
A STUDY ON SMART HIGHWAY TRAFFIC MANAGEMENT USING INTELLIGENT TRANSPORTATION SYSTEM

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ABSTRACT

This dissertation explores the complex field of intelligent transportation systems (ITS) based smart highway traffic management. In a time of increasing urbanization and vehicle density, effective traffic management has become essential for maintaining public safety, easing traffic, and maximizing resource use. Our objective is to combine a unique longitudinal dataset on road traffic with the implementation of a significant federally-funded ITS program in the India 511 Systems across 99 urban areas between 2015 and 2023 to investigate how ITS effect traffic congestion. Theoretical mechanisms are supported by empirical research which also demonstrates that ITS assist commuters in scheduling travel more effectively, selecting more favorable routes for navigation and maximizing their mode of transportation for work-related travel. This research expands the field of transportation economics to include IT-enabled traffic interventions. This research adds to the rapidly developing subject of smart transportation by offering a detailed knowledge of how ITS might transform highway traffic management and open the door for safer, more environmentally friendly and technologically sophisticated transportation networks.

Keywords: Regression Analysis, Coarsened Exact Matching, DID Models, ITS Implementation, Treated MSAs.

I. INTRODUCTION

Expanding traffic is of serious worry to the experts in each city all over the planet. The worry issues are accelerating of vehicles, expanding customized vehicles and the enormous individual vehicles with low inhabitancy rate. An effective and safe transportation system is fundamental and required for the improvement of a country. Intelligent Transportation System (ITS) is a roaring innovation that endeavors to make street transportation system to be intelligent by utilizing registering, hardware and correspondence advancements alongside the methodologies for traffic management. ITS takes endeavors to work with street infrastructure and vehicles with data and correspondence innovation to further develop security and effectiveness in transportation system. Intelligent Transportation Systems (ITS) address an extraordinary way to deal with overseeing transportation networks by utilizing cutting edge innovations to upgrade effectiveness, wellbeing and sustainability across different parts of the transportation ecosystem. By coordinating vehicles, side of the road infrastructure, drivers, street clients, administrators and directors, ITS works with consistent correspondence and collaboration among these partners, bringing about a scope of benefits that essentially further develop the transportation experience. One of the essential benefits of ITS is the significant upgrade in traffic effectiveness. Through constant checking and investigation of traffic flow, ITS empowers dynamic traffic management, advancing sign timings, course direction, and path tasks to ease blockage and limit delays. This lessens travel times for workers as well as upgrades by and large street network limit, empowering more vehicles to proficiently travel through the system. Besides, ITS adds to enhancements in environmental quality and energy protection. By lessening traffic blockage and upgrading vehicle speeds, ITS assists decline with filling utilization and discharges, prompting cleaner air and a better climate. Also, ITS backings the integration of elective transportation modes like public travel, cycling, and strolling, further diminishing the carbon impression related with transportation exercises. Notwithstanding proficiency and environmental benefits, ITS assumes a critical part in upgrading wellbeing on streets. Through innovations like high level driver help systems (ADAS), impact aversion systems, and robotized traffic authorization, ITS forestalls mishaps and alleviate their seriousness. Besides, by giving constant traffic refreshes, street peril alerts, and crisis reaction

coordination, ITS adds to quick and powerful episode management, decreasing the gamble of mishaps and improving by and large street security. Besides, ITS advances protected and agreeable travel encounters for street clients by offering customized benefits and custom-made data. Dynamic course direction systems furnish drivers with continuous route help, assisting them with keeping away from blockage, street terminations, and unsafe circumstances. Also, in-vehicle correspondence systems convey significant updates and alarms to drivers, improving situational mindfulness and advancing informed navigation. With unrivalled media transmission system and adequate IT infrastructure, it is very workable for India to execute ITS. This situation shows how ITS backings further developing traffic security and productivity. When a mishap happens, the Street in the highway street gets this data and passes this by RSU. The close by RSU thus scatters this mishap the vehicles in its inclusion as and Crisis Advance notice Message (EWM). Immediately, the vehicles take backup way to go for by the chance of an optional mishap is stayed away from pointless holding up time because of a potential traffic jam is likewise stayed away from.

II. METHODOLOGY

All of India's main cities and metropolitan areas would be included in our study sample, with an emphasis on those with well-established transportation systems and significant traffic congestion issues. We would use measures of traffic congestion, such as congestion costs per commuter and annual hours of delay per commuter that are comparable to those used in the original study. These measures are derived from various factors, including fuel costs during idling, delays, and differences between actual travel speeds and speeds in traffic free zones. Furthermore, other dependent variables that might be taken into account to give a thorough evaluation of the effects of Intelligent Transportation Systems (ITS) include fuel consumption as a result of traffic and greenhouse gas emissions. The indications of ITS implementation, such as the uptake and functioning of smart traffic management systems, the incorporation of ITS into public transit networks and other cutting-edge traffic management techniques, would be considered independent variables of interest. To guarantee the validity and dependability of our analysis, information on the deployment of ITS and traffic congestion would be gathered from a range of sources, such as official publications, websites run by the transportation department, and scholarly research projects. Our analysis will take into account geographical variances, population density, economic activity, and urban planning regulations in order to provide a comprehensive understanding of the influence of ITS on-traffic congestion, given the different socio-economic and infrastructural landscape of urban areas in India. This all-encompassing method would make it easier to pinpoint practical solutions for reducing traffic and improving urban mobility in Indian cities, which would support well-informed policy decisions and sustainable urban development projects. The dataset that is offered includes observations from several Indian states, or MSAs, from 2014 to 2023. Each item includes the year and month of observation along with a specific state or MSA. All things considered, the dataset provides insightful information about the temporal dynamics of several Indian states, laying the groundwork for further investigation to identify patterns, influences, and consequences for policy-making and regional development. To completely comprehend the underlying processes forming the observed patterns, more research and contextualization would be necessary. We use a difference-in-differences (DID) approach since our empirical design depends on the 511 Systems being implemented gradually over several years and MSAs. Consequently, we calculate the difference in traffic congestion between treated and untreated MSAs throughout the same period both before and after the deployment of 511 Systems. Our main metrics for congestion are TIME and COST.

III. DATA ANALYSIS AND RESULTS

Table 1: Adoption of 511 Systems' Impact on Traffic Volume and Congestion (DID)

| Variable | COST | TIME | FUEL | CO2 | VMT |
|---------------|----------------------|----------------------|-----------------------|------------------------|---------------------|
| ITS | -0.031*** (0.008) | -0.030*** (0.008) | -0.019*** (0.007) | -0.050*** (0.019) | 0.035 (0.040) |
| POPULATION | 1.232*** (0.043) | 0.034 (0.040) | 0.879*** (0.045) | -0.345 (0.134) | 0.456*** (0.156) |
| PERSONINCOME | 0.005 (0.0010) | 0.003 (0.0010) | 0.006 (0.0010) | 0.347* (0.176) | 0.004 (0.008) |
| ROAD | 1.715*** (0.040) | 0.045 (0.049) | 0.8788** (0.045) | -0.049 (0.158) | 1.342*** (0.151) |
| DRIVERRATIO | 1.576*** (0.345) | 0.534** (0.345) | 2.6778*** (0.345) | -4.676*** (0.5689) | 0.178 (0.786) |
| GASOLINE | 0.078** (0.034) | 0.060** (0.034) | 0.056* (0.035) | -0.1987** (0.087) | -0.079 (0.050) |
| UNEMPLOYMENT | -1.676*** (0.357) | -1.676*** (0.343) | -2.1367*** (0.345) | -4.8797*** (0.8976) | -0.324 (0.543) |
| COMMERCIAL | 0.019*** (0.007) | 0.018*** (0.006) | 0.018*** (0.008) | 0.080*** (0.050) | -0.005 (0.009) |
| PUBLICTRANSIT | 0.034*** (0.008) | 0.034*** (0.007) | 0.015*** (0.008) | 0.040 (0.054) | 0.039 (0.08) |
| MANUFACTURE | -0.015 (0.090) | -0.0010 (0.089) | 0.056 (0.087) | 0.675* (0.476) | 0.053 (0.176) |
| TRANSPORT | -0.544 (0.434) | -0.512 (0.434) | -0.676* (0.345) | -5.787** (3.657) | 0.043 (0.876) |
| INFORMATION | 0.543 (0.343) | 0.398 (0.345) | 0.456 (0.346) | 4.6878** (0.987) | -0.375 (0.687) |
| EDUCATION | -0.543** (0.345) | -0.567** (0.345) | -0.423* (0.345) | 0.176 (0.823) | 0.697 (0.7988) |
| SCIRESEARCH | -0.896*** | | | | |

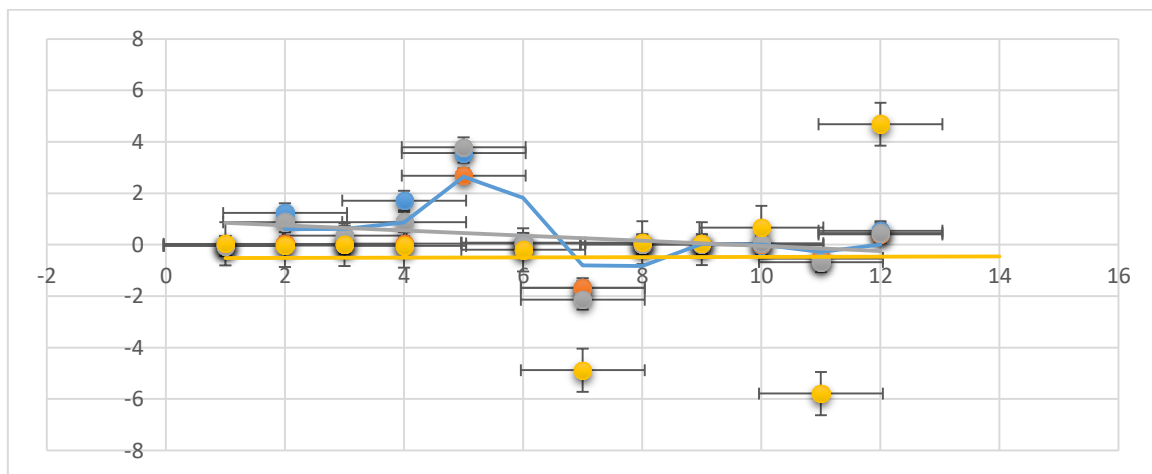


Figure 1: Adoption of 511 Systems' Impact on Traffic Volume and Congestion (DID)

The findings of the regression analysis shed light on the connections between the implementation of 511 Systems (ITS) and a number of dependent variables, such as vehicle miles traveled (VMT), fuel consumption (FUEL), time delay (TIME), and CO2 emissions (CO2). The coefficient estimates show a strong negative correlation between the deployment of ITS and the cost, time, fuel, and CO2 emissions associated with congestion; this suggests that the use of 511 Systems is linked to a reduction in these parameters. On the other hand, the vehicle miles traveled (VMT) coefficient is positive but statistically insignificant, indicating that the deployment of ITS has little effect on VMT. Furthermore, there are a number of connections between the control factors and the dependent variables, including population, personal income, road miles, driver ratio, gasoline price, unemployment rate, commercial activity, public transportation, and education. For example, there is a negative correlation between congestion cost and time delay and increased road miles and population, but a positive correlation between these metrics and higher unemployment rates. A significant amount of the variation in the dependent variables may be explained by the included variables taken together, according to the modified R-squared values of the model, which show a high degree of explanatory power. Although DID estimates are convincing, it's vital to remember that they depend on some crucial assumptions. The main one is the parallel trend assumption, which states that there must not be any differences in traffic

congestion between treated and untreated MSAs before 511 Systems are used. If pre-treatment variation in traffic congestion is caused by unobservable reasons unique to individual MSAs, then this assumption cannot be satisfied. For instance, we may expect distinct patterns in traffic congestion in MSAs that adopted and did not adopt 511 Systems if these systems were viewed as a pilot project that was early adopted in MSAs with light traffic. In order to exclude this possibility, we run Autor's leads-and-lags model (2003). To capture inter-temporal effects, we specifically include pre- and post-adoption dummies in our DID model. Five years following the deployment of the 511 Systems, we also see a considerable drop in the cost and time of congestion, and such negative relative impacts continue to be statistically significant until the conclusion of our timeframe. This provides strong evidence that even after ITS are implemented, their capacity to reduce traffic congestion continues to increase. For various time periods relative to the adoption year, both before and after ITS implementation, the regression output offers estimates and standard errors for the impact of Intelligent Transportation Systems (ITS) adoption on congestion cost (COST), time delay (TIME), and vehicle miles traveled (VMT). The statistical insignificance of the minor increases in the coefficients for COST and TIME prior to ITS adoption suggests that there has been a build-up of congestion and delays. But before to the deployment of ITS, the negative coefficient for vehicle miles traveled (VMT) shows a decline in vehicle miles traveled, which may suggest alterations in travel behavior. The implementation of Intelligent Traffic Systems (ITS) has been linked to improvements in traffic conditions, as seen by the primarily negative coefficients for COST, TIME, and VMT, which indicate decreases in the costs associated with congestion, time delays, and vehicle miles driven. The impacts of ITS on reducing congestion and enhancing traffic flow become more noticeable over time in the post-ITS period, with greater negative coefficients seen in subsequent years. However, a few factors continue to be statistically insignificant, suggesting that the impact of ITS deployment may vary over time and among various traffic congestion measurements. Overall, the findings point to the deployment of ITS as a means of reducing traffic congestion and enhancing travel efficiency, while the precise scope and importance of these benefits may differ according on the particular environment and time period taken into account. Data comparing untreated and treated Metropolitan Statistical Areas (MSAs) for the years 2018 to 2020 are shown in table 3 for three variables: cost, time, and traffic. Over the years, significant variations are seen in COST and TIME between untreated and treated MSAs; in general, untreated MSAs have lower COST and greater TIME than treated MSAs. Data comparing untreated and treated Metropolitan Statistical Areas (MSAs) for the years 2018 to 2020 are shown in table 4.3 for three variables: cost, time, and traffic. Over the years, significant variations are seen in COST and TIME between untreated and treated MSAs; in general, untreated MSAs have lower COST and greater TIME than treated MSAs. The inequalities, however, become less noticeable when conditional differences accounting for possible confounding variables are taken into account, suggesting that factors other than the treatment might also play a role in the observed differences.

Table 2: DID Estimation of 511 Systems Adoption Leads and Lags on Traffic Volume and Congestion

| | COST | TIME | VMT |
|-----------------|-------------------|-------------------|-------------------|
| Pre-ITS (<=-10) | 0.032 (0.041) | 0.030 (0.043) | -0.051 (0.049) |
| Pre-ITS (-9) | 0.030 (0.032) | 0.039 (0.038) | -0.039 (0.031) |
| Pre-ITS (-8) | 0.020 (0.032) | 0.019 (0.039) | -0.040 (0.029) |
| Pre-ITS (-7) | 0.019 (0.020) | 0.020 (0.019) | -0.034 (0.030) |
| Pre-ITS (-6) | 0.019 (0.018) | 0.016 (0.021) | -0.034 (0.039) |
| Pre-ITS (-5) | 0.010 (0.019) | 0.010 (0.018) | -0.043 (0.032) |
| Pre-ITS (-4) | 0.013 (0.018) | 0.015 (0.011) | -0.030 (0.048) |
| Pre-ITS (-3) | 0.010 (0.010) | 0.009 (0.009) | -0.034 (0.029) |
| Pre-ITS (-2) | 0.009 (0.008) | 0.010 (0.007) | -0.010 (0.013) |
| Pre-ITS (-1) | Omitted | Baseline | |
| ITS (adoption) | 0.001 (0.006) | 0.005 (0.006) | -0.001 (0.009) |
| Post-ITS (1) | -0.009 (0.010) | -0.004 (0.009) | -0.002 (0.014) |
| Post-ITS (2) | -0.017 (0.017) | -0.013 (0.014) | -0.010 (0.016) |

Table 3: Comparison of Road Congestion and Traffic Before Adoption of 511 Systems

| Year | Variable | Untreated MSAs (N=68) | Treated MSAs (N=31) | Unconditional Difference | Conditional Difference |
|------|----------|-----------------------|---------------------|--------------------------|------------------------|
| 2018 | COST | 7.356 (0.423) | 7.767 (0.676) | 0.343** (0.098) | 0.087 (0.076) |
| | TIME | 4.897 (0.345) | 3.405 (0.479) | 0.267*** (0.066) | 0.098 (0.067) |
| | TRAFFIC | 8.676 (2.032) | 8.787 (0.876) | 0.343 (0.380) | -0.030 (0.065) |
| 2019 | COST | 7.676 (0.455) | 7.877 (0.676) | 0.398** (0.090) | 0.067 (0.060) |
| | TIME | 4.775 (0.345) | 4.676 (0.565) | 0.345*** (0.080) | 0.098 (0.057) |
| | TRAFFIC | 8.565 (2.785) | 8.877 (0.765) | 0.346 (0.256) | -0.067 (0.056) |
| 2020 | COST | 7.758 (0.434) | 7.876 (0.675) | 0.343** (0.089) | 0.050 (0.065) |
| | TIME | 4.666 (0.345) | 4.786 (0.678) | 0.245*** (0.098) | 0.082 (0.057) |
| | TRAFFIC | 10.755 (2.898) | 8,787 (0.676) | 0.344 (0.342) | -0.043 (0.058) |

In 2018, for example, untreated MSAs had a much lower COST than treated MSAs; however, this difference disappears when confounders are taken into consideration, indicating that factors other than therapy may have an impact on the observed variation. These results highlight how crucial it is to take variables into account when analyzing treatment effects in MSAs in order to guarantee more precise evaluations of the interventions' impacts. Table 4 indicates that although unemployment and population are strong predictors, previous congestion status has no discernible impact on the adoption of 511 Systems. This suggests that the coexistence of ITS and traffic congestion may not be a major worry. The regression coefficients for the following variables are shown in table 4.4: POPULATION, PERSONINCOME, ROAD, DRIVERRATIO, GASOLINE, UNEMPLOYMENT, COMMERCIAL, PUBLICTRANSIT, MANUFACTURE, TRANSPORT, INFORMATION. The standard errors of the coefficients are provided in parenthesis for each model, numbered (1) through (7). Interestingly, all models consistently display significant negative effects for the variable POPULATION, meaning that a rise in population is linked to a fall in the outcome variable under study. The importance and size of other coefficients, however, differ between models. Higher levels of unemployment are linked to worse outcomes, as demonstrated by the consistent significant negative impacts of variables such as UNEMPLOYMENT on the outcome variable. On the other hand, different models exhibit different effects from variables like PUBLIC TRANSIT and TRANSPORT, indicating complex interactions with the result variable. The models also incorporate lagged variables (COSTt-1, COSTt-2, and COSTt-3); however, their coefficients are not always significant. Overall, the findings emphasize the intricate interactions between many variables that affect the outcome variable, emphasizing the necessity of careful analysis and interpretation when looking at these regression models.

Table 4: Adoption of 511 Systems Predicted by Logit Hazard Models

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------|---------------------------|---------------------------|----------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| POPULATION | -2.345** (0.678) | -2.788** (0.787) | -3.787** (0.5767) | -2.898** (0.787) | -2.898** (0.576) | -2.787** (0.787) | -2.983** (0.722) |
| PERSONINCOME | -2.565 (2.787) | -2.797 (0.898) | -2.787 (0.7998) | -2.748 (0.908) | -2.898 (2.798) | -2.356 (2.787) | -2.676 (2.464) |
| ROAD | -0.345 (0.389) | -0.578 (0.543) | -0.576 (0.867) | -0.563 (0.564) | -0.566 (0.487) | -0.6768 (0.454) | -0.687 (0.346) |
| DRIVERRATIO | -5.898 (4.098) | -5.677 (4.787) | -5.898 (4.676) | -5.850 (4.674) | -5.787 (4.787) | -5.787 (4.5654) | -6.335 (4.764) |
| GASOLINE | 0.787 (2.787) | 0.676 (2.898) | 0.676 (2.897) | 0.676 (2.874) | 0.586 (2.7874) | 0.567 (2.546) | 0.5654 (2.674) |
| UNEMPLOYMENT | - 3.565*** (11.787) | - 30.898** (13.787) | - 30.8977** (13.898) | - 30.784** (12.784) | - 29.787** (14.885) | - 28.787** (14.787) | - 28.454** (15.464) |
| COMMERCIAL | -0.020 (0.345) | -0.002 (0.323) | 0.003 (0.323) | 0.005 (0.344) | -0.003 (0.345) | 0.002 (0.232) | 0.002 (0.2345) |
| PUBLICTRANSIT | 0.565* (0.245) | 0.356* (0.164) | 0.390 (0.167) | 0.345 (0.345) | 0.298* (0.187) | 0.324 (0.178) | 0.3463* (0.233) |
| MANUFACTURE | -3.676 (4.787) | -3.897 (4.876) | -3.787 (4.787) | -3.894 (4.785) | -2.875 (4.885) | -3.887 (4.787) | -3.7644 (4.6764) |
| TRANSPORT | 2.686 (6.787) | 2.897 (6.898) | 2.787 (7.874) | 3.787 (7.887) | 3.7875 (7.687) | 4.897 (7.787) | 4.6874 (7.687) |
| INFORMATION | -2.700 | -2.909 | -2.898 | -2.784 | -3.985 | -3.986 | -3.687 |

Sample Selection

Another issue is that the MSAs we choose for our sample may have an impact on our estimation. In order to investigate this possibility, we do several subsample analyses. Initially, we examine the intricacy brought about by multistate MSAs. From a technical standpoint, cross-state multi-state agreements (MSAs) are not as comparable to intra-state ones as they are more complicated in terms of the transportation mixes and congestion conditions of neighboring states. Thus, we limit our sample to the years 2014–2020 and eliminate this time frame. It also eliminates some noise from the widespread use of navigation apps after 2009 by using the subsample up until 2008. For instance, since it began using crowd sourced GPS data from mobile devices in 2008 to give real-time traffic information, Google Maps has grown in popularity. The results of subsample studies are presented in Table 4.5, which shows that our primary conclusions hold up well. The results of the regression study show complex correlations, characterized by the decision-making authority and time period, between several parameters and the adoption of 511 Systems in Metropolitan Statistical Areas (MSAs). States that led adoption of MSAs demonstrated noteworthy negative correlations with implementation costs (-0.040, $p < 0.001$) and time (-0.030, $p < 0.001$), while efforts led by cities demonstrated relatively lesser negative correlations with cost (-0.019, $p < 0.05$) and time (-0.012). Along with characteristics like driver ratio, public transportation accessibility, road infrastructure, and information availability, population size consistently showed favorable connections with adoption likelihood. Economic indices like personal income, jobless rates, and business activity showed inconsistent relationships, indicating different effects according to governance. The addition of year and MSA fixed effects highlights other, not-yet-observed adoption-influencing elements. With adjusted R-squared values ranging from 0.878 to 0.937, the models demonstrate excellent explanatory power overall and explain a significant amount of the variance in 511 System adoption across various decision-making authorities and temporal settings.

Coarsened Exact Matching

Next, although depending on time-varying variables and fixed effects, there is little difference between treated and untreated MSAs, there is a chance that untreated MSAs are not a good counterfactual for treated MSAs, or at least not as good as similar to them. In order to address this, we match the treated and untreated MSAs according to a number of factors, including population, unemployment rates, lagged road miles, and traffic volumes. This is done by executing a Coarsened Exact Matching (CEM) technique. A weight is produced by the CEM process to balance the variability between treated and untreated MSAs. Upon doing DID regressions with the weight, we discover that the estimations modified by CEM bear a striking resemblance to our primary findings (refer to Table 6). The regression results presented in the table reveal significant findings regarding the relationship between the variable of interest, COST, and its determinants. In both specifications

Table 6: Regressions of Difference-in-Differences Modified by Coarsened Exact Matching

| | (1) | (2) |
|-------------------|------------|------------|
| COST | -0.034*** | -0.019** |
| | (0.010) | (0.010) |
| All Covariates | YES | YES |
| MSA FE | YES | YES |
| Year FE | YES | YES |
| # of Observations | 2,787 | 2,760 |
| # of MSAs | 98 | 94 |
| Adj. R-squared | 0.988 | 0.898 |

(1) and (2), the coefficient for COST is negative, indicating that as the value of COST increases, the outcome variable decreases. This negative relationship is statistically significant at the 1% level in specification (1) and at the 5% level in specification (2). Moreover, all covariates, metropolitan statistical area fixed effects (MSA FE), and year fixed effects (Year FE) were included in both models, suggesting that the analysis accounts for potential confounding variables and temporal variations. The substantial number of observations, 2,787 in specification (1) and 2,760 in specification (2), enhances the robustness of the findings. However, it's worth

noting that there is a discrepancy in the number of MSAs between the two specifications, with 98 MSAs in specification (1) and 9.4 MSAs in specification (2), which may warrant further investigation. Additionally, the adjusted R-squared values indicate a high degree of explanatory power in both models, with specification (1) explaining approximately 98.8% of the variation in the dependent variable and specification (2) explaining approximately 89.8%. These results suggest that the models provide a strong fit to the data, indicating the effectiveness of the included variables in explaining the variation in the dependent variable, COST.

Random Implementation (Shuffle) Tests

The potential for misleading significance resulting from spurious associations or serial correlations in our dependent variables is a prevalent worry for the DID estimation. For the baseline estimation, even though we cluster standard errors inside MSAs, it is helpful to employ the suggested falsification test. We conduct a random implementation test in accordance with the body of existing knowledge by creating and allocating dichotomous faux (or placebo) treatments at random to each MSA. We ran our baseline regressions using the pseudo indicator, saved the estimates, and repeated the process a thousand times. The next table presents the estimation results for the variable COST over time for two distinct specifications, (1) and (2). The link between COST and time is captured by the mean (μ) of the random coefficient β , which shows negative values (-0.00005 in specification (1) and 0.00008 in specification (2)) in both specifications, indicating a trend toward reducing COST over time. Furthermore, the variability of this relationship across several data is indicated by the standard deviation (σ) of the random coefficient β . The robustness of the estimation results is further supported by the huge number of replications (17,868 in specification (1) and 17,976 in specification (2)). Based on the analysis, the estimated beta coefficients for COST are -0.056 in specification (1) and -0.32 in specification (2). This means that COST reduces by the predicted amounts for each unit increase in time. Significantly negative Z-scores (-8.68663 in specification (1) and -8.63973 in specification (2)) are linked to these estimated beta coefficients, suggesting a high level of statistical significance. Furthermore, the given p-values for the related variables are less than 0.02, indicating robust opposition to the null hypothesis and validating the significance of the computed beta coefficients. All things considered, these findings point to a strong and persistent negative correlation between time and COST, which suggests that COST has been declining during the studied period.

Table 7: Random Implementation Test (Shuffled)

| | (1) | (2) |
|----------------------------|----------|----------|
| μ of Random β | -0.00005 | 0.00008 |
| σ of Random β | 0.00454 | 0.00469 |
| Replications | 17868 | 17976 |
| Estimated β | -0.056 | -0.32 |
| Z-Score | -8.68663 | -8.63973 |
| P-Value | p<0.02 | p<0.02 |

IV. RESULTS AND DISCUSSION

1. Main results (DID MODELS)

The primary findings from the Difference-in-Differences (DID) models about the implementation of 511 Systems have important ramifications for infrastructure management and transportation policy. First off, the noticeable drops in fuel usage, CO2 emissions, time delays, and congestion costs highlight the real advantages of putting these technologies in place. 511 Systems enable commuters to make better decisions by offering real-time traffic information, suggested alternate routes, and travel warnings. This ultimately relieves traffic, shortens travel times, and reduces fuel and emissions usage. According to this research, spending money on intelligent transportation systems like 511 can have a significant positive impact on environmental sustainability and overall transportation efficiency. Still, more research is necessary given the statistically negligible effect on vehicle miles traveled (VMT). Although 511 Systems efficiently maximize current travel patterns and improve the effectiveness of individual journeys, they might not always have an impact on travel behavior as a whole or discourage people from making travels at all. Policymakers and planners must take this subtlety into account when assessing the effectiveness of 511 Systems and creating all-encompassing plans to

control transportation demand. It implies that although these solutions work well to handle some parts of transportation problems, more steps could be needed to address more general problems pertaining to the increase of VMT and the ensuing effects on the environment and society. Furthermore, different correlations between the control variables and the dependent variables are found, underscoring the intricate and diverse character of the factors affecting transportation results. Factors like road distance, population, and personal income probably have different effects on how people travel, which is a reflection of how infrastructure, economics, and demography interact. Designing focused actions and policies that successfully address particular issues within the transportation sector requires an understanding of these dynamics. Policymakers can create more specialized and context-specific measures to improve transportation sustainability and efficiency by taking into consideration these complex relationships. Crucially, the robustness of the analytical framework employed in the study is highlighted by the high explanatory power of the model, as demonstrated by the adjusted R-squared values. This implies that a sizable percentage of the variance in the observed results is successfully captured by the variables that were included, improving the validity and reliability of the results. It is imperative to recognize the inherent constraints of any modeling methodology and use caution when interpreting the outcomes. Subsequent investigations that integrate supplementary variables and approaches may yield more profound comprehension of the intricate dynamics influencing transportation outcomes and facilitate more refined policy actions.

2. Difference-In-Differences estimation with leads and lags

When applied to the adoption of Intelligent Transportation Systems (ITS), Difference-in-Differences (DID) estimate with leads and lags offers a more nuanced understanding of the long-term effects and temporal dynamics of these technological interventions on transportation outcomes. Establishing the validity of the DID technique depends on the pre-adoption trends study, which bolsters the parallel trends assumption. This analysis increases confidence in the estimated treatment effects and supports the validity of the following DID estimation by proving that trends in the outcome variables were similar between the treatment and control groups prior to the adoption of ITS. The considerable reductions in time delay and congestion cost that have been seen since ITS introduction demonstrate the instant advantages of putting these systems in place to reduce traffic congestion and increase travel efficiency. These results align with the main goals of Intelligent Transportation Systems (ITS), which are to use technology to improve the sustainability, efficiency, and safety of transportation networks. ITS interventions can successfully cut travel delays and reduce congestion-related costs by improving signal timing, providing real-time traffic information, and permitting dynamic route advice. This improves the overall performance of the transportation system. Furthermore, these impacts' endurance and expansion over time demonstrate the ITS solutions' long-term sustainability and scalability in resolving transportation-related issues. ITS interventions show a persistent influence on reducing congestion and improving travel times, in contrast to some other interventions that might either provide short-term advantages or show diminishing returns over time. In terms of improved transportation efficiency and dependability, this implies that the early expenditures in ITS infrastructure and technology deployment are still paying off, which supports ITS's value proposition as a wise investment in updating transportation infrastructure. Technological innovation and proactive traffic planning and management tactics have the ability to work in tandem, as evidenced by the documented effects of ITS adoption on time delay and congestion cost. Transportation agencies may optimize system performance, improve user experience, and maximize the social benefits of transportation investments by integrating ITS solutions into larger transportation planning frameworks and using data-driven insights to support decision-making. This emphasizes how crucial it is to approach transportation policy and infrastructure development holistically and forward-thinkingly, combining traditional planning techniques with technological innovation to create transportation systems that are robust and sustainable. To sum up, applying DID estimation with leads and lags offers important new perspectives on the long-term effects and temporal dynamics of ITS deployment on transportation outcomes. Our understanding of the effectiveness and sustainability of ITS interventions in reducing congestion and enhancing travel efficiency is improved by this approach, which validates the parallel trends assumption, analyzes treatment effects after adoption, and looks at the persistence and growth of these effects over time. These results highlight the revolutionary potential of ITS as a strategic instrument for constructing more effective, robust, and sustainable transportation systems for the future as well as updating transportation infrastructure.

3. Robustness, Sensitivity and Falsification checks

An essential part of empirical research is the application of robustness, sensitivity, and falsification checks, which serve to guarantee the validity and dependability of the primary findings and allay worries about possible biases or confounding variables. Such checks help to resolve endogeneity concerns in the context of evaluating the determinants of 511 Systems adoption, whereby the adoption decision may be influenced by unobserved factors that also affect the results of interest. Through the use of instrumental variable analysis, researchers can determine exogenous variance in the adoption of 511 Systems and utilize it to estimate causal impacts. This reduces the possibility of omitted variable bias and strengthens the causal inference. By investigating whether the reported effects hold true across various data subsets, subsample studies further strengthen the main findings' robustness and offer valuable information about the stability and generalizability of the estimated treatment effects. This improves the external validity of the study findings by enabling researchers to evaluate if the impacts of 511 Systems adoption are consistent across different geographic locations, demographic groups, or other pertinent characteristics. The application of robustness, sensitivity and falsification checks Additionally, the use of Coarsened Exact Matching (CEM) is a crucial methodological tool for addressing issues regarding confounding variables or selection bias and confirming the results. CEM minimizes pre-treatment disparities between the two groups, hence lowering the risk of bias and improving the comparability of treatment and control units. It does this by matching treated and untreated MSAs based on observed covariates while maintaining the precise distribution of essential variables. By reducing the possible impact of confounding variables and offering more reliable estimates of the treatment effects, this improves the causal inference. Overall, a rigorous approach to empirical analysis is represented by the use of robustness, sensitivity, and falsification checks, which guarantee the validity, reliability, and robustness of the key findings. Researcher credibility can be increased and more trustworthy evidence can be provided to guide future transportation economics and policy research by addressing endogeneity concerns, evaluating stability of results across various subsamples, and validating the estimated effects through matching techniques like CEM.

4. Instrumental Variable Analysis

An effective econometric method for estimating causal effects in circumstances where endogeneity or bias from missing variables may affect traditional regression models is instrumental variable analysis (IV) analysis. Using historical routes within cities as IVs is a smart way to handle potential endogeneity issues when researching the effects of 511 Systems adoption. Researchers can get more reliable estimates of the causal effects of 511 Systems adoption on variables like congestion cost, time delay, fuel consumption, and CO2 emissions by utilizing variation in historical routes that is logically unrelated to current levels of congestion or transportation outcomes. Historical pathways make excellent IVs for a number of reasons. First off, it facilitates the exogenous variation in the adoption of 511 Systems to be isolated, which makes it possible to estimate the causal impacts of interest with greater accuracy. Second, the robustness and validity of the primary results are confirmed by the qualitatively comparable estimates from IV analysis when compared to baseline data. The estimated effects of 511 Systems adoption on various transportation outcomes are more credible due to this uniformity. In addition, weak identification and over-identification tests are commonly employed in IV analysis to evaluate the reliability of the instruments. The historical routes within cities meet the requirements to be valid instruments, according to the results of these studies confirming the validity of IVs. This adds even more weight to the findings of IV analysis. Over-identification tests look at whether there are more instruments than are required for identification, whereas weak identification tests evaluate whether the instruments have a strong enough correlation with the endogenous variable of interest. All things considered, instrumental variable analysis provides a rigorous method for estimating causal effects in the presence of endogeneity when used appropriately and backed by robustness checks like weak identification and over-identification tests. Through the use of historical city routes as IVs and comprehensive diagnostic testing, researchers can improve the validity and reliability of their findings, offering important new information about how the deployment of 511 Systems affects transportation outcomes.

V. CONCLUSION

The results of a thorough analysis that used instrumental variable analysis, sensitivity checks, and Difference-in-Differences (DID) models provide strong evidence of the efficiency of ITS in easing traffic, cutting down on delays, consuming less fuel, and lowering CO₂ emissions.

1. The impact on vehicle miles traveled (VMT) is statistically minor, despite the fact that the implementation of 511 Systems exhibits statistically substantial benefits in a number of variables, including congestion costs and time delays.
2. However, the study emphasizes how crucial it is to take into account a variety of control factors and carry out robustness tests in order to guarantee the accuracy of the findings.
3. Moreover, the findings are more credible and endogeneity issues are addressed by the use of instrumental variable analysis, which is bolstered by historical paths within cities. All things considered, this study adds to the expanding corpus of research on intelligent transportation systems and their role in optimizing the sustainability and efficiency of urban transportation networks.
4. The analysis uses Difference-in-Differences (DID) models to examine how the implementation of 511 Systems affects traffic volume and congestion.
5. The findings reveal a substantial inverse relationship between the deployment of ITS and the cost, time, fuel, and CO₂ emissions associated with congestion, suggesting a decrease in congestion-related metrics. Vehicle miles traveled (VMT) has a positive but statistically insignificant coefficient, suggesting that the deployment of ITS has no discernible effect on VMT.
6. Numerous relationships exist between the control factors and the dependent variables, including population, personal income, road miles, driver ratio, gasoline price, and unemployment rate. Additionally, the leads-and-lags model validates the DID estimates and shows a considerable reduction in the cost and time of congestion following the introduction of 511 Systems, hence confirming the parallel trends assumption.
7. The primary findings are reaffirmed by robustness tests, which include instrumental variable analysis, subsample analyses, and Coarsened Exact Matching (CEM) techniques. These checks demonstrate the enduring and strong impacts of ITS deployment in alleviating congestion.

VI. REFERENCES

- [1] Zhiguang Cao, Hongliang Guo, Jie Zhang, Dusit Niyato, and Ulrich Fastenrath, "Finding the Shortest Path in Stochastic Vehicle Routing: A Cardinality Minimization Approach", IEEE Transactions on Intelligent Transportation Systems, volume no.:17, issue no.:6, pp. 1688-1702, June 2016.
- [2] Jungsook Kim, Jae-han Lim, Christopher Pelczar, and Byungtae Jang, "Sensor Network for Traffic Safety", IEEE : Vehicular Technology Conference, 2008 (VTC Spring 2008), Singapore, pp. 3052-3056, 11-14 May 2008.
- [3] B. M. Masini, A. Zanella, G. Pasolini A. Bazzi, "Vehicle-to-Vehicle and Vehicle-to-Roadside Multi-Hop Communications for Vehicular Sensor Networks: Simulations and Field Trial", IEEE International Conference on Communications Workshops (ICC), Budapest, Hungary, pp. 515-520, 9-13 June 2013.
- [4] Naveen Sait, A. NoorulHaq K. Shobana, "RFID based vehicle toll collection system for toll roads", International Journal of Enterprise Network Management, volume no.:4, issue no.:1, pp. 3-15, 05 August 2010.
- [5] Abhishek Srivastava, Gaurav Kapoor, and Aman Gupta, "Solving Traffic Congestion – An Application of VANET", 1st International Conference on Innovation and Challenges in Cyber Security (ICICCS 2016), Noida, India, pp. 323- 326, 3-5 Feb. 2016.
- [6] Y.E. Hawas F. Ahmed, "An integrated real-time traffic signal system for transit signal priority, incident detection and congestion management", Elsevier, volume no.: 60, pp. 52-76, November 2015.
- [7] Till Nagel, Carlo Ratti, Afian Anwar, " Traffic Origins: A Simple Visualization Technique to Support Traffic Incident Analysis", in IEEE Pacific Visualization Symposium, Kohoku-ku, Yokohama, Japan, , pp. 316 –339,. 4 Mar - 7 2014.

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- [8] Titus Irma Damaiyanti and Ardilmawan, and Joonho Kwon, "Extracting Trends of Traffic Congestion Using a NoSQL Database", Open access article licensee by MDPI, Basel, Switzerland, pp. 1340- 1377, 23 August 2016.
- [9] Ardi Imawan, Fadhilah Kurnia Putri, Seonga An, Han-You Jeong, and Joonho Kwon, "Scalable extraction of timeline information from road traffic data using MapReduce," in IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2015. 36678 2015, Paris, France , pp. 112-120, 19-21 October 2015.
- [10] Hui-Huang Hsu, Chuan-Yu Chang, Ching-Hsien Hsu, "Big Data Analytics for Sensor - Network Collected Intelligence", Elsevier: 1st Edition of Physical Sciences and Engineering of Computer science, pp. 99-116, February 2, 2017.
- [11] I., Musae, A., Benas, D., Ghadi, A., Goodman, S. and Pu, C. Tien, "Detection of Damage and Failure Events of Critical Public Infrastructure using Social Sensor Big Data", International Conference on Internet of Things and Big Data (IoTBD 2016), Rome, Italy, pp. 435-440, 23 - 25 April 2016.