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Induced Travel Demand: Measuring the Contribution of Additional Lane Miles on the Increase in U.S. Vehicle Miles Traveled from 1980 to 2019

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INDUCED TRAVEL DEMAND: MEASURING THE CONTRIBUTION OF ADDITIONAL LANE MILES ON THE INCREASE IN U.S. VEHICLE MILES TRAVELED FROM 1980 TO 2019

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in Civil Engineering in the
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ABSTRACT OF THESIS

INDUCED TRAVEL DEMAND: MEASURING THE CONTRIBUTION OF ADDITIONAL LANE MILES ON THE INCREASE IN U.S. VEHICLE MILES TRAVELED FROM 1980 TO 2019

Induced travel demand is the effect of increasing the amount of vehicle miles traveled because of an increase in roadway capacity. It is explained by the idea that increasing capacity makes driving on those roads more desirable, thereby causing more people to use them. In1962, Robert Downs postulated that "On urban commuter expressways, peak hour traffic congestion rises to meet maximum capacity," referring to this as the law of peak hour traffic congestion. Since then, there have been ongoing debates about the effectiveness and environmental impact of roadway expansion projects, and efforts to quantify induced demand to inform those debates. Broadly, we observe that despite increasing roadway capacity over the past several decades, vehicle miles traveled (VMT) have increased faster, and congestion has worsened.

In this study I calculate how much of the increase in vehicle miles traveled in the United States can be attributed to increased lane miles. I find that between 1980 and 2019, total lane miles increased by 13%, resulting in 8% to 24% more VMT. I also find that population growth results in 41% more VMT and rising per capita incomes result in 19% more VMT, driving most of the increase in vehicle miles traveled. Other factors contribute 7%, with an important portion of the increase unexplained. These results suggest both that expanding roadway capacity will have only a modest effect on growing congestion, and that stopping capacity expansion projects will have only a modest effect on slowing VMT growth. This finding is important both to those who seek to mitigate growing traffic congestion, and to those who seek to limit the environmental impact of vehicular travel.

KEYWORDS: Induced Travel Demand

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CHAPTER 1. INTRODUCTION

1.1 Introduction

Researchers observed that often when a roadway has its capacity expanded to reduce congestion problems, the roadway is congested again after a short period. This rebounding congestion is due to an effect known as induced travel demand. Induced travel demand has been previously defined as "…additional travel that is induced by the lower costs that result from capacity expansion." (Milam, et al., 2017) This means that when the available roadway increases, the congestion on that road goes down initially. Because lower congestion makes it more appealing for drivers who had previously avoided driving - either because they did not want to deal with waiting in traffic or have waited to make trips until times when there was less congestion – people drive more on the expanded road. This increased vehicular travel offsets at least some of the congestion reduction benefit of the capacity expansion, and can contribute to other environmental impacts, such as higher emissions.

When measuring travel conditions on road networks, traffic engineers commonly focus on three related metrics: traffic volume, travel time and delay. Traffic volume is typically measured in vehicles per hour, or as the average daily traffic (ADT). Travel time is measured in minutes or hours to traverse a segment of roadway, and delay is the difference between the travel time and the free-flow travel time. As the traffic volume approaches the road capacity and congestion occurs, travel time and delay rise at increasing rates. As congestion worsens, the traffic volume may decrease because the flow is constrained by slow speeds. Induced demand occurs because the relationship between traffic volume and travel time is endogenous—not only do changes in traffic volume affect travel time, but changes in travel time affect traffic volume. Changes to either have a bigger effect when the road is congested—usually during the peak periods and in urban areas.

When researchers are trying to measure the amount of induced travel that will occur with a roadway expansion or construction, they typically measure it as the elasticity of VMT with respect to a change in lane miles (Cervero, 2002; Duranton and Turner, 2011; Fulton et al., 2000; Hsu and Zhang, 2014; Hymel 2019). For instance, an elasticity of 1.0, would suggest that for every 1% increase in lane miles, there would be a corresponding 1% increase in VMT. While measuring the VMT to lane miles relationship is a simplification of a more complex relationship, it side-steps the non-linear relationship with travel time and relies on data that are widely available in the US through the Highway Performance Monitoring System (HPMS)—a system by which the Federal Highway Administration (FHWA) compiles road performance metrics reported by the states (FHWA, 2022).

The literature broadly agrees that there is an induced demand effect and generally agrees on the variables correlated with it, although they disagree on their magnitude. The estimated elasticity of VMT with respect to lane-miles varies in different studies, which has been noted by many evidence reviews and can be found by a review of highly cited modeling studies (Cervero, 2002; Cervero & Hansen, 2001; Dunkerley et al., 2018; Handy & Boarnet., 2014; Hymel et al, 2010; Litman, 2017; Milam et al., 2017; Noland & Lem, 2002). Elasticities of VMT with respect to lane miles have generally been less than 1 with a range of around 0.3 to 0.7 before a 2011 study by found a value of 1.03 using a wider range of explanatory variables and instrumental variables (Duranton & Turner, 2011).

Understanding the magnitude of this elasticity is important to understanding the expected benefits and impacts of road expansion projects. Because different projects will have different induced travel effects, travel demand models can be used to measure project-specific impacts. It is worth asking if travel demand models capture the correct level of induced demand. A case study looking at the effect that major road projects have on traffic volumes found that the forecasted traffic volume was almost always less than the actual traffic and the study's authors postulate that induced demand is not correctly incorporated into traffic forecast models (Davies, 2015). Another study also found that the "induced travel" effect is often ignored or underestimated during the planning process and attempt to help fix that by developing an induced demand calculator (Volker et al., 2020). Notably, they use the value for VMT with respect to lane miles elasticity of 1.0 for interstate highways.

Traffic forecast accuracy has changed over time. Historically, post-opening traffic has historically been higher than forecast which might suggest that forecasts do not adequately capture induced demand, but this relationship has changed in the 2000s. Hoque et al. (2021) illustrate this change in Figure 1.1 below, where each point represents an individual forecast, and the blue line represents the rolling average of the percent difference of post-opening traffic from the forecast. They show that the accuracy trend is aligned in time with aggregate trends in VMT. Could it be that forecasting methods have improved? Or perhaps the trend in both is driven by induced demand—as we built road capacity at a higher rate in the 1980s and 1990s, that capacity expansion led to higher VMT. It may also be that both are driven primary by changing economic conditions. To answer these questions, we must first understand what is driving the changes in VMT, and specifically how much of that change is attributable to induced demand.

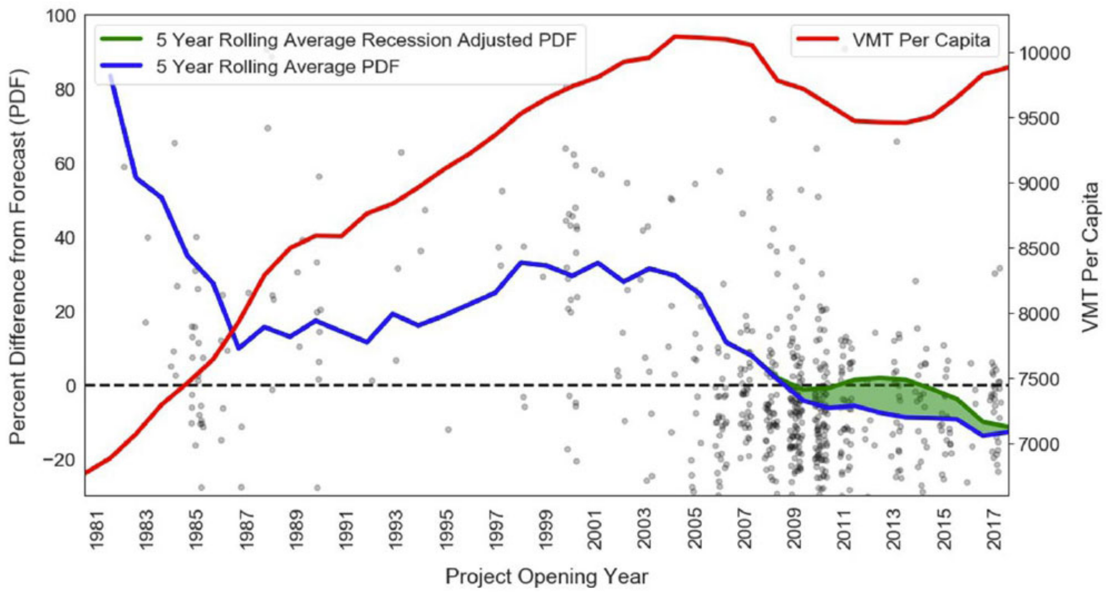

Figure 1.1: Trend in percent difference from forecast, excluding resurfacing projects (Hoque et al., 2021)

To try to understand what causes changes in VMT and how much change can be attributed to induced demand, I begin by quantifying the factors contributing to the change in VMT in the US between 1980 and 2019. Using data from the HPMS and several other sources, I examine the state-by-state change in VMT as a function of lane miles, population, retail gas price, per capita income, and the employment rate. Overall, VMT increases 109% in the US over this period, and I find that induced demand is responsible for 8 to 24 % of this increase. These results provide important context to understand the scale of the induced demand effect relative to other factors that also contribute to higher VMT.

1.2 Literature Review

The estimated elasticity of VMT with respect to lane miles varies widely depending on where you find it. This has been noted by several evidence reviews including a 2018 study commissioned by RAND Europe and a 2014 report looking at the relationship of induced travel and passenger vehicle use as well as greenhouse gas emissions (Dunkerley, 2018; Handy & Boarnet, 2014). There have been relationships found between several factors and the estimated elasticities of VMT in relation to lane miles. It has been noted that "…induced travel effects generally decrease with the size of the unit of study." (Litman, 2010) Some researchers have wondered if travel forecasting models provided a better estimate of short-term induced travel effects while research provided a better estimate of long-term effects (Milam et al., 2017).

Table 1.1 Elasticities of lane miles with respect to VMT based on table by Hymel, 2019

Study	*Sample*	*Elasticity Range*	*Estimator*	*Facility Type*	*Time Period*
Fulton et al.					
(2000)	County Level Data from MD, VA, NC, DC	0.564-0.587	FE	All	Short Run
	(1985-1995)	0.433-0.434	OLS FE	All	Short Run
		0.457-0.505	2SLS FE IV	All	Short Run
Noland and Cowert					
(2000)	US Urbanized Areas	0.655	FE	Freeways and Arterials	Short Run
	(1982-1996)	0.647	FE TE	Freeways and Arterials	Short Run
		0.284	FE DL	Freeways and Arterials	Short Run
		0.904	FE DL	Freeways and Arterials	Long Run
		0.289-0.760	2SLS FE IV	Freeways and Arterials	Short Run
Noland					
(2001)	State Level	0.166-0.287	OLS FE	All	Short Run
	(1984-1996)	0.549-0.627	OLS FE	Interstates	Short Run
		0.268-0.632	OLS FE	Arterials	Short Run
		0.542-0.892	OLS FE	Collectors	Short Run
		0.119-0.128	OLS FE DL	All	Short Run
		0.365-0.413	OLS FE DL	All	Long Run
Cervero and Hansen					
(2002)	Californian Urban Counties	0.588	3SLS FE IV	State Highways	5 Year
	(1976-1997)				
Hymel et al.					
(2010)	State Level	0.032-0.037	3SLS FE IV	All	Short Run
	(1966-2004)	0.160-0.186	3SLS FE IV	All	Long Run
Duranton and Turner					
(2011)	US Metropolitan Statistical Areas	0.92-1.06	OLS	Urban Interstates	10 Year
	(1983-2003)	0.66-0.90	OLS	Urban Arterials and Collectors	10 Year
		0.82-1.24	FE	Urban Interstates	10 Year
		0.94-1.03	2SLS ML FE IV	Urban Interstates	10 Year
Melo et al.					
(2012)	US Urbanized Areas	0.989	GMM	Arterials	Long Run
	(1982-2010)				
Hsu and Zhang					
(2014)	Japanese Urban Employment Areas	1.02-1.17	OLS	National Expressways	3-5 Year
	(1990-2005)	1.13-1.34	FE	National Expressways	3-5 Year
		1.24-1.34	2SLS ML FE IV	National Expressways	3-5 Year
Hymel					
(2019)	US Urbanized Areas	0.022	OLS DL	Limited Access Roadways	Short Run
	(1981-2015)	0.855	OLS DL	Limited Access Roadways	Long Run
		0.180	OLS FE DL	Limited Access Roadways	Short Run
		0.703	OLS FE DL	Limited Access Roadways	Long Run
		0.322-0.364	2SLS FE IV DL	Limited Access Roadways	Short Run
		0.892-1.056	2SLS FE IV DL	Limited Access Roadways	Long Run
		0.369	2SLS FE TE IV DL	Limited Access Roadways	Short Run
		1.063	2SLS FE TE IV DL	Limited Access Roadways	Long Run
		0.187	GMM DL	Limited Access Roadways	Short Run
		0.874	GMM DL	Limited Access Roadways	Long Run
		0.080-0.131	GMM DL IV	Limited Access Roadways	Short Run
		0.714-0.852	GMM DL IV	Limited Access Roadways	Long Run

Note: OLS = pooled ordinary least squares, 2SLS = two-stage least squares, 3SLS = three-stage least squares, GMM = generalized method of moments, ML= maximum likelihood, PS = propensity scores, FE = fixed effects, RE = random effects, TE = Time Effects, IV = instrumental variable, DL = Distributed Lag

A study done in 2000 by Fulton et al. used a fixed effects model to try to estimate the elasticity of VMT with respect to lane miles using a cross-sectional time series model of county level data from Maryland, Virginia, North Carolina, and Washington, DC. They had data for all these states from 1985-1995 although the data range for each individual state varied from this. The types of facilities they looked at included interstates, state-maintained roads, and some data about other primary roads. They chose this method because using a fixed effect model means that you do not have to know all the factors that could be affecting the dependent variable. They also say that fixed effects models can help reduce the problem of endogeneity. The endogeneity in this case comes from the idea that it seems reasonable to think that more people driving on roads would lead to those roads seeing expansion. They also use a first difference model, meaning that they the additive difference of the logs of variables was used. This is done to remove the multicollinearity that was in the base model. Multicollinearity means that there is a strong intercorrelations between the explanatory variables. They also use an instrumental variable in a two least squares regression to help control for endogeneity. The instrumental variable in this case is lagged lane miles. They chose this because it is highly correlated with lane miles but not VMT. Using the base fixed effects model, they found an elasticity between 0.564-0.587. Using the first difference model gave them a range of 0.433-0.434. The two-stage least squares model gave them an elasticity range of 0.457-0.505.

Noland and Cowert in 2000 performed an analysis on freeways and arterials in US urbanized areas between 1982-1996 also using a cross-sectional time series model fixed effects model. They also use an instrumental variable to help control for endogeneity. Using the fixed effects model, they found an elasticity of 0.655 and with the time effects added they found a similar elasticity of 0.647. They also use a distributed lag model to estimate both a short run and long run elasticities. The short run and long run elasticities were 0.284 and 0.904 respectively. For their instrumental variable the used urbanized area. They found an elasticity of 0.760 for the model that included population density and 0.289 for the one that did not.

Noland in 2001 ran a state level analysis using a one-least squares model on panel data considering state level effects. He chose not to use an instrumental variable because he found that most that were correlated to lane miles were also correlated to VMT. He also tested using a distributed lag model arguing that this allowed him to calculate short-term and long-term elasticities. He broke down VMT and lane miles in multiple ways, from using all of them combined to using the individual road types. Using all the combined road types he found that elasticities range from 0.166 to 0.287 depending on the amount of time the lane miles were lagged. When he split out the roadway types, he found that interstates ranged from 0.549-0.627, arterials ranged 0.286-0.632, and collectors ranged 0.542 – 0.892 depending on the amount of lag. When we used a distributed lag model, he found short term elasticates of 0.119-0.128 depending on if that variable was lane miles or lane miles per capita and long-term elasticities of 0.365-0.413 depending on the same factor.

A 2002 study conducted by Cervero and Hanson looking at county level data for state highways in California using a 5-year lag to try to account for the time it can take for newly expanded facilities to reach equilibrium. They used a three-stage least square model to account for cross-equation correlation of error terms and a right-hand side endogenous error term. They found an elasticity of 0.588.

A study by Hymel et al., in 2010 attempts to model both induced demand and the rebound effect at the state level to study their effect on each other and how they are interdependent using a three-stage least squares model. They found a short-run VMT elasticity range of 0.032-0.037 and a long run elasticity range of 0.160-0.186. They speculate that the numbers may be so low because they consider traffic statewide and also allow that they may be using different control variables, time spans, capacity measures, and overall model structure.

Duranton and Turner in 2011 use a variety of models to try to get estimates of both interstates and what they call "major roads" within metropolitan statistical areas (MSAs). They define a major road as either a collector, minor arterial, principal arterial, or other highway. They use an OLS regression first and find elasticities ranging from 0.92 -1.06 for interstates and 0.66-0.90 for major roads depending on the other explanatory variables used in the model. When they use a model that accounts for fixed effect and time effects, they find a range of 0.82 – 1.24 for interstates. They did not have enough data to find the elasticity for major roads. Then they use a second stage least square model with three instrumental variables: the 1947 interstate highway plan, an 1898 map of US railroads and routes of major explorations in 1835 to 1850. They use these because these are logically places where roads would be built so they would be heavily correlated with lanes miles but not necessarily with VMT. Using this model, they come up with a range of 0.94-1.03. They use a maximum likelihood estimation because they say it provides a more reliable point estimate and test statistic.

Melo at al., use two generalized method of moments (GMM) estimators to look at US urbanized areas because they say that these will give consistent parameter estimates through dynamic panel models. They look at a difference-GMM estimator, which they say involves taking the first difference of the model to eliminate individual effects, but it has been shown to perform poorly when data changes little over time. The second estimator is the system-GMM which they say estimates regressions in differences and levels simultaneously, is more efficient, and has less finite sample bias. They found a long-term elasticity of 0.989 for arterial streets.

In 2014, Hsu and Zhang repeated Duranton and Turner's methods but looking at Japanese urban employment areas. As might be expected from such a dense area, they found higher elasticities with the OLS model range being 1.02-1.17, the fixed effect model being 1.13-1.14, and the second stage least squares model giving them a range of 1.24-1.34.

Hymel ran a study utilizing many different model estimation methods in 2019 to try to examine the link between roadway capacity and the amount of vehicle travel. He uses data from urbanized areas within the United States from the years 1981 through 2015 for freeways and other limited access roadways. All his models use a distributed lag to get a short- and long-run elasticity. When he uses OLS models, he gets a range between 0.022-0.180 for short-run and 0.703-0.855 for long run elasticities. When he uses a 2SLS estimation model he gets a short-run range of 0.322 to 0.369 and a long-run range of 0.892 to 1.063. When he uses GMM he gets a short run range of 0.080

Table 1.2: Ranges of elasticities of lane miles with respect to VMT by different criteria

Criteria	*Short Run Elasticity Range*	*Long Run Elasticity Range*
Geography		
State Level	0.03-0.29	0.16-0.41
County Level	0.43-0.59	0.59
Urban Areas	0.02-0.76	0.66-1.34
Facilty Type		
All	0.03-0.59	0.16-0.41
Interstates	0.55-0.63	0.92-1.24
Interstates and Arterials	0.02-0.76	0.70-1.06
Arterials	0.27-0.63	0.99
Arterials and Collectors	-	0.66-0.91
Collectors	0.54-0.89	-
National Expressway (Japan)	-	1.02-1.34
Estimation Method		
OLS	0.02-0.76	0.37-1.17
2SLS	0.29-0.76	0.89-1.34
3SLS	0.03-0.04	0.16-0.59
GMM	0.08-0.19	0.71-0.99
Time Period		
Short Run	0.02-0.89	-
Long Run	-	0.16-1.34

There are different ranges of elasticities of lane miles with respect to VMT depending on many different factors including the geographic area you are looking at, the facility types being considered, which estimation method is used and the time period. When looking at the state level, the range for short run elasticities is 0.03-0.29 and the long run elasticity is 0.16-0.41. There are only a couple of studies that looked at the county level and they were looking at specific parts of the country, not the United States as a whole, so there is not as broad of a range as with the state and urban area levels. The short run range for county level is 0.43-0.59 and there was only one long run elasticity found at this level of 0.59. Looking at urban areas the short run range is 0.02-0.76 and the long run range is 0.66-1.34. Looking at the high end of each of these ranges, the state level is the lowest, the county level is in the middle and the urban level is the highest for both long and short range. This could possibly be because the state level is going to be considering many more rural facilities which it is unlikely would be subject to the same level of pent-up demand as urban facilities. County level is in the middle because they still contain some rural areas, but the counties selected by the researchers were chosen because they contain urban areas.

When considering all facility types the short run range is 0.03-0.59 and the long run range is 0.16-0.41. For interstate highways the short run range is 0.55-0.63 and the long run is 0.92-1.24. For arterials the short run is 0.27-0.63 and there was only one long range study done which found an elasticity of 0.99. For collectors, only a range of short run elasticities was found which was 0.54-0.89. It is a little more difficult to see a pattern here. I would think that interstates would have higher elasticities across the board because they have been built in places that have the highest value for travel so there would be the most pent-up demand for them but although the low end of the range for short run elasticities for arterials is lower than interstates, the high end is the same and for collectors the range is surprisingly higher than for both interstates and arterials. This could possibly just be because the data for collectors is not as high quality as the data for larger facilities.

Depending on the estimation method used to obtain the elasticity, there are different ranges for both long and short run. Researchers using OLS found a range for the short run between 0.02 to 0.76 and a long run range of 0.37-1.17. Using 2SLS a range was found for the short run of 0.29-0.76 and the long run was 0.89-1.34. Interestingly, using 3SLS came up with much lower elasticities with a short run range of 0.03-0.04 and a long run range of 0.16-0.59. Using GMM, researchers found a short run range of 0.08-0.19 and a long run range of 0.71-0.99. Looking at short run elasticity ranges, OLS and 2SLS have the same high end but 2SLS has a little bit higher of a low end, meaning there is a little less variability. Both 3SLS and GMM have much lower short run ranges. Looking at the long run, again OLS and 2SLS have similar high ends but much different low ends with the 2SLS being much higher. The 3SLS has a much lower long run range than any of the other estimation methods and GMM is in the middle of the OLS and 2SLS ranges. Since I am going to be looking at short run elasticities, I feel comfortable using OLS since it is comparable to the more complicated 2SLS favored by many researchers without as much work.

As might be expected, the time range of elasticities affects the range of them. Somewhat unexpectedly, both time periods have very large ranges with the long run range being higher but still having a lot of spread. The range of short run elasticities is 0.02-0.89 and the long run elasticity range is 0.16-1.34. You would expect there to be more induced travel demand effects the more time from the expansion of capacity as people switch travel pattens, so it makes sense that the long run elasticity range is higher than the short run.

With elasticities having such a wide variety of ranges it is worth asking how much the change in VMT can be attributed to the change in lane miles. I will be using an analysis method that has been previously used to assess how much change in the dependent variable is due to each explanatory variable to determine how much change in VMT can be attributed to the change in lane miles (Erhardt, et al., 2021).

To make sure that I am capturing the most important factors related to car travel I reviewed several articles that explored what variables are related to car travel. These articles are attempting to explain why car use has "peaked" and people are less likely to travel by car than in the past. They run models to find what variables best explain the trends in car travel. The United States saw a leveling of car travel between 2008 and 2013 but since then travel has resumed climbing, albeit at a slightly slower pace than before the economic recession of 2008. These researchers found that incomes (Bastian & Borjesson, 2015) (Bastian et al., 2016) (Stapleton et al., 2017), fuel cost (Bastian & Borjesson, 2015) (Bastian et al., 2016) (Stapleton et al., 2017), population (Headicar, 2013) (Metz, 2013) and urbanization (Headicar, 2013) (Metz, 2013) (Stapleton et al., 2017) could explain the vast majority of all car travel. I make sure to include the variables in my model to capture what most influences car travel.

CHAPTER 2. DATA AND METHODS

2.1 Introduction

For my analysis I chose to use state level data from the Federal Highway Administration (FHWA) for the years 1980 through 2019. I chose to include all road types for my lane miles and VMT except for local roads. The data for local roads was possibly inaccurate because it is difficult to measure the number of local roads and additionally the lane miles for them are calculated with the assumption that all local roads have only two lanes. The data I used contains Washington, D.C. but I excluded it from my final model because I was looking at state level data, including urban and rural areas to get a sense of how overall changes in non-local lane miles affect the overall non-local VMT in the state. Since D.C. is almost entirely an urban area it seemed like an obvious outlier. There were also issues with Delaware and Hawaii not tracking rural interstates, but because my final model combines all road types this was determined to not be a problem for how I measure the effect of additional lane miles on VMT. Another benefit of combining all non-local road classes together is I do not have to worry about roads being reclassified either between urban and rural or between different classes of roads. While interstates have a strict definition, it is more subjective to classify between arterials and collectors, depending on the amount of traffic they carry, so it is not uncommon for roads to be reclassified from an arterial to a collector or vice-versa, depending on how its traffic changes.

2.2 Data

To determine which model would be best for assessing the effect of lane miles on VMT I looked at several common variables used in previous studies. The first of these is my dependent variable VMT. VMT is estimated yearly by individual states based on hourly count data from traffic counting locations. Estimates are then readjusted to match the data from the Highway Performance Monitoring System (HPMS). The VMT data from the FHWA had no obvious outliers and it understandably became more variable as the classes of roadways went down i.e., VMT data from interstate highways exhibited a linear upward trend while the data for collectors still trended upwards but there was more variance between years.

The data for lane miles also comes from the FHWA, which compiles data from individual states in a similar manner to VMT. There was a change in how states estimated lane miles in before 2010 and after 2010. Before 2010 states used lower resolution maps to estimate lane miles after 2010 states started using GIS based maps, giving them a much higher resolution. Different states switch over at different times, and judging from graphs of lane miles, most states switch between the period of 2007 through 2010. Many states saw a noticeable jump in the number of lane miles during this period as they were able to measure the length and number of lanes more accurately on each section of road. When cleaning the data these jumps were left intact since they stayed consistently higher after the jump, indicating this was not an outlying data point. The lane-mile data contained many more outliers than the VMT data did. If there was a large change in the number of lane miles that reverted in the following year, that data point was removed, and the lane-mile value was filled by interpolating between the surrounding years. This is because it is unlikely that states would greatly increase capacity by expanding or building more roads, only to offset that the following year by removing lanes or whole roads in an amount that is very close to the amount they added the previous year.

Other variables that were considered were population, per capita income, median income, cost, or gasoline per million BTUs, retail gasoline cost, labor force participation, unemployment rate, number of car and truck registrations, yearly truck VMT, the share of people living in central metro areas, the share of people in fringe or small metro areas, the share of people living in non-metro areas, and number of registered drivers. Population came from the Census Bureau and is based on the decennial census with interim years being estimated by taking the base population counts from the census then updating them by year using measures of population change including births, deaths, and net migration. Per capita income and median income came from the United States Bureau of Economic Analysis (USBEA) and have been adjusted to 2019 dollars. Cost per million British thermal units (BTUs) of gasoline and retail fuel cost came from the Energy Information Administration (EIA). Retail fuel cost is derived from cost per million BTUs of gasoline by multiplying the cost by the heat content per barrel of gasoline for that year, the price is then adjusted to 2019 dollars. Labor force participation and unemployment rate are recorded by the Bureau of Labor Statistics (BLS) by month and from there the yearly average is calculated. Car and truck registrations, truck VMT, and number of registered drivers came from the FHWA. Truck registrations were included in with car registrations because FHWA includes pickups, vans, sports utility vehicles (SUVs), and other light trucks in its tabulation. Since these types of vehicles make up a large portion of the vehicles owned by the public, I wanted to make sure those contributions to traffic were taken into consideration. To find the share of the population that was in a central metro area, fringe or small metro area, or non-metro area, I used data from the National Cancer

Institute. A central metro area was defined as having a population of over 1 million people, a fringe or small metro area was less than 1 million but more than 250,000, and a non-metro area was defined as less than 250,000 people. Truck VMT is not given by the FHWA directly but had to be calculated using national level truck VMT and state level diesel consumption. Somewhat confusingly, despite truck registrations including pickups, vans, SUVs and other light trucks, these vehicle types are included in the "light duty vehicles" category for VMT. So, in this case, truck VMT refers to the VMT of single-unit 2-axel, 6-tire or larger vehicles. This seemed like a good proxy variable for shipping being done within a state since vehicles that large are primarily used to ship goods. These trucks also tend to use diesel gas and plotting truck VMT against gallons of diesel fuel used gave a strong linear relationship, so it seemed reasonable to assume that diesel fuel usage would be a good way to approximate truck VMT. So, I calculated a yearly ratio of truck VMT per gallons of diesel fuel consumed and used that ratio to split the national truck VMT proportionally to states based on the amount of diesel consumed in the state for the year. The truck VMT was then subtracted from the total VMT to estimate the VMT driven by passenger vehicles, which I ended up using as my dependent variable.

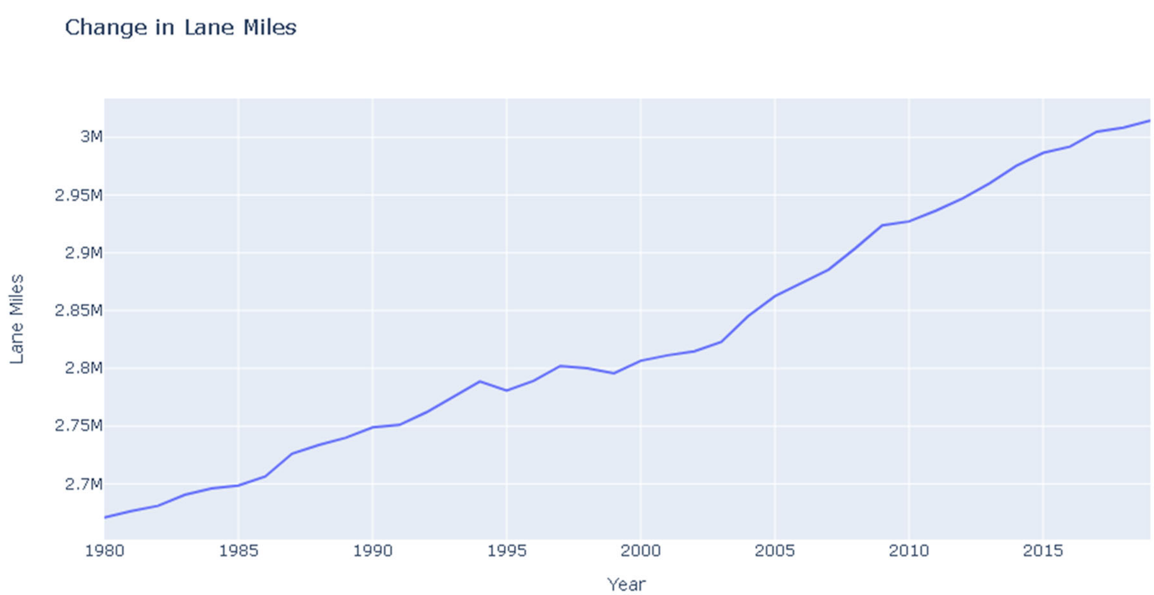

Figure 2.1: Change in lane miles over time

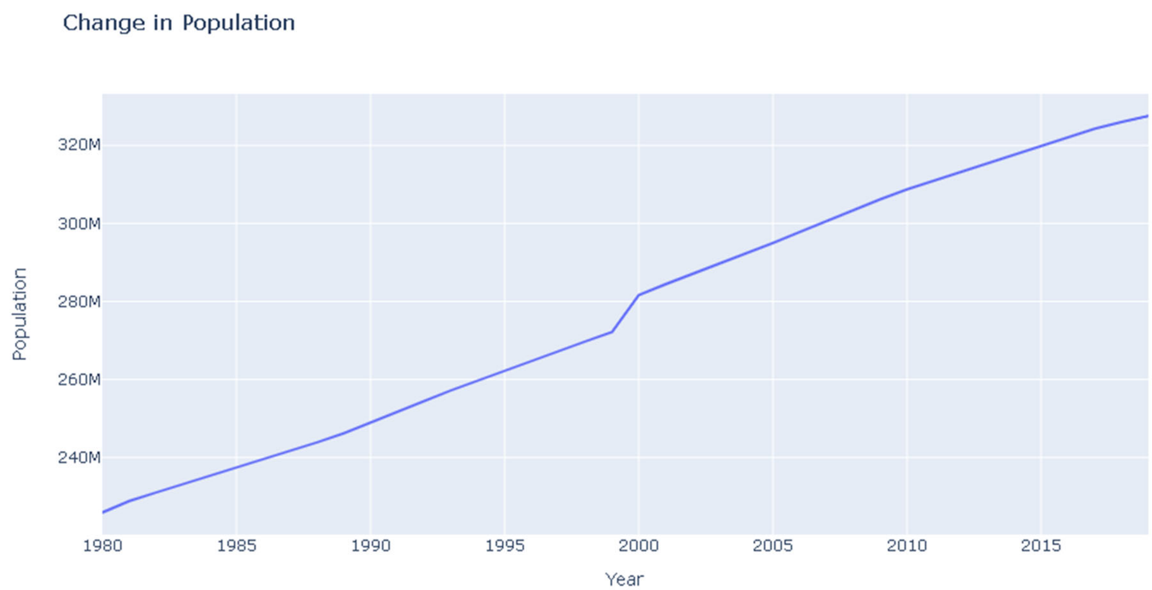

Figure 2.2: Change in population over time

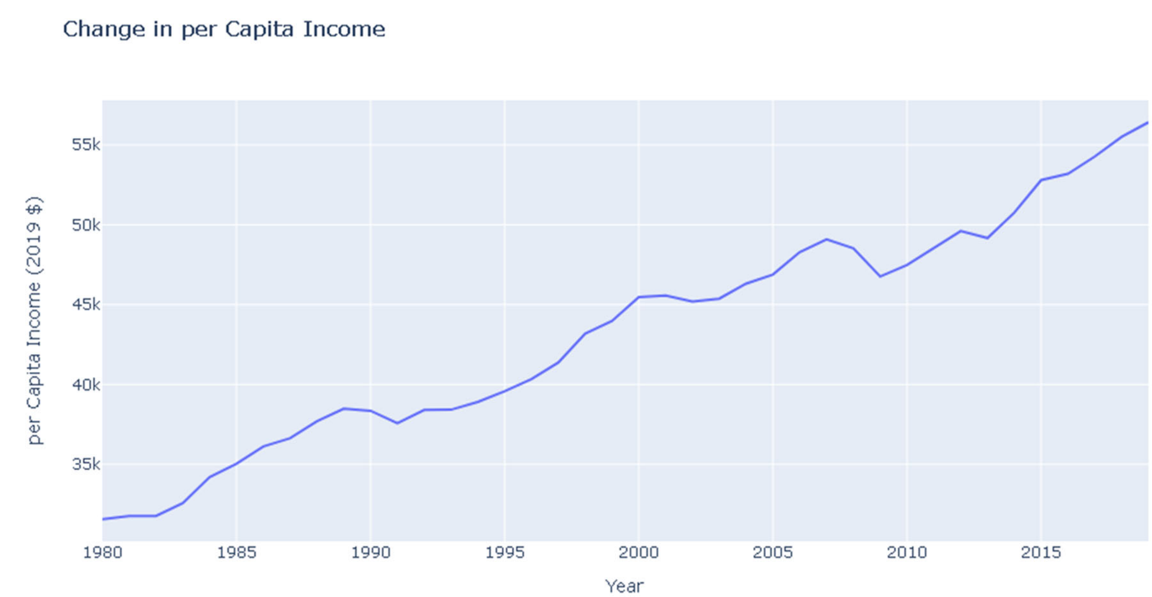

Figure 2.3: Change in per capita income over time

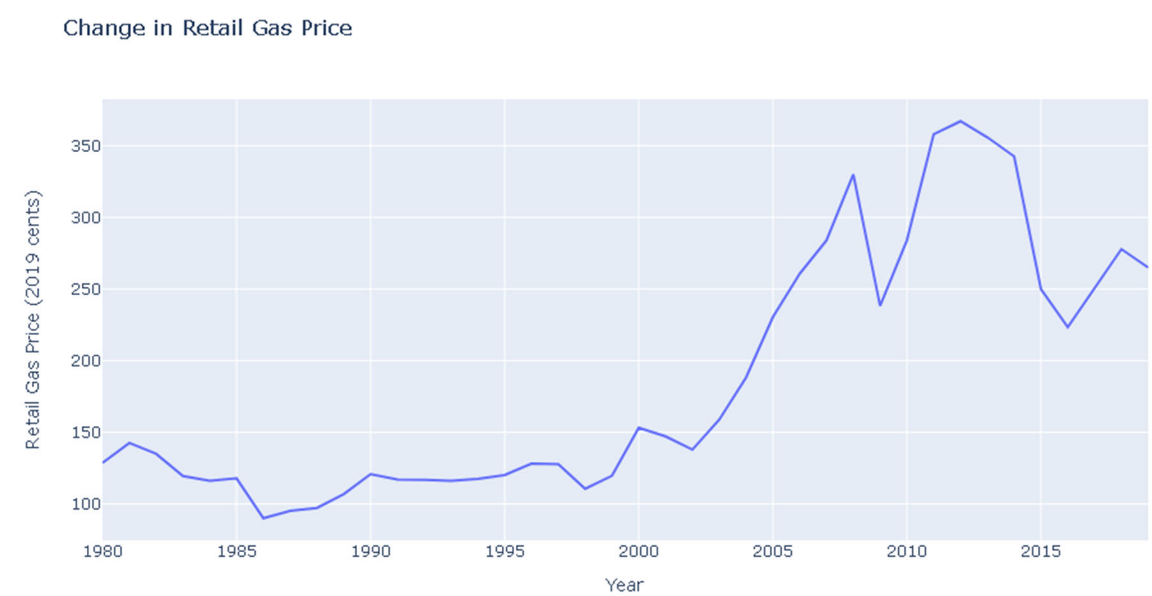

Figure 2.4: Change in retail gas price over time

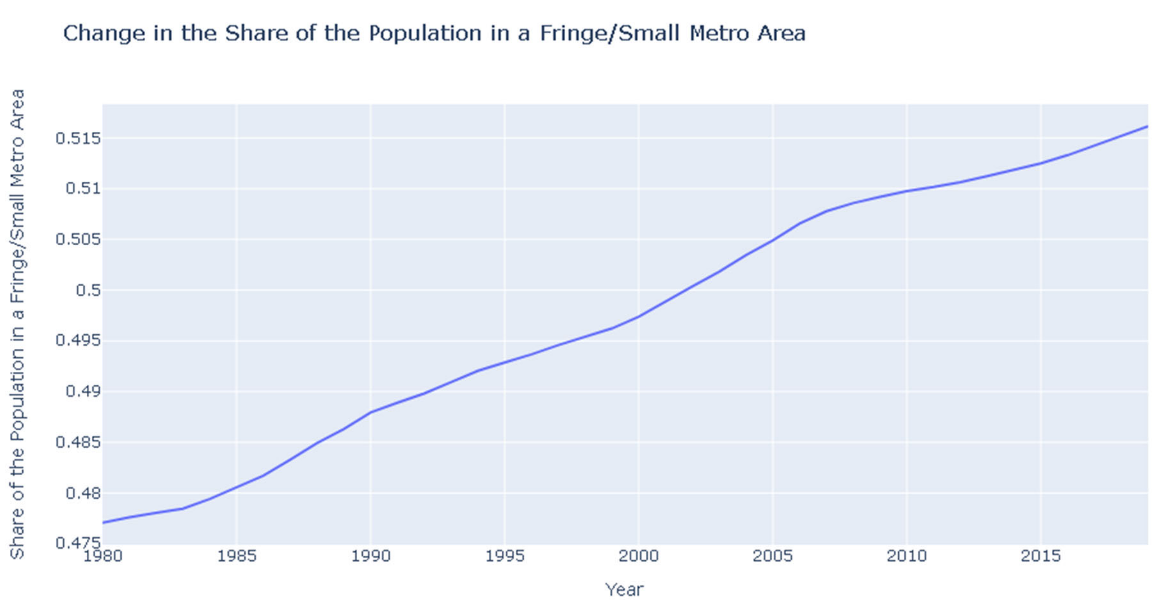

Figure 2.5: Change in the share of the population in a small/fringe metro area over time

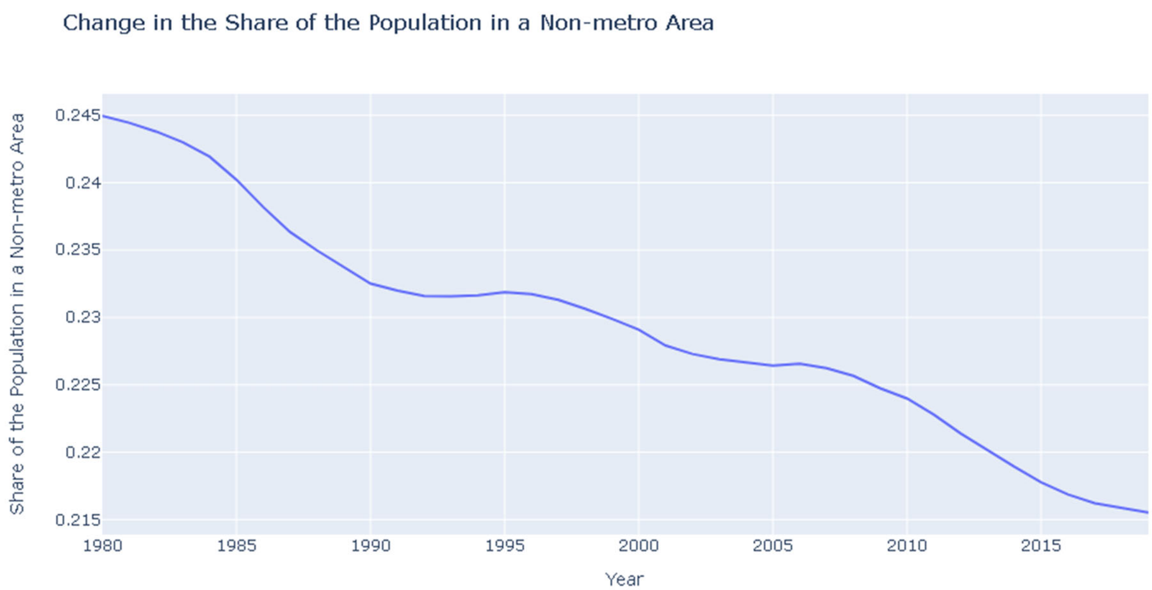

Figure 2.6: Change in the share of the population in a non-metro area over time

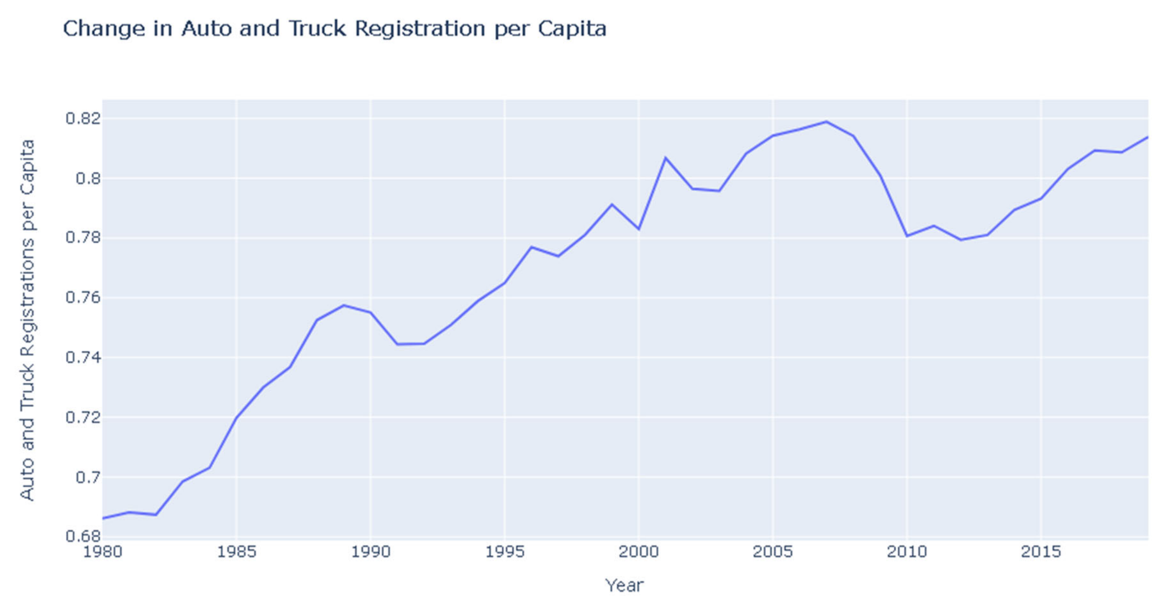

Figure 2.7: Change in the auto and truck registrations per capita over time

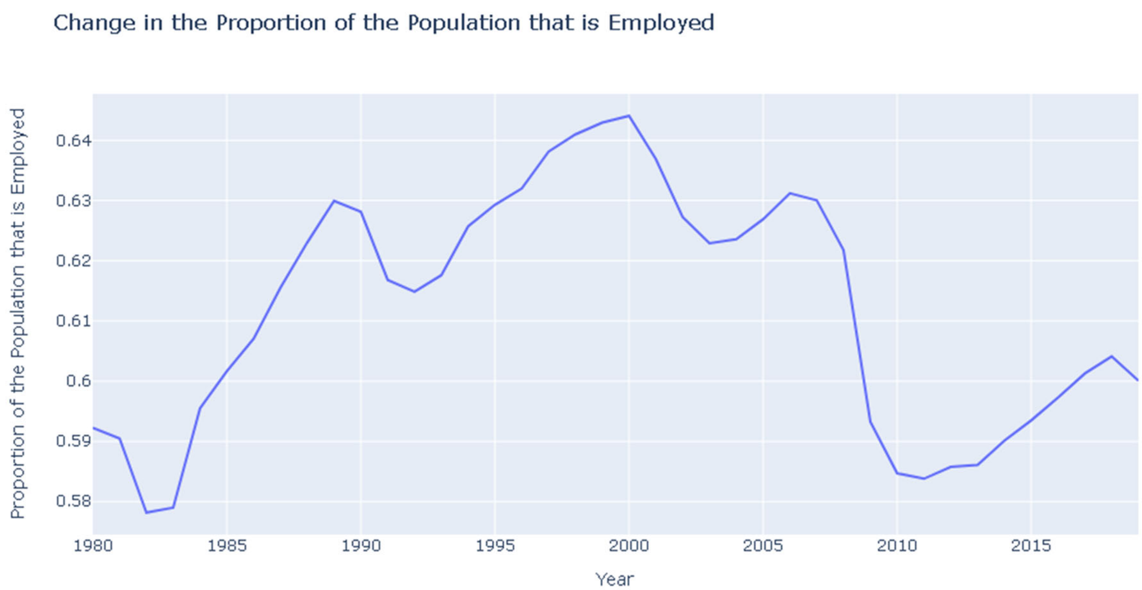

Figure 2.8: Change in the proportion of the population that is employed over time

2.3 Model Selection

As noted above, the elasticity for lane miles with respect to VMT increases the smaller the area of interest is. I looked at several different models, separating VMT and lane miles in rural and urban and additionally into the classification of interstate, arterial, and collector. I also tried several common variables to find what correlated with the changes in VMT. I decided on combining all my data both to negate effects from reclassifying roadways and to give a sort of "minimum" on what amount of change in VMT can be attributed to changes in lane miles. As noted above, the more localized of an area you look at, the higher the elasticity of lane miles with respect to VMT tends to get (Litman, 2010).

I chose to use an ordinary least square (OLS) fixed effects panel model since that data I had consisted of many data points spread across states and time. I chose to consider both fixed effects and time effects to try to account for variable that I did not have the data for, which seemed likely given there is a lot of possible things that could affect people's driving. OLS models also have the benefit of being easy to perform so I would not have to learn advanced statistical methods to preform my analysis. Previous studies that used state level data and a OLS fixed effect model found elasticities in the range of 0.160-0.434. If I had chosen to break out specific road types I likely would have gotten higher elasticities. I also likely would have had higher elasticities if I used another statical method such as a two stage least squares regression or generalized method of moments. Combining rural and urban areas was going to likely give me a lower elasticity but I wanted to try to eliminate the problem of urban boundaries growing and so additional lane miles would just from reclassifying roads. This is also why I combined all the road types, because with the exception of interstates, these classifications are fluid and in fact there is a large jump in the amount of arterial lane miles around 2007 because of collectors being reclassified.

As I was testing variables in my chosen regression, several variables that had been used in previous studies were found to not be statistically significant and so they were dropped from the final model. The discarded variables are labor participation rate and number of registered drivers. Additionally median income was found to be less significant than per capita income, and indeed, per capita income is the common metric used in induced demand studies to represent how much money people had. The retail cost of gasoline was only slightly more statistically significant than the cost per million BTU of gasoline, which makes sense since one is derived from the other. When I modeled time effects the significance of the share of the population within fringe/small metro areas and within nonmetro areas dropped as did the car and truck registrations, so those were dropped from the model that included time effects.

I built my model by starting out with VMT, lane miles, and population as my only variables and then testing out commonly used explanatory variables until I found the ones that were statistically significant and had a high R^2 value. I ultimately settled on my variables being VMT minus truck VMT, lane miles, population, per capita income, retail gasoline price, share of population in fringe/small metro areas, share of population in non-metro areas, auto and truck registrations per capita, and the employment rate. I tried using population in a number of different ways, including having both VMT and lane miles be in a per capita form, but found that there was little difference in the results I got and ultimately decided on using pure VMT and lane miles, both because this made later calculation simpler and also because I thought it would be useful to see the effect population has on VMT since I could be thought that population is the main driver of increasing VMT. As mentioned above when I included time effects, I dropped the variables of share of population in fringe/small metro areas, share of population in non-metro areas, auto and truck registrations per capita.

2.4 Model Estimation

The general formula for my model is as follows:

$$\ln(VMT_{itr}) = c + \alpha_i + T_t + \sum_k \beta^k \ln\left(X_{it}^k\right) + \lambda \ln(LM_{itr}) + \varepsilon_{it}$$

With:

VMT_{it} = VMT in state *i,* for year *t*

c = constant

α_i = state-specific effect

T_t = time effect for year *t* (only used in model the included time effects)

β^k = coefficient for explanatory variable *k*

λ = coefficient for lane miles

X_{it}^k = variable *k* in state *i,* for year *t*

LM_{it} = lane miles in state *i,* for year *t*

ε_{it} = error term

2.5 Model Application

After I got my coefficients for each of the variable, I could use those to calculate how much each explanatory variable contributed to the overall change in VMT between years. This is following an approach used previously to determine the effect different factors had on transit ridership (Erhardt et al., 2021). Since VMT is log transformed we can use the exponential of that term to find a ratio that can be used to determine the change in VMT if all other terms were held constant.

$$\frac{VMT_{it}}{VMT_{i,t-1}} = e^{\beta^k(X_{it}^k - X_{i,t-1}^k)}$$

The individual variables effect on VMT changes is called the factor affecting change (FAC). The FAC for each variable *k* is calculated as:

$$FAC_{kit} = VMT_{i,t-1}(e^{\beta^k\left(X_{it}^k - X_{i,t-1}^k\right)} - 1)$$

After each FAC is calculated for each variable, those FACs are summed and any remaining change is considered unexplained change, FAC_u:

$$FAC_{uit} = VMT_{it} - VMT_{i,t-1} - \sum_k FAC_{kit}$$

The unexplained change is thus like the error term in my general model. The total FAC for variable *k* is then found by summing the FAC across states and time:

$$FAC_k = \sum_{i \in S} \sum_{t \in T} FAC_{kit}$$

Where:

T = years from 1980 to 2019

S = states

In addition to using the coefficients that were produced from each model to calculate the FACs, for both the model including and not including time effects, a FAC was calculated as if the elasticity of lane miles with respect to VMT was 1. This was done as a “worst case scenario” given that models such as Duranton and Turner’s produce an elasticity around 1.

The final calculation of FAC for each variable are found in Tables 3.3, 3.4, 3.5 and 3.6.

To generate the graphs in Figure 3.1, I take the cumulative change in VMT attributed to each variable and add or subtract it to the overall VMT, thereby showing what the VMT would be without the effect of that specific variable.

CHAPTER 3. RESULTS

3.1 Introduction

I ran two different models. Both accounted for fixed effects and one accounted of time effects. This was done to try to control for both unobserved variables that change between the states but also those that change over time and to get an idea of how much time dependent variables affect the elasticities of each variable.

3.2 Estimation Results

Table 3.1: Fixed-effects panel data without time effects considered

Dependent variable is log of Car VMT	Model Summary	
	Coefficient	T-Stat
LN (lane miles)	0.483	10.073
LN (population)	0.891	38.085
LN (per capita income)	0.561	23.840
LN (retail gas price)	-0.050	-6.481
Share of population in fringe/small metro	0.856	4.302
Share of population in non-metro	0.441	2.017
Auto and truck registrations per capita	0.072	2.866
Employed per capita	1.956	21.483
Constant	-15.991	-38.757
R^2	0.901	

Table 3.1 shows the results of the model that does not consider the time effects. All the variables have the expected sign, and all are significant at a 95% confidence level. Since both VMT and lane miles are expressed as log values, the coefficient of lane miles is the same as the elasticity. In this case the elasticity is 0.483 which is on the high side of the range of 0.160-0.434 found by other researchers using OLS fixed effect models. It is possible that this is because my data continues farther than other researchers’ which stop

at 1996 at the latest. It is however in the middle of all models which have a range from 0.16 to 1.03.

Other variables elasticities also make sense. It is completely reasonable to think that as there are more people then there will be an almost equal rise in the amount of travel. Additionally, as people get more money, they will have more money to spend on leisure, shopping, and travel. This would obviously drive up the amount of VMT. Accordingly, when gas prices go up, people are going to be slightly less likely to travel. People will still have to go to work and buy things, but it seems reasonable to think that higher gas prices will lead to fewer unnecessary trips. People moving to both fringe/small metro areas and non-metro areas having an effect of increasing travel also makes sense as those places are less likely to be walkable and to have public transit. As more people get cars and register them that means that there's going to be likely more people traveling. Employment per capita has a high elasticity which makes sense, as more people are employed not only are more people going to be driving to work, but also more people will have money to spend on leisure, shopping, eating out, or any number of activities that either require somebody to drive somewhere or in the case of online shopping and food delivery services, to cause somebody else to drive on your behalf.

Table 3.2: Fixed-effects panel data with time effects considered

Dependent variable is log of Car VMT	Model Summary	
	Coefficient	T-Stat
LN (lane miles)	0.334	8.856
LN (population)	0.654	35.340
LN (per capita income)	0.204	6.200
LN (retail gas price)	-0.074	-2.181
Employed per capita	0.453	4.143
Constant	-5.642	-9.625
R^2	0.942	

When taking time effects into account there are several changes that happen to the coefficients for each variable. First, they uniformly drop. The coefficient for lane miles drops from 0.483 to 0.334, which is still in the upper half range of what other researchers have come up with using OLS fixed effects models. It is on the low side taking into consideration all models. The employment per capita coefficient has the largest drop, going from 1.956 to only 0.453. As mentioned earlier, three of the variables lose significance at even the 90% confidence level and so those were dropped from the model. All the remaining variables have the expected sign and are significant at the 95% confidence level.

3.3 Model Application

Since the coefficients for each of the variables represents the percent change in the non-local car VMT for each one-unit change in the explanatory variable, I can use that to calculate each variable's contribution to the overall change in VMT. Even when using all the variables in my model, they are not going to show all the factors that contribute to the change in the VMT. Any difference between the change that comes from the explanatory variables and the overall change is called the "unexplained change." Since there is a range of elasticities of VMT with regards to lane miles in the literature I chose to use my estimate from the model taking into account time effects as well as the high end of the elasticity range found in others' research, which is 1. This will help us to see what the highest possible contribution to VMT from lane miles will be. I chose to use the elasticity from the model with time effects because it would account for the most variables that I had not included in my model.

Table 3.3: FAC table using lane miles coefficient given by the model in Table 3.1

	1980-1990		1990-2000		2000-2010		2010-2019		1980-2019	
	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable
Lane miles	1.85%	2.92%	1.52%	2.10%	2.28%	4.30%	1.64%	2.98%	11.23%	12.86%
Population	10.73%	10.16%	13.01%	13.15%	8.90%	9.63%	5.60%	6.10%	55.78%	44.99%
Per capita income	12.06%	21.52%	11.53%	18.59%	2.87%	4.41%	9.92%	18.82%	52.28%	78.79%
Retail gas price	0.16%	-19.52%	-1.55%	0.49%	-3.32%	56.49%	0.31%	-6.26%	-7.45%	105.13%
Share of population in fringe/small metro	1.39%	1.08%	1.00%	0.95%	1.20%	1.24%	0.62%	0.64%	6.14%	3.90%
Share of population in non-metro	-0.40%	-1.25%	-0.19%	-0.34%	-0.28%	-0.51%	-0.37%	-0.85%	-1.88%	-2.95%
Auto and truck registrations per capita	0.54%	6.90%	0.23%	2.80%	-0.02%	-0.24%	0.24%	3.32%	1.30%	12.78%
Employed per capita	9.01%	3.59%	4.02%	1.59%	-13.69%	-5.93%	3.38%	1.54%	-3.64%	0.78%
Car Vehicle Miles Traveled	-	41.59%	-	27.55%	-	4.41%	-	10.94%	-	109.21%
Unexplained Change	6.24%	-	-2.02%	-	6.47%	-	-10.40%	-	-4.54%	-

Table 3.4: Same FAC table as Table 3.3 except using lane miles coefficient set to 1

	1980-1990		1990-2000		2000-2010		2010-2019		1980-2019	
	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable
Lane miles	3.87%	2.92%	3.21%	2.10%	4.77%	4.30%	3.43%	2.98%	23.50%	12.86%
Population	10.73%	10.16%	13.01%	13.15%	8.90%	9.63%	5.60%	6.10%	55.78%	44.99%
Per capita income	12.06%	21.52%	11.53%	18.59%	2.87%	4.41%	9.92%	18.82%	52.28%	78.79%
Retail gas price	0.16%	-19.52%	-1.55%	0.49%	-3.32%	56.49%	0.31%	-6.26%	-7.45%	105.13%
Share of population in fringe/small metro	1.39%	1.08%	1.00%	0.95%	1.20%	1.24%	0.62%	0.64%	6.14%	3.90%
Share of population in non-metro	-0.40%	-1.25%	-0.19%	-0.34%	-0.28%	-0.51%	-0.37%	-0.85%	-1.88%	-2.95%
Auto and truck registrations per capita	0.54%	6.90%	0.23%	2.80%	-0.02%	-0.24%	0.24%	3.32%	1.30%	12.78%
Employed per capita	9.01%	3.59%	4.02%	1.59%	-13.69%	-5.93%	3.38%	1.54%	-3.64%	0.78%
Car Vehicle Miles Traveled	-	41.59%	-	27.55%	-	4.41%	-	10.94%	-	109.21%
Unexplained Change	6.24%	-	-3.72%	-	3.98%	-	-12.19%	-	-16.82%	-

Tables 3.3 and 3.4 both show calculated FACs for each decade and for the entire time frame considered. Also shown in those tables are how much each variable changed during the given time period. Please note that adding the percent changes for each decade will not equal the percent change from 1980-2019. This is because the change in each decade only shows the change for the value of each variable from the beginning of each

decade. This means that increases (or decreases) in each variable do not get compounded the way it would when looking at the whole 40-year period.

Looking at these tables we can see that most of the change in VMT is due to the rising population and per capita income which have contributed to a rising in VMT by 55.8% and 52.3% respectively. Meanwhile the change in VMT due to increasing lane miles is only 11.2% or in our worst-case scenario of lane miles having an elasticity of 1 then it would be responsible for an increase in VMT of 23.5%. This indicates that while additional lane miles are a driver of an increase in VMT, that VMT would be rising at a rate close to the current one even if we stopped all capacity expansions.

The rate of lane miles increasing has stayed steady at about 2-4% per decade and saw an overall increase from 1980-2019 of about 12.86%.

As would be expected, we can see the effects of the 2008 recession on per capita income as well as the employment rate. Per capita income had a modest rise when compared to how much it increased in each of the other three decades. The employment rate took a major hit and became negative. This corresponded to a 5.0% dip in VMT.

As would be expected from current trends, more people move from rural to urban areas, the share of people from non-metro areas dropped, although somewhat modestly, and the share in fringe or small metros grew.

There is a wide range of unexplained change depending on the decade, going from negative 10.4% to positive 6.5% with the overall unexplained change being -4.54%.

Table 3.5: FAC table using lane miles coefficient given by the model in Table 3.2

	1980-1990		1990-2000		2000-2010		2010-2019		1980-2019	
	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable
Lane miles	1.28%	2.92%	1.05%	2.10%	1.58%	4.30%	1.13%	2.98%	7.75%	12.86%
Population	7.86%	10.16%	9.53%	13.15%	6.52%	9.63%	4.11%	6.10%	40.87%	44.99%
Per capita income	4.35%	21.52%	4.16%	18.59%	1.02%	4.41%	3.58%	18.82%	18.85%	78.79%
Retail gas price	0.26%	-19.52%	-2.28%	0.49%	-4.87%	56.49%	0.48%	-6.26%	-10.88%	105.13%
Employed per capita	2.09%	3.59%	0.93%	1.59%	-3.17%	-5.93%	0.78%	1.54%	-0.84%	0.78%
Car Vehicle Miles Traveled	-	41.59%	-	27.55%	-	4.41%	-	10.94%	-	109.21%
Unexplained Change	25.76%	-	14.16%	-	7.86%	-	3.34%	-	53.46%	-

Table 3.6: Same FAC table as Table 3.5 except using lane miles coefficient set to 1

	1980-1990		1990-2000		2000-2010		2010-2019		1980-2019	
	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable	Change in VMT due to variable	Change in variable
Lane miles	3.87%	2.92%	3.21%	2.10%	4.77%	4.30%	3.43%	2.98%	23.50%	12.86%
Population	7.86%	10.16%	9.53%	13.15%	6.52%	9.63%	4.11%	6.10%	40.87%	44.99%
Per capita income	4.35%	21.52%	4.16%	18.59%	1.02%	4.41%	3.58%	18.82%	18.85%	78.79%
Retail gas price	0.26%	-19.52%	-2.28%	0.49%	-4.87%	56.49%	0.48%	-6.26%	-10.88%	105.13%
Employed per capita	2.09%	3.59%	0.93%	1.59%	-3.17%	-5.93%	0.78%	1.54%	-0.84%	0.78%
Car Vehicle Miles Traveled	-	41.59%	-	27.55%	-	4.41%	-	10.94%	-	109.21%
Unexplained Change	23.17%	-	11.99%	-	0.15%	-	-1.43%	-	37.71%	-

When taking time effects into account there are several changes that happen to the coefficients for each variable. First, they uniformly drop. The coefficient for lane miles drops from 0.483 to 0.334, which is still in the range of what other researchers have come up with. The employment per capita coefficient has the largest drop, going from 1.956 to only 0.453. As mentioned earlier, three of the variables lose significance at even the 90% confidence level and so those were dropped from the model. All the remaining variables have the expected sign and are significant at the 95% confidence level.

Looking at the calculated FACs using these coefficients, there is a far greater amount of unexplained change, going from -4.54% to 53.46%. This implies that a lot of the change in VMT comes from something related to the effect of time. Population change still accounts for a large amount of the change in VMT at 40.87% and when combined with per capita income, those two variables still account for most of the change in VMT.

In this model, if we assume the coefficient for lane miles to be 1 then it does become more of a factor in increasing VMT than the change in per capita income, but it stays below how much population change contributes to increasing VMT.

Using the model that included time effects, I created graphs showing the change in VMT and how the change in VMT would look without the specified variable contributing to the change in VMT.

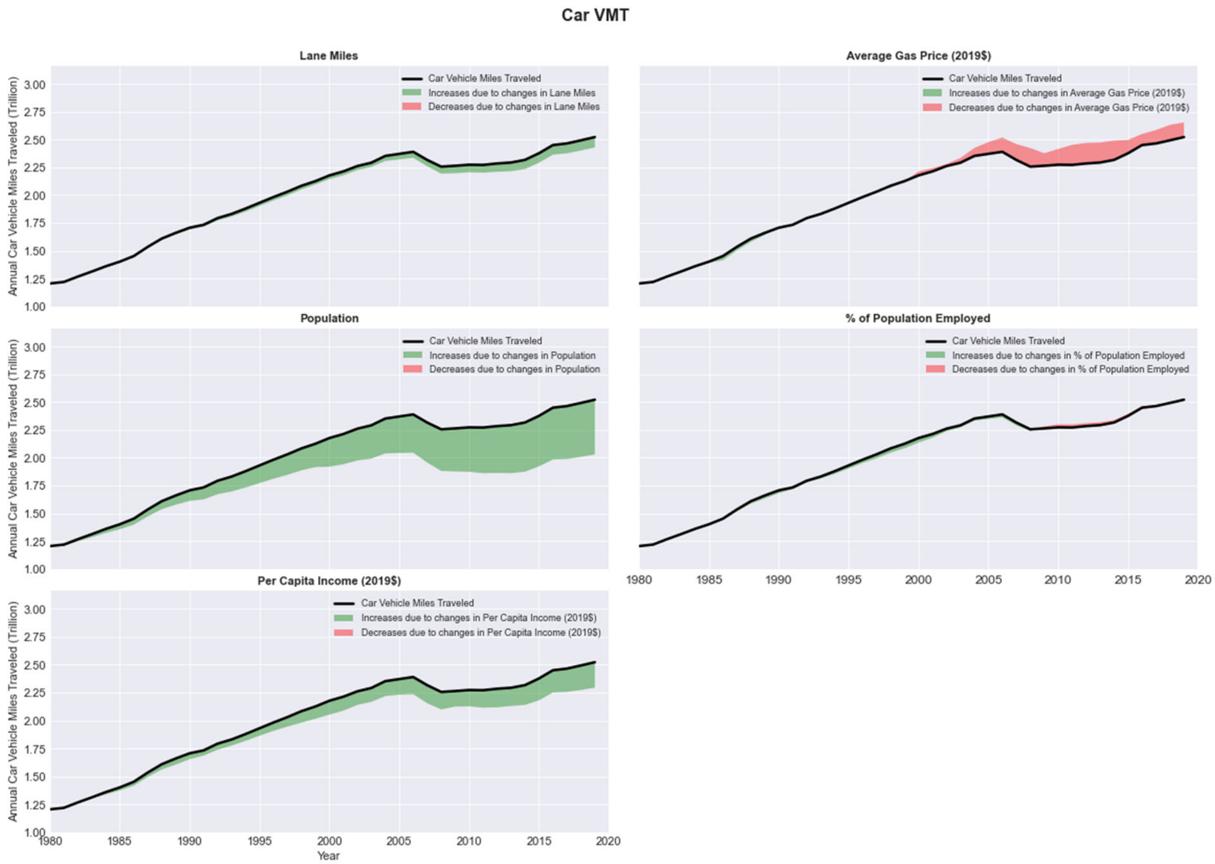

Figure 3.1: Graphs for each variable included in the model considering time effects showing the change in VMT and how each variable contributes to the change.

Figure 3.1 shows that increasing lane miles does contribute to an increase in VMT but even without increases in lane miles VMT would still be growing at a similar rate. As stated before, population growth is responsible for a significant portion of the increase in VMT. If population had stayed at 1980 levels, then VMT would have stagnated starting around 2005. Additionally, rising gas prices has lowered VMT, starting significantly around the year 2000.

Something to take notice of is that all the graphs of the VMT without the effect of each variable fails to account for the economic recession in 2008. The graphs for each FAC still follows the trendline of the dip in VMT that is likely due to the recession so there is something there that I am not capturing in this model. The price of gasoline almost fills in the gap but there is still a plateauing and a small dip in the VMT that would have occurred without the price of gasoline changing.

CHAPTER 4. DISCUSSION

4.1 Conclusions

The elasticities of VMT with respect to lane miles that I have estimated are on the higher side of the range found from other researchers that use state level data on all road types using OLS fixed effects models. This could possibly be because I am using more years of data than previous researchers. This could mean that the induced travel demand is increasing as time progresses. I have also found that while lane miles do contribute to increasing vehicle miles traveled, they are not the largest contributor. Even assuming an elasticity of 1, population change is still the largest driver of the increase in VMT. This makes sense as you would expect the more people that exist in America the more people will be driving. Also, population has increased at a much higher rate than lane miles so it makes sense this would be a larger driver of an increase in VMT. Also per capita income has increased a lot over the past 40 years so assuming the elasticity I found for VMT with respect to lane miles is correct, it would also make sense for per capita income to be a large reason that more people are driving. People having more money means more deliveries being made in addition to more people driving to leisure activities.

There have been debates about whether capacity expansions are a good idea considering the research on induced travel demand. Detractors point to highways that have extra lanes added and end up just as congested as they were without the extra lane. Having the additional cars on the road increases the amount of emissions from automobiles and contributes to climate change.

But, even if there were no more capacity expansions, if population continues to increase and so does per capita income then there will still be more VMT and therefore more emissions. Stopping capacity expansion may slow this but VMT will continue to rise. Since it would be unwise and probably unethical to promote population reductions because it would lead to a decrease in economic output, and decreasing the per capita income will only mean more people in poverty, that means that there must be other solutions to the constant increase in driving. Emissions could be cut by more environmentally friendly vehicles and reducing congestion could come in the form of promoting other forms of transportation such as mass public transit or making cities more walkable, so people do not have to take a vehicle to get somewhere in the first place.

Conversely, for the lane miles to VMT ratio to have stayed at 1980 levels, we would have had to have increased lane miles by 109% instead of 12.9%. This would mean massive expansions of existing roadways and a large amount of construction of new roadways. This would be both very costly and would risk removing a lot of existing business and residential areas to expand highways. So, it is not reasonable to think that we can build our way completely out of ever-increasing congestion.

4.2 Limitations and further study

Some limitations of this study are that all road types are combined, and the data is at a state level. Urban and rural areas are likely going to have different elasticates as other studies have confirmed. Additionally, it is not reasonable to think that all classes of roadway will have the same effect on VMT. More study should go into figuring out how different classes of roadways in rural and urban areas contribute to the increase in VMT. Other limitations include that we do not know for certain that the amount of VMT is affecting the amount of lane miles, if there are other variables that influence increasing VMT, and there are limitations on how the data is measured as much of it is an estimation. Ideal data would be accurately measured roads and the associated lanes for each instead of the estimation that currently takes place by FHWA. More accurately measured VMT would also be ideal, as it is also currently estimated.

Additional study should focus on more detailed data, such as the data from the HPMS to generate more accurate elasticities for lane miles with respect to VMT. These more accurate elasticities can be used to see how more specific road types have contributed to increasing VMT and see if there is value in expanding capacity in say collector roads over arterials or arterial over interstates.

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