combat automobile related emissions. New highway or rail lines cannot be built if they create or contribute to violations of the NAAQS, but this restriction does not apply to HOV lanes or any of the other traffic control measures mentioned in 1990 Clean Air Act Section 108(f).[10]

Additional papers have used attainment status as a proxy for regulatory stringency and provide support to the claim that non-attainment areas will take more abatement actions than attainment counties. Henderson (1996) and Auffhammer, Bento, and Lowe (2009) find areas in non-attainment that exceed NAAQS are more likely to see improvements in air quality. This work implies federal regulations can cause local officials to successfully manage their air quality, but these studies do not break down the impact of each technique used. Other studies have explored how non-attainment status and regu-

[10]Traffic control management measures include programs for improved transit; employer-based transportation management plans; trip-reduction ordinances; traffic flow improvement programs; parking facilities and other programs that augment transit and high occupancy vehicles; programs to limit portions of roads to non-motorized vehicles and pedestrians; improved bicycle facilities including lanes; parking and storage facilities; programs to reduce idling; programs to encourage flexible work schedules; and programs to retire and replace pre-1980 light duty vehicles and trucks.

lation influence firms. This literature has been focused on stationary sources (Benton, 2011; Greenstone, 2004; Gray, 1997) and has little to say about the impact of NAAQS on emissions from mobile sources. Vehicle emissions fall under the mobile source category, and this is the only known econometric study on the impact of HOV lanes nationwide that uses traffic outcome data. Other studies on HOV lanes have relied on simulations (Plotz, Konduri, and Pendyala, 2010; Kwon and Varaiya, 2008; Small, Winston, and Yan, 2006; Dahlgren, 1998; Johnston and Ceerla, 1996), finding very different results depending on assumptions and location.

Attainment status is based on pollutant, but not all pollutants are the product of vehicle emissions. Over two-thirds of SO_2 emissions come from electricity generation (Environmental Protection Agency, 2010) and hence we would not expect SO_2 attainment status to be a good predictor of HOV lane placement. Even when motor vehicles substantially contribute to pollution, driving reductions are not the primary instrument used by policy makers. Driving reductions have been used to reduce peak-period ozone and particulate matter, while other motor vehicle pollutants have been tackled through technology. Carbon monoxide, NO_2, and lead emissions, especially in urban areas, are produced by motor vehicles, but these pollutants have been controlled mainly through catalytic converters and unleaded gasoline. NO_2 is a precursor to ozone, but most MSAs have been in attainment since 1980.[11] Thus ozone is used as an instrument rather than SO_2, carbon monoxide, lead, or NO_2 which empirically have little to no impact on HOV lane building. To capture regional differences in geography, sources of electricity and MSA density, the impact of attainment status is allowed to vary by region.

IV. Data

This project merges data from the Texas Transportation Institute (TTI), the EPA, the U.S. Census Bureau, work by Duranton and Turner (2011), and the Federal Highway Administration (FHWA). The first dataset comes from the 2010 Urban Mobility Report published by TTI and consists of yearly statistics on population, peak period travel, daily VMT, lane-miles for highway and arterial streets, fuel consumption, and congestion broken out into ninety-eight MSAs.[12] The TTI data is a compilation of other datasets including the Highway Performance Monitoring System, the U.S. Census Bureau, and traffic speed information from a private company. The TTI data takes information on average daily traffic (ADT) on roads measured by the Highway Performance Monitoring System and assigns them to urbanized areas, which are designated by state transportation agencies when they submit traffic data to FHWA.[13] Summary statistics are presented in Table 1.

The second dataset is yearly attainment status, by county and year, from the EPA. The data contain the names and states of counties that were in whole or partial non-attainment for 1-hour and 8-hour ozone, PM, carbon monoxide, lead, NO_2, and SO_2. Counties were grouped into MSAs to calculate the number and percentage of counties in

[11] Only Riverside-San Bernardino, CA, during the years of 1991 through 1998 has been in partial non-attainment for NO_2.

[12] There are actually one hundred areas listed in the TTI data but two are parts of larger MSAs. The data is available at http://mobility.tamu.edu/ums/.

[13] Boundaries are available from the FHWA at http://hepgis.fhwa.dot.gov/hepgis_v2/Highway/Map.aspx.

each MSA that were in various states of non-attainment. Whole non-attainment means the entire county was included in the non-attainment area while partial non-attainment identifies a smaller area that is affected by a single source or group of sources that causes the non-attainment issue.[14] To get a population weighted measure of non-attainment, the census estimates of population by county and by year were used. If a county was in non-attainment, its population was added to the population of other counties in non-attainment to get an MSA-wide measure and named Exposed Population. For brevity only exposed population statistics for ozone are presented in Table 2.

To make this paper comparable to Duranton and Turner (2011) their data on ruggedness and terrain, as well as climate variables are used as additional controls. The final source of data is a nationwide database of HOV lanes which includes information on the location of lanes, the year built, the number of HOV and general purpose lanes on a road, the number of lane miles, the hours of operation for HOV lanes, and the vehicle restrictions such as HOV2+, HOV3+, or bus only (Chang et al., 2008a). Some of this information was incomplete, so the researcher made calls to HOV managers, looked at maps to fill in missing lane miles and years built, visited transportation libraries and even traveled to some HOV lanes to better understand how HOV facilities functioned and the miles of HOV travel lanes. Some of the areas in the TTI data were on a finer scale than Chang et al.'s compendium of HOV lanes. For instance, states report data for both San Jose and San Francisco separately while Chang et al. reported on HOV lanes in the more general Bay Area. San Jose and San Francisco, along with Oakland, form a Combined Statistical Area, but they are separate Metropolitan Statistical Areas. Since the unit of analysis is MSA, not CSA, calls were made to facility managers and maps were examined to assign each HOV lane to an MSA. This information was consolidated by MSA and year for statistics on the number, lane miles, and types of HOV facilities available in each MSA each year. Considerable measurement error still exists in this dataset, is mitigated by using the instrumental variable technique Angrist and Krueger (2001) but exacerbated by examining differences in HOV lanes by year. Segments that were excluded because they were missing information are listed in Table 3.

V. Results

Tables 4 and 5 examine the impact of HOV lanes on traffic volume using pooled OLS. Table 4 controls for variables such as the statewide cost of fuel, population, and qualitative measures of population (small, medium, large, and very large), as well as year and MSA fixed effects. When using VMT and lane miles, it appears HOV lanes increase VMT by more than general purpose freeway lanes except when MSA fixed effects are included. When MSA fixed effects are used, the impact of HOV lanes is still positive and statistically significant but similar to the impact of general purpose lanes. The higher impacts of HOV lane miles versus general purpose lane miles seems counterintuitive since the restricted lane should naturally have fewer cars than general purpose lanes. However, HOV lanes are more likely to be placed in areas that already have heavy congestion and hence are more likely to stimulate traffic than new roads in parts of a city that have not seen much development. Looking at the same regressions

[14]Definition provided by Rob Rainey at the City of Nashville's Pollution Control Division.

in logs, Panel B shows that HOV lanes increase citywide VMT by 2% to 3% except when MSA fixed effects are added when the sign flips and HOV lanes decrease citywide VMT by 2%. Table 5 replicates regressions found in Duranton and Turner (2011) by using variables from Duranton and Turner's data such as the elevation range, terrain ruggedness, and mean heating and cooling degree-days. The coefficient on freeway lane miles is significant across regressions, close to one in logs, and similar to what Duranton and Turner found. The number of observations is smaller when using the Duranton and Turner variables since the match between TTI and Duranton and Turner data was imperfect and three MSAs were left out of Duranton and Turner's data. Again we see the same pattern that controlling for more city variables reduces the magnitude of the coefficient on HOV lanes.

Tables 6 and 7 use an IV approach to estimating the impact of HOV lanes on VMT. In Table 6 the instrument is the number of counties in an MSA that are in whole non-attainment for either 1-hour or 8-hour ozone by year. This instrument is weak as judged by the first-stage F-statistics which are all less than 2. To avoid bias introduced by weak instruments, most authors argue for an F-statistic above 10 (Staiger and Stock, 1997).

A better instrument is presented in Table 7, which measures non-attainment as the number of people living in a non-attainment county by census region (west, midwest, north and south). The impact of HOV lanes is generally positive (and very large) except when MSA fixed effects are included. With four instruments and only one endogenous variable, the model is over-identified thus the validity of my instruments can be tested with Hansen's J-statistic. The J-statistics are low, a failure to reject the null hypothesis that the instruments are valid.

In addition to the impact of freeway VMT, HOV lanes may impact traffic on more than just highways. Tables 8 and 9, show how VMT on arterial roads (high capacity urban roads that connect collector roads to freeway roads)[15] respond to HOV lanes. Generally arterial road show similar but weaker impacts of HOV lanes on VMT. Table 8 runs the same regressions as Table 4 but with arterial VMT and arterial lane miles instead of freeway VMT and freeway lane miles. In more regressions, arterial lane miles increase with HOV lanes however at lower levels than seen in Table 4 and when MSA fixed effects are included the sign flips and HOV lanes appear to decrease arterial VMT. In Panel B, there is a similar story but here the estimates of the percentage impact of HOV lanes on arterial VMT is almost identical to Table 4. Table 9 uses the Duranton and Turner Duranton and Turner (2011) variables to explain arterial VMT and finds that arterial VMT is less responsive to HOV lanes and arterial lane miles than freeway VMT.

VI. Conclusion

Many economists describe HOV lanes as a second best strategy to combat congestion, but it is unclear that they improve welfare compared to the status quo and they may actually be exacerbating existing distortions. This paper analyzes the impact of HOV lanes on daily VMT for the years from 1978 to 2009 for ninety-eight MSAs across the United States. Non-attainment status is a weak instrument on its own, but not when

[15] `http://ops.fhwa.dot.gov/arterial_mgmt/index.htm`

interacted with population by region. The empirical evidence suggests HOV lanes have an ambiguous impact on VMT. This is in contrast to what the proponents of HOV lanes claim and the Clean Air Act assumes.

This research does not mean we should remove all HOV lanes and replace them with general purpose lanes. HOV lanes may increase social welfare by removing vehicles with two or more people from congestion and may be an important part of a city's transit plan by providing time savings to even higher occupancy vehicles such as busses and vanpools that exhibit economies of scale. There is some evidence that an additional HOV lane increases traffic less than a general purpose lane thus converting HOV to general purpose may be an undesirable expansion in capacity. This research does imply that HOV lanes are not an "environmentally friendly road" that should be exempt from environmental review. HOV lanes should be evaluated much like general purpose lanes.

Finally, while CO_2 emissions are roughly a function of VMT, local air pollutant emissions such as NO_x, an important precursor to ozone, and carbon monoxide are dependent on vehicle speeds. Vehicles stuck in traffic release more NO_x and carbon monoxide per mile than vehicles in free flow conditions. Thus HOV lanes may increase the miles travelled in a city but may decrease NO_x and carbon monoxide emissions in the short run as congestion is relieved. This is precisely what Cambridge Systematics (2002) found in a study of HOV lanes in the Minneapolis-St. Paul area. This simulation study found that removing HOV lanes would decrease VMT but worsen air quality. This tradeoff is less clear in the long run. If induced demand fills up space on both the HOV and general purpose lane in the long run, HOV lanes may be just as counterproductive as general purpose lanes when seeking to improve air quality.

This research was motivated by a desire to understand when and whether HOV lanes can reduce traffic volume and total travel costs to commuters. It appears that HOV lanes fail to reduce traffic volume in areas that are being encouraged to build them. Transportation agencies spend billions of dollars building HOV lanes and promoting carpooling. Local and state governments are encouraged to build HOV lanes to reduce vehicle-trips and will sometimes argue that HOV lanes are a win-win for all commuters. However, this supposed win-win does not reduce VMT and comes at a cost to the environment.

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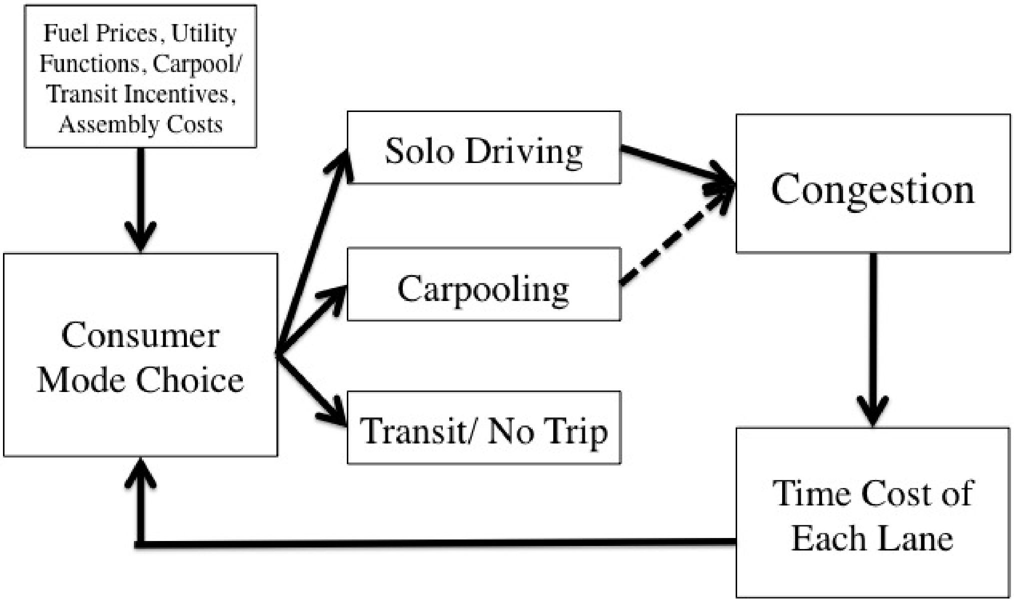

Figure 1. : Consumer Mode Choice

Table 1—: Summary Statistics for Traffic Outcomes Data between 1982 and 2009

	Mean	Min	Max	Standard Deviation
Population	1,434,000	95,000	18,768,000	2,266,000
Peak Period Travelers	690,000	39,000	8,915,000	1,043,000
Daily VMT Freeway	11,500,000	110,000	139,000,000	17,400,000
Daily VMT Arterial	11,700,000	435,000	126,000,000	16,000,000
Lane Miles Freeway	804	20	7,220	975
Lane Miles Arterial	2,360	155	20,900	3,040
Average State Fuel Cost	1.55	0.93	3.86	0.66
Annual Passenger Miles on Transit	408	0	21,700	1,800
Percent of System with Congestion	33	0	75	14

Table 2—: Percentage and Number of Counties in Non-Attainment Status Between 1982 and 2009

	Average	Standard Deviation	Min	Max
Number of Counties in Partial Non-Attainment				
1-Hour Ozone	0.13	0.50	0	4
8-Hour Ozone	0.03	0.18	0	2
CO	0.50	1.15	0	13
Lead	0.02	0.15	0	1
NO_2	0.01	0.11	0	2
SO_2	0.10	0.34	0	3
PM_{10}	1.12	0.40	0	2
$PM_{2.5}$	0.01	0.12	0	2
Number of Counties in Whole Non-Attainment				
1-Hour Ozone	1.52	3.08	0	23
8-Hour Ozone	0.39	1.77	0	22
1-Hour or 8-Hour Ozone	1.87	3.35	0	23
CO	0.21	0.93	0	11
Lead	0.0	0.00	0	0
NO_2	0.002	0.05	0	1
SO_2	0.06	0.56	0	7
PM_{10}	0.04	0.26	0	4
$PM_{2.5}$	0.23	1.51	0	36
Population Living in Counties in Whole Non-Attainment (in millions)				
1-Hour or 8-Hour Ozone	0.94	2.21	0	20

Each observation is an MSA-Year for a total of 3,234 observations. The years covered are 1978 through 2010 and a list of the 98 MSAs is available in the appendix.

Table 3—: Open HOV Lane Segments Missing Data

Urban Area	Road	Segment	Missing Information
San Jose, CA	Central Expressway	Bowers Avenue to Scott Boulevard	Year Opened
Los Angeles, CA	State Road 30	Unknown	Year Opened, Length
Honolulu, HI	Kahekili Highway	Unknown	Year Opened
Honolulu, HI	Kalanianaole Highway East	Unknown	Year Opened
Honolulu, HI	Kalanianaole Highway	West Halemaumau Street to Ainakoa Avenue	Length
Honolulu, HI	H-1, H-2	Unknown	Year Opened
Boston, MA-NH-RI	I-93	Somerville to Boston	Year Opened
New York, NY-NJ-CT	I-287S	North Maple to I-80	Year Opened
New York, NY-NJ-CT	12th Street	12th Street Approach to Holland Tunnel	Year Opened
New York, NY-NJ-CT	Turnpike	Weehawken Approach to Toll Plaza	Year Opened
Dallas-Fort Worth, TX	Unknown	SW Medical Center	Year Opened

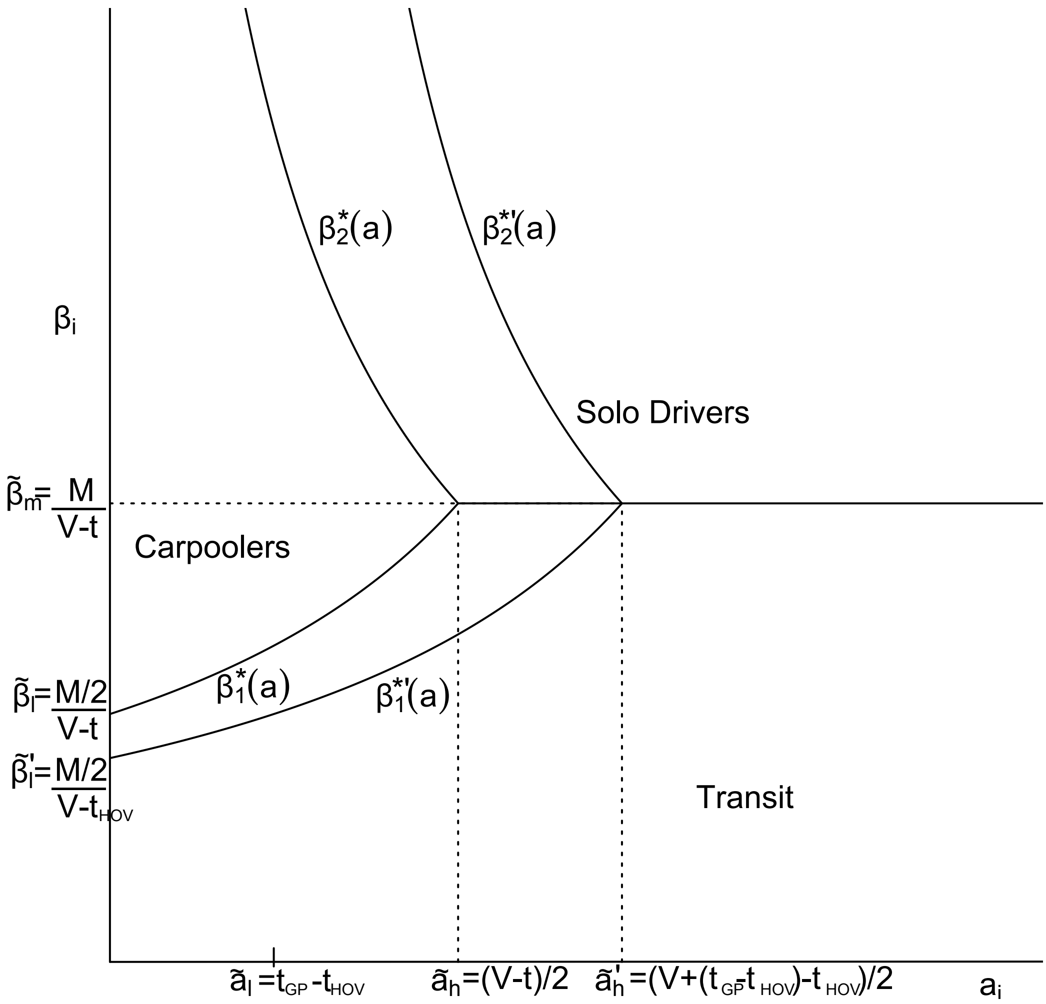

Figure 2. : The Influence of Assembly Costs (a_i) and Value of Time (β_i) on Mode Choice

Source: Author's Calculations.

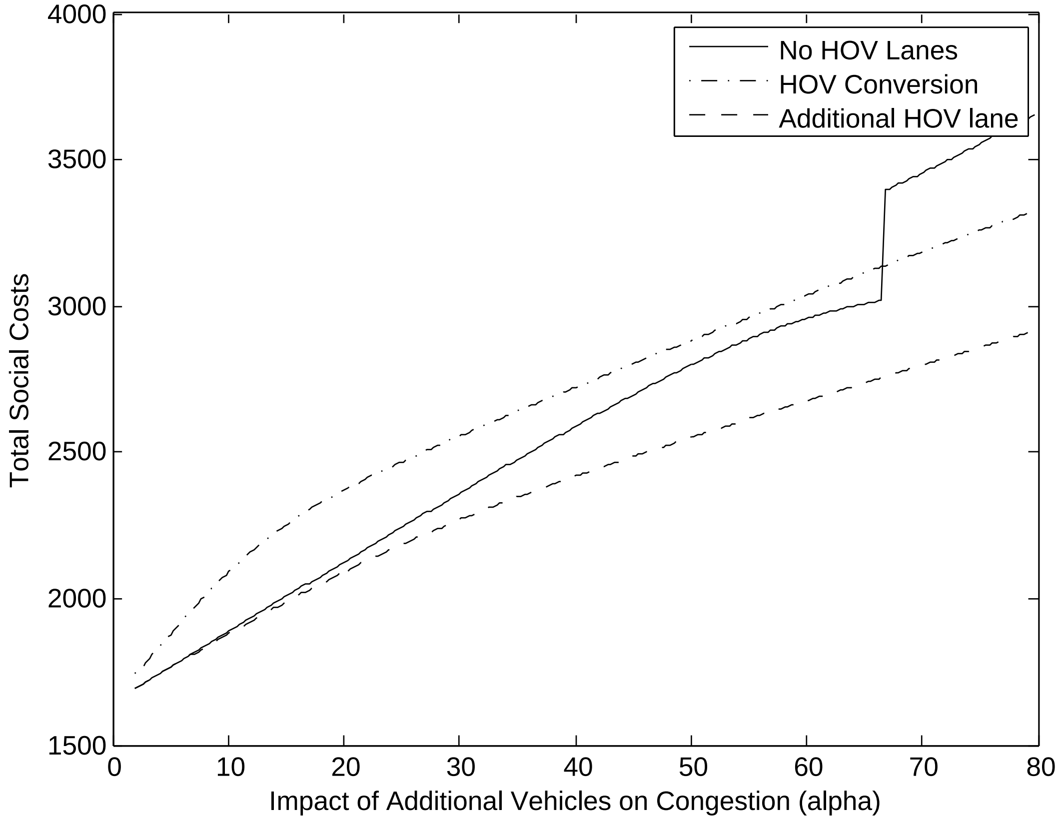

Figure 3. : Simulation Results of HOV Lanes on Total Social Costs with Varying α

Note: These simulations were run using two general purpose lanes for the case without HOV lanes, one general purpose and one HOV lane for the HOV Conversion case, and two general purpose lanes and one HOV lane for the case with an additional HOV lane. The time cost without congestion is $\delta = 20$, the monetary costs of driving alone are $M = 300$, the reservation time cost of transit/not driving is $V = 75$. The distribution of assembly costs is a degenerate distribution at $a = 5$ and the distribution of time costs is a uniform distributionwhere the maximum value of time is $\overline{\beta} = 100$ and the minimum value of time is $\underline{\beta} = 0$.Total Social Costs for a given α under each scenario is calculated as the weighted sum of the costs of each mode:

$$TSC(\alpha) = \int_{\underline{\beta}}^{\beta_1^*} C_x(\beta_i) f(\beta_i) d\beta_i + \int_{\beta_1^*}^{\beta_2^*} C_y(\beta_i) f(\beta_i) d\beta_i + \int_{\beta_2^*}^{\overline{\beta}} C_z(\beta_i) f(\beta_i) d\beta_i$$

where $f(\beta_i)$ is the uniform distribution.

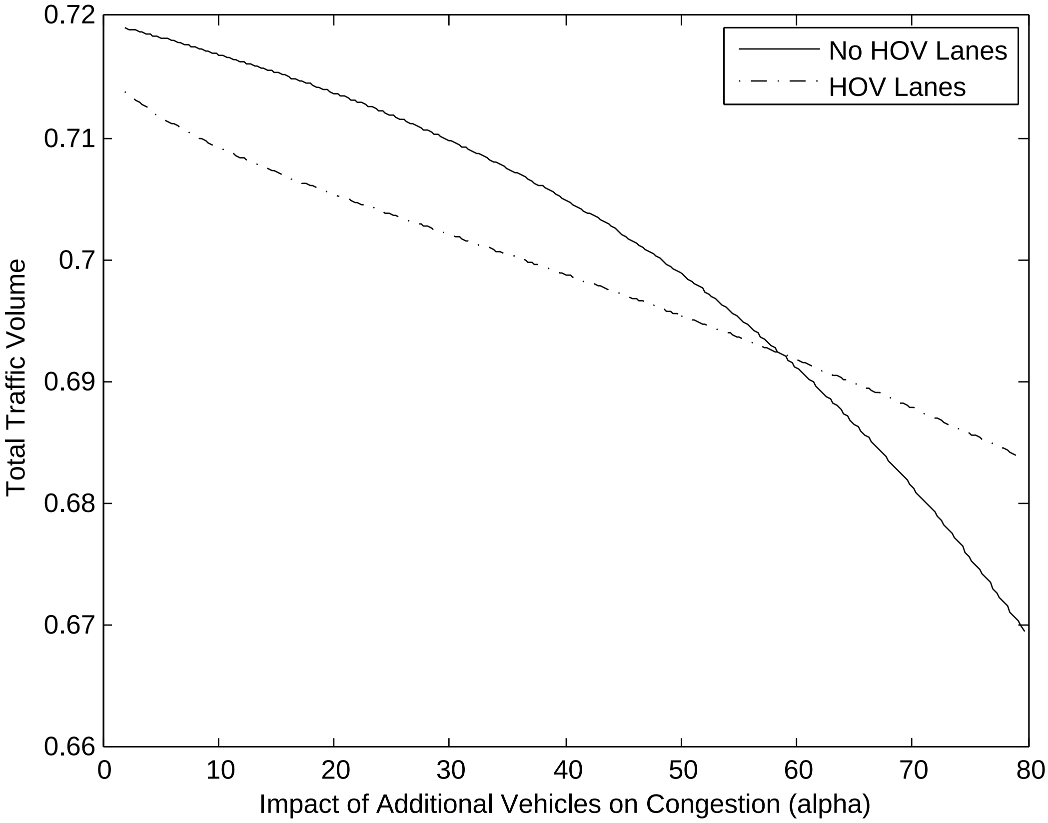

Figure 4. : Simulation Results of The Influence of α on Total Traffic Volume

Note: These simulations were run using two general purpose lanes for the case without HOV lanes and two general purpose lanes and one HOV lanes for the case with HOV lanes. The time cost without congestion is $\delta = 20$, the monetary costs of driving alone are $M = 300$, the reservation time cost of transit/not driving is $V = 75$. The distribution of assembly costs is a degenerate distribution at $a = 5$ and the distribution of time costs is a simple distribution that places more mass on the lower values of time:

$$f(x) = \begin{cases} \frac{2}{(\overline{\beta}-\underline{\beta})^2}(\overline{\beta} - x) & \text{if } x \in [\underline{\beta}, \overline{\beta}] \\ 0 & \text{otherwise} \end{cases}$$

where the maximum value of time is $\overline{\beta} = 100$ and the minimum value of time is $\underline{\beta} = 0$.

Table 4—: Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, Pooled OLS

Panel A					
Daily Freeway VMT in thousands by MSA and year.					
HOV Lane Miles	60.23***	59.38***	57.64***	56.93***	11.00**
(lagged)	(12.44)	(12.73)	(13.21)	(13.09)	(3.37)
Lane Miles	13.65***	13.60***	13.58***	13.99***	11.82***
(lagged)	(1.06)	(1.05)	(1.06)	(1.06)	(0.98)
Population	0.89	0.91	0.93	0.80	9.02***
	(0.85)	(0.85)	(0.85)	(0.80)	(0.78)
Statewide Fuel		4.29*	17.22	18.31	-0.28
Cost		(2.46)	(15.42)	(15.10)	(6.49)
City Size Controls				Yes	
Year Fixed Effects			Yes	Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,646	2,646	2,646
R^2	0.96	0.96	0.96	0.96	0.996
Panel B					
Natural log of Daily Freeway VMT in thousands by MSA and year.					
ln(HOV)	0.03***	0.03***	0.02**	0.02*	-0.02**
(lagged)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(Lane Miles)	0.97***	0.96***	0.95***	0.95***	0.79***
(lagged)	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
ln(Population)	0.18***	0.19***	0.20***	0.17**	0.41***
(in millions)	(0.04)	(0.04)	(0.04)	(0.07)	(0.10)
ln(Fuel Cost)		0.17***	0.37**	0.42**	-0.10
(by state)		(0.02)	(0.18)	(0.19)	(0.08)
City Size Controls				Yes	
Year Fixed Effects			Yes	Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,646	2,646	2,646
R^2	0.97	0.97	0.98	0.98	0.99

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 5—: Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, Pooled OLS

Panel A					
Daily Freeway VMT in thousands by MSA and year.					
HOV Lane Miles	60.23***	57.22***	51.19***	55.57***	49.46***
(lagged)	(12.44)	(11.45)	(9.89)	(11.90)	(10.34)
Lane Miles	13.65***	14.18***	14.62***	13.94***	14.30***
(lagged)	(1.06)	(1.08)	(0.98)	(1.09)	(0.97)
Population	0.89	0.70	0.70	0.80	0.83
	(0.85)	(0.82)	(0.75)	(0.82)	(0.74)
Elevation Range		1.00*	0.50	0.99*	0.51
(meters)		(0.55)	(0.66)	(0.57)	(0.66)
Terrain Ruggedness		-65.40	-51.49	-62.01	-49.60
(meters)		(55.58)	(54.16)	(56.23)	(54.18)
Mean cooling			0.56		0.45
degree-days			(0.81)		(0.82)
Mean heating			-0.03		-0.08
degree-days			(0.34)		(0.34)
Census Divisions			Yes		Yes
Year Fixed Effects				Yes	Yes
Observations	2,646	2,565	2,565	2,565	2,565
R^2	0.96	0.96	0.97	0.97	0.97
Panel B					
Natural log of Daily Freeway VMT in thousands by MSA and year.					
ln(HOV)	0.03***	0.02**	0.01	0.01	-0.00
(lagged)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(Lane Miles)	0.97***	0.98***	1.00***	0.95***	0.95***
(lagged)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ln(Population)	0.18***	0.18***	0.19***	0.21***	0.23***
(in millions)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Elevation Range		0.00	-0.00	0.00	-0.00
(meters)		(0.00)	(0.00)	(0.00)	(0.00)
Terrain Ruggedness		0.00	0.00	0.00	0.00
(meters)		(0.00)	(0.00)	(0.00)	(0.00)
Mean cooling			-0.00		-0.00**
degree-days			(0.00)		(0.00)
Mean heating			-0.00*		-0.00**
degree-days			(0.00)		(0.00)
Census Divisions			Yes		Yes
Year Fixed Effects				Yes	Yes
Observations	2,646	2,565	2,565	2,565	2,565
R^2	0.97	0.97	0.98	0.98	0.99

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 6—: Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, 2SLS Using Number of Counties in Ozone Whole Non-Attainment

Panel A					
Daily Freeway VMT in thousands by MSA and year.					
HOV Lane Miles	169.15**	181.62**	240.28	253.00	158.28
(lagged)	(81.30)	(90.89)	(238.18)	(302.21)	(524.11)
Lane Miles	12.18***	9.05**	6.26	6.16	9.38
(lagged)	(2.82)	(4.02)	(10.51)	(12.04)	(7.15)
Population		1.23	1.59	1.49	-3.30
(millions)		(0.93)	(1.48)	(1.47)	(43.10)
Geography Controls			Yes	Yes	
Census Divisions			Yes	Yes	
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,565	2,565	2,646
R^2	0.88	0.86	0.76	0.73	0.95
First Stage F-stat	1.46	1.44	0.53	0.37	0.10
Panel B					
Natural log of Daily Freeway VMT in thousands by MSA and year.					
ln(HOV)	0.81	0.39	-0.89	-0.06	0.06
(lagged)	(2.87)	(0.34)	(3.93)	(0.22)	(0.10)
ln(Lane Miles)	0.49	0.98***	1.25	0.98***	0.81***
(lagged)	(2.36)	(0.09)	(1.07)	(0.06)	(0.10)
ln(Population)		-0.16	0.90	0.26	0.34**
		(0.36)	(3.10)	(0.18)	(0.14)
Geography Controls			Yes	Yes	
Census Divisions			Yes	Yes	
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,565	2,565	2,646
R^2	0.88	0.86	0.76	0.73	0.95
First Stage F-stat	0.07	1.08	0.05	0.24	1.33

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
First stage estimates presented in Table **??**.

Table 7—: Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, 2SLS Using Exposed Population By Region

Panel A					
Daily Freeway VMT in thousands by MSA and year.					
HOV Lane Miles	120.98***	123.19***	123.79***	124.44***	-38.28
(lagged)	(33.13)	(27.20)	(29.61)	(29.34)	(23.69)
Lane Miles	13.71***	11.27***	11.20***	11.10***	12.64***
(lagged)	(0.95)	(1.76)	(1.97)	(1.79)	(1.50)
Population		1.07	1.14*	1.17*	13.13***
(millions)		(0.71)	(0.67)	(0.63)	(1.13)
Geography Controls			Yes	Yes	
Census Divisions			Yes	Yes	
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,565	2,565	2,565	2,646
R^2	0.93	0.93	0.94	0.94	0.99
First Stage F-stat	42.78	45.24	30.53	32.44	2.00
Hansen's J-stat	4.45	4.16	4.43	4.59	
Panel B					
Natural log of Daily Freeway VMT in thousands by MSA and year.					
ln(HOV)	0.06**	0.06**	0.02	0.03	-0.02
(lagged)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
ln(Lane Miles)	1.10***	0.97***	1.00***	0.96***	0.79***
(lagged)	(0.03)	(0.04)	(0.04)	(0.04)	(0.09)
ln(Population)		0.16**	0.18***	0.19***	0.40***
(millions)		(0.05)	(0.03)	(0.03)	(0.10)
Geography Controls			Yes	Yes	
Census Divisions			Yes	Yes	
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,565	2,565	2,565	2,646
R^2	0.97	0.97	0.98	0.98	0.99
First Stage F-stat	11.14	12.79	19.97	22.00	1.68
Hansen's J-stat	5.40	4.77	4.95	2.75	

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Instrument in both panels is the five year lag of population (in millions) living in counties in whole non-attainment status for ozone interacted with region.
First stage estimates presented in Table ??.

Table 8—: Arterial Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, Pooled OLS

Panel A					
Daily Arterial VMT in thousands by MSA and year.					
HOV Lane Miles	40.43**	40.38***	40.23**	38.89**	-11.48**
(lagged)	(11.93)	(11.69)	(12.44)	(11.84)	(4.64)
Arterial Lane Miles	5.51***	5.51***	5.46***	5.26***	2.10**
(lagged)	(0.87)	(0.87)	(0.95)	(1.16)	(0.65)
Population	-1.00	-1.00	-0.93	-0.87	10.53***
	(0.96)	(0.96)	(1.04)	(1.06)	(1.71)
Statewide Fuel		0.25	-10.01	-6.90	-10.98
Cost		(2.65)	(23.43)	(22.46)	(8.52)
City Size Controls				Yes	
Year Fixed Effects			Yes	Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,646	2,646	2,646
R^2	0.95	0.95	0.95	0.95	0.99
Panel B					
Natural log of Daily Arterial VMT in thousands by MSA and year.					
ln(HOV)	0.03**	0.03**	0.03**	0.02*	-0.01
(lagged)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(arterial)	0.68***	0.68***	0.63***	0.64***	0.50***
(lagged)	(0.04)	(0.04)	(0.05)	(0.05)	(0.09)
ln(population)	0.32***	0.32***	0.36***	0.28***	0.44***
(in millions)	(0.05)	(0.05)	(0.05)	(0.07)	(0.11)
ln(fuel cost)		0.08***	-0.35*	-0.26	-0.15
		(0.02)	(0.19)	(0.18)	(0.10)
City Size Controls				Yes	
Year Fixed Effects			Yes	Yes	Yes
MSA Fixed Effects					Yes
Observations	2,646	2,646	2,646	2,646	2,646
R^2	0.96	0.96	0.96	0.96	0.99

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9—: Arterial Vehicle Miles Travelled (VMT) as a Function of HOV Lanes, Pooled OLS

Panel A					
Daily Arterial VMT in thousands by MSA and year.					
HOV Lane Miles	40.43**	38.64**	31.59**	37.61**	30.38**
(lagged)	(11.93)	(12.96)	(12.55)	(12.56)	(12.15)
Arterial Lane Miles	5.51***	5.53***	5.84***	5.51***	5.81***
(lagged)	(0.87)	(0.90)	(0.81)	(0.93)	(0.84)
Population	-1.00	-1.01	-1.32	-0.98	-1.28
	(0.96)	(0.98)	(0.82)	(1.01)	(0.85)
Elevation range		0.47	0.36	0.48	0.38
(meters)		(0.35)	(0.50)	(0.36)	(0.50)
Terrain Ruggedness		-19.48	16.20	-19.26	16.42
(meters)		(31.81)	(33.00)	(31.81)	(32.94)
Mean cooling			-0.45		-0.45
degree-days			(0.72)		(0.72)
Mean heating			-0.87**		-0.87**
degree-days			(0.38)		(0.38)
Census Divisions			Yes		Yes
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,548	2,548	2,470	2,470	2,548
R^2	0.95	0.95	0.96	0.95	0.96
Panel B					
Natural log of Daily Arterial VMT in thousands by MSA and year.					
ln(HOV)	0.03**	0.03**	0.01	0.02	-0.00
(lagged)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(arterial)	0.68***	0.69***	0.76***	0.66***	0.72***
(lagged)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
ln(population)	0.32***	0.32***	0.28***	0.35***	0.32***
(millions)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Elevation Range		0.00	-0.00	0.00	-0.00
(meters)		(0.00)	(0.00)	(0.00)	(0.00)
Terrain Ruggedness		-0.00	0.00**	-0.00	0.00**
(meters)		(0.00)	(0.00)	(0.00)	(0.00)
Mean cooling			-0.00		-0.00
degree-days			(0.00)		(0.00)
Mean heating			-0.00**		-0.00**
degree-days			(0.00)		(0.00)
Census Divisions			Yes		Yes
Year Fixed Effects				Yes	Yes
MSA Fixed Effects					Yes
Observations	2,548	2,548	2,470	2,470	2,548
R^2	0.96	0.96	0.97	0.96	0.97

Standard errors are clustered on MSA.
Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$