EMISSIONS AND AIR QUALITY IMPACTS OF THE COVID-19 PANDEMIC

MEMORANDUM

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Texas A&M Transportation Institute

TECHNICAL MEMORANDUM

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INTRODUCTION

The global outbreak of Coronavirus disease 2019 (COVID-19) and resulting social distancing strategies to contain the spread of the virus have had a tremendous impact on transportation. In the United States, the total vehicle travel dropped from mid-March to the end of June 2020 compared to total vehicle travel in February 2020, with the largest travel reduction of 48% being observed on April 9th, 2020 (*1*). A consequence of those social distancing strategies and travel reduction is the improvement in air quality. In the U.S., Nitrogen Dioxide (NO_2) concentrations declined 25.5% during March and April 2020 compared to previous years while $PM_{2.5}$ concentrations decreased by 4.5% (*2*).

In Texas, the reduced vehicle miles traveled (VMT) during the COVID-19 pandemic is also correlated with air quality improvements. For example, in Dallas-Fort Worth area, the freeway volume dropped 25% by the end of April compared to early March, while the average daily NO_2 concentration dropped from 7.7 parts per billion (ppb) to around 6.1 ppb during the same period (possibly due to traffic restrictions, given that 38% of oxides of nitrogen [NO_X] emissions in the Dallas-Fort Worth area come from on-road vehicles) (*3*).

An opportunity in the post-pandemic recovery period is to understand the opportunities of a 'new normal', i.e., potential changes in social norms that may have a lasting effect on travel beyond COVID-19. Some of the travel impacts such as reduced commuting can last after this pandemic, which may lead to air quality improvements. On the other hand, some air quality improvements observed during the early stage of the lockdown may prompt citizens and policymakers to seek long-term measures that would sustain improved air quality. It is important to understand if the potential air quality benefits from the pandemic can have implications for longer-term regional air quality and the attainment of ambient air quality standards.

This study, conducted as part of Subtask 2.1 (TWG Technical Issues Analysis) under the TTI-TxDOT Air Quality and Conformity Interagency Contract (IAC) investigates the potential changes in travel patterns and implications for air quality based on ongoing observations from the COVID-19 pandemic.

LITERATURE REVIEW

It is expected that work culture in the U.S. will experience long-term changes under the impact of COVID-19, with more employees likely to work remotely even after the pandemic. If immunity to COVID-19 is not permanent, like seasonal flu and other coronaviruses, then COVID-19 will likely enter long-term circulation over the next five years (*4*). In this case, some form of social distancing will be upheld to prevent seasonal outbreaks. Also, a large portion of employees have remote working experience (also known as 'telecommuting' or 'work from home') during the pandemic and are willing to continue working from home, and many employers also support some form of telecommuting. During March 2020, about 62% of U.S. workers have worked remotely according to a recent survey on 2,276 employed U.S. adults (*5*). According to a national survey on 1200 full-time employees in the U.S., 43% of respondents suggested they prefer to work from home after the pandemic and 65% of respondents are confident that their employers will allow more flexibilities (*6*). Finally, a substantial portion of jobs in the U.S. can be accommodated remotely and employees are eligible to continuing remote work if they work in specific industries. About 37% of the jobs can be done entirely at home in the U.S., and at least 28% of jobs can be done at home even for small metropolitan areas (*7*). In Texas, cities have higher opportunities to work from home; 48% of jobs in Austin can function remotely, and 42% in Dallas, 40% in Houston, and 37% in San Antonio (*8*). In conclusion, the work culture in the U.S. is likely to be more friendly to workers who want to telecommute, and a portion of work trips can be reduced due to telecommuting after the pandemic.

Another important factor that impacts travel and hence air quality is the economy. Under the impact of COVID-19, the unemployment rate in May 2020 could reach 16% predicted by the U.S. government (*9*). Part of observed travel reduction could be attributed to the loss of jobs and interrupted economic development. Further, the automobile industry appears to be heavily impacted by the public health and economic crisis, though with electric vehicles (EVs) less impacted than their conventional counterparts. (*10*, *11*). According to International Energy Agency (IEA) estimates, during the first 4 months in 2020, the global conventional passenger car sales dropped by 15% compared to 2019, while the EV sales broadly remained at the same level as 2019. Under the impact of COVID-19 and an assumed sustainable development scenario, 30% of new vehicle sales will be electric vehicles by 2030 in the U.S. forecasted by IEA (*10*). The growing market share of EVs has the potential to positively impact air quality as well.

In addition to commute patterns, transit ridership and freight movement have also been heavily impacted by COVID-19 (*1*, *12*). Depending on service area and service type (bus or rail), the transit ridership reduced by 40%- 97% across the U.S. (*12*). The long-term impact on transit ridership is still being investigated at the time of the current study. The truck trips also reduced by about 20% in mid-April 2020, but appear on track to slowly return to normal (*13*).

In conclusion, the on-going COVID-19 pandemic has drastically changed travel patterns across the U.S. Some of the changes in travel patterns, triggered by individuals' preference and policy changes could last beyond the pandemic period, with implications for vehicle emissions and regional air quality.

Study Goal

The goal of this study is to investigate the emissions and air quality implications if travel patterns shift after the pandemic. This work can inform policymakers and practitioners about potential changes in regional air quality and implications for public health. In this study, the impact of post-pandemic travel patterns on congestion, emissions, air quality, and health are assessed using the Transportation and Emissions Modeling Platform for Optimization (TEMPO) developed by the Texas A&M Transportation Institute (TTI) (*14*). The main objectives included:

1. Investigate potential travel pattern changes after the pandemic in Texas, and identify plausible scenarios based on trends from existing data sources.
2. Quantify the effects of post-pandemic travel patterns on traffic operation, vehicle emissions, air quality, and health, for a Texas case study.

Following this introductory section, the next section of the report discusses the latest travel data during the COVID-19 pandemic to understand the impact of COVID-19 on travel patterns in Texas. These findings are used to identify potential future scenarios for a case study assessment conducted in El Paso, Texas, followed by a discussion of results, and findings and conclusions.

IMPACT OF COVID-19 ON TRAVEL TRENDS IN TEXAS

As of July 2020, the COVID-19 cases in Texas are still on the rise, and Texas is still one of the epicenters in the U.S. with more than 400,000 cases (*15*). The State of Texas has only issued one stay-at-home order ('SAH order' in the following sections) from April 3 to April 30 by the time of this study to enforce social distancing measures statewide (*16*). In this case, although there are no readily available post-pandemic travel data, the travel data collected during pandemic under social distancing measures are still available. These data can be used for understanding the impact of COVID-19 on transportation and make inferences on future conditions.

The major data source used in this analysis comes from the COVID-19 impact analysis platform developed and maintained by the University of Maryland (UMD) (*17*, *18*). This platform provides mobility, COVID-19 case, demographic information, and economic impact for every county and state within the U.S. since January 2020, using privacy-protected mobile device location data, integrated with COVID-19 case data and census population data. With comprehensive transportation, economic, and health data provided in this dataset, the UMD data is selected as the primary data source in this analysis. In this case, this study adopts the subset of UMD data, which includes state-level and county-level daily data within Texas from Jan 1st to June 23rd, 2020. Several additional mobility data sources during COVID-19 are used to validate the travel trend reflected by UMD data in Texas.

TEXAS MOBILITY TRENDS DURING COVID-19

The passenger travel trends since January were analyzed using the UMD data's Texas subset. The daily trip counts by trip purpose and passenger miles traveled per person, along with weekly average trend line, are provided for entire Texas and El Paso County (location of the case study) respectively in Figure 1 below. From Figure 1, we can see Texas and El Paso County share similar trends in all the metrics, with El Paso County has slightly lower work trips, a lower fraction of active cases in population and higher passenger mileage than Texas average. Based on Figure 1, the number of trips and the passenger miles per person started to decline around mid-March, when the COVID-19 cases began to rise. When the SAH order coming into effect in early April, the number of trips and travel distance were already close to the lowest level. However, the trends started to diverge by trip purpose since the middle of the SAH order, with work trips staying at a low level (~0.4 trips/person) and non-work trips slowly growing back to normal level (~2.5 trips/person) by the end of June. The total miles per person follows a similar trend as non-work trips due to the large fraction of non-work trips in daily travel.

By the end of June, even though the numbers of COVID-19 cases are still increasing in both Texas and El Paso County, there is no indication from the data that non-work trips and total miles started to decline again. In conclusion, the progress of the COVID-19 pandemic and the implementation of SAH order shows a lasting impact on personal work trips but only a short-term impact on non-work trips and total miles per person in Texas.

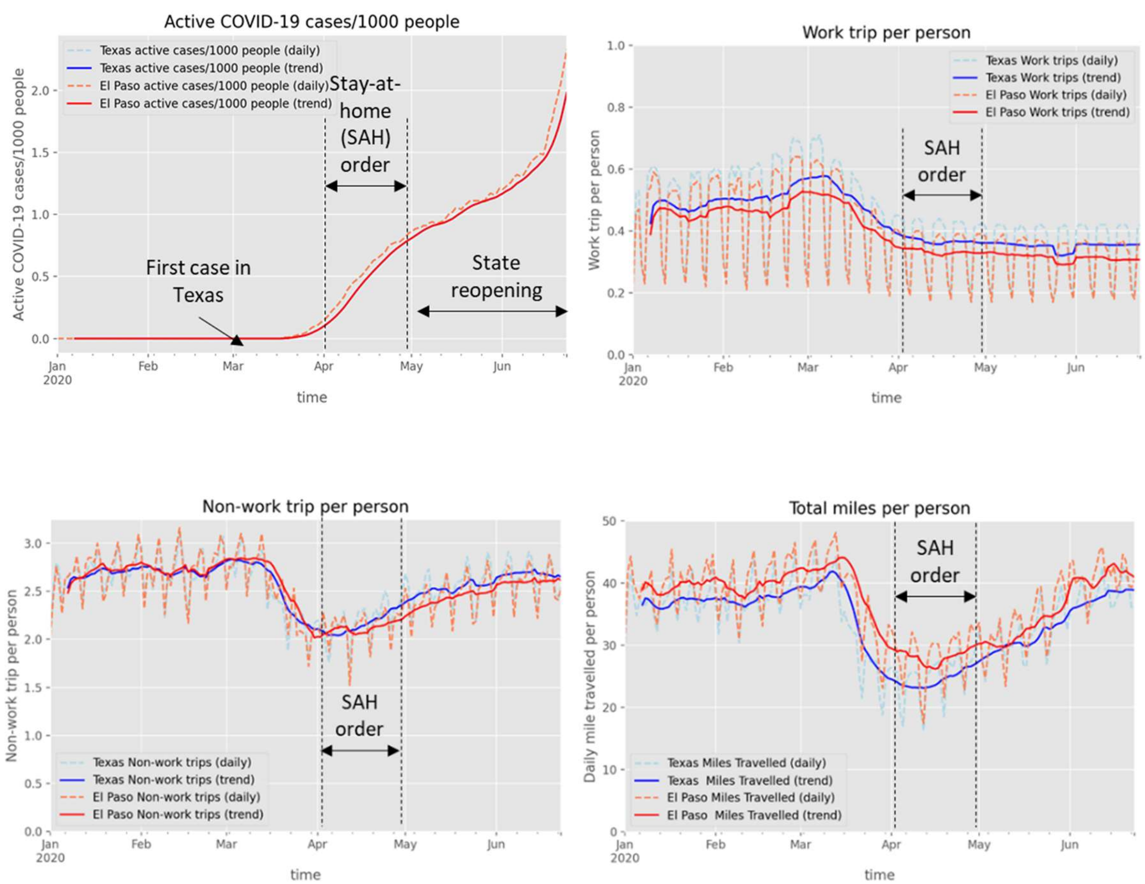


Figure 1 COVID-19 cases and passenger travel trends in Texas during COVID-19.

TRAVEL TRENDS VALIDATION

Several other data sources are used to validate the results from the UMD data presented previously, and the findings are summarized in Table 1. The detailed data trends from other sources are provided in Appendix A. Due to different data collection methods adopted and different baselines for measuring mobility changes, the scales of travel impact of COVID-19 vary by the data source. The following are key findings reflected in the trends observed from the various sources:

1. Passenger vehicle travel experienced a large reduction around April 2020, when the COVID-19 cases started to rise, and the state implemented SAH order.
2. Passenger vehicle travel has recovered from the lowest point since April, with travel patterns getting close to the pre-pandemic period.
3. The impact of COVID-19 on truck movement seems to be small as of July 2020 based on traffic data from MS2 Software.

The findings on passenger travel from multiple data sources are consistent with travel trends reflected in the UMD data. After the initial travel reductions caused by the rise of COVID-19 cases and SAH orders, travel patterns are slowly going back to the pre-pandemic level, except for work-related travel. The impact of COVID-19 on freight movement seems to be limited based on truck data collected by MS2 software from July 2020. There was no available transit ridership data for Texas at the time of this study. However, as the transit mode share is only 1.4% in Texas (*17*), the impact is not considered further.

Table 1. Summary of Trends in Texas from Multiple Mobility Data Sources

Dataset	Source	Region	Baseline	Travel trend
MS2 Traffic Dashboard (*19*)	Traffic count data from field devices or reported data from transportation agencies	Texas	The same time from the previous closest calendar year with available data	By mid-July, the reductions of traffic volumes and truck volumes are less than 10%
North Central Texas Council of Governments (NCTCOG) (*3*)	Traffic radar on Dallas and Fort Worth Districts	Dallas-Fort Worth Metropolitan area	The first week of March 2020	Freeway volumes from all vehicles dropped by: • 33% (end-of-March) • 25% (end-of-April)
Google Mobility Report (*20*)	Mobile device data from Google users who shared their locations with Google	Entire Texas and all counties in Texas	Median value from Jan and Feb 2020	By mid-July, the workplace trips reduced by 18% in Texas and 15% in El Paso, other non-work trips reduced as well except for residential trips
Apple Mobility Report (*21*)	Mobile device data from Apple users who shared their locations with Apple	Entire Texas and all counties in Texas	Travel data from Jan 13th, 2020	Passenger travel in Texas: • Reduced by nearly 50% (early April) • No reduction (mid-July) Passenger travel in El Paso County: • Reduced by nearly 60% (early April) • Increased by 20% (mid-July)
Facebook Mobility Dashboard (*22*)	Aggregated population movement data from mobile devices	Entire Texas and all counties in Texas	Travel data from Feb 2020	Passenger travel in Texas: • Reduced by nearly 40% (early April) • Reduced by 10% (mid-July) Passenger travel in El Paso County: • Reduced by nearly 40% (early April) • Reduced by 20% (mid-July)

Impact of COVID-19 on Work-related Travel

As discussed in the introductory section, the drop in work-related trips can potentially be attributed to increases in employees who work from home and to increased unemployment levels due to the COVID-19 pandemic. Figure 2 provides further insight into the trends of telecommuting employees and the unemployment rate during the COVID-19 pandemic, and their correlations with work trip frequency per person. In the UMD data, the work trips per person were observed using mobile device data and the fraction of telecommuting and unemployment rates are were weekly data that are derived from models or other data sources (*17*, *18*). The county-level results appear to share the same work-from-home fraction and unemployment rate as the state-level results.

The fraction of telecommuting employees started to rise in early March, at the same time the COVID-19 cases began to rise. The fraction of telecommuting employees reached a maximum of 35% during the SAH order and slightly fell back to 30% after the state reopening. The trend of daily work trips per person (weekly moving average of work trips per person) decrease with a higher fraction of telecommuting workers, due to the commute trips avoided by telecommuting. On the other hand, the unemployment rate, which is the fraction of unemployed people in the total labor force (*23*), first started to rise in mid-February and keep increasing since mid-March, reached the peak at nearly 25% in early June and fell back to 17% at the end of June. The unemployment rate follows a different trajectory compared to work from home fractions and shows a negative correlation with work trip frequency as more people lost work and had no reason to travel. Therefore, we can conclude the higher fraction of telecommuting employees and higher unemployment rates both contributed to the decrease of work-related trips in Texas during the pandemic.

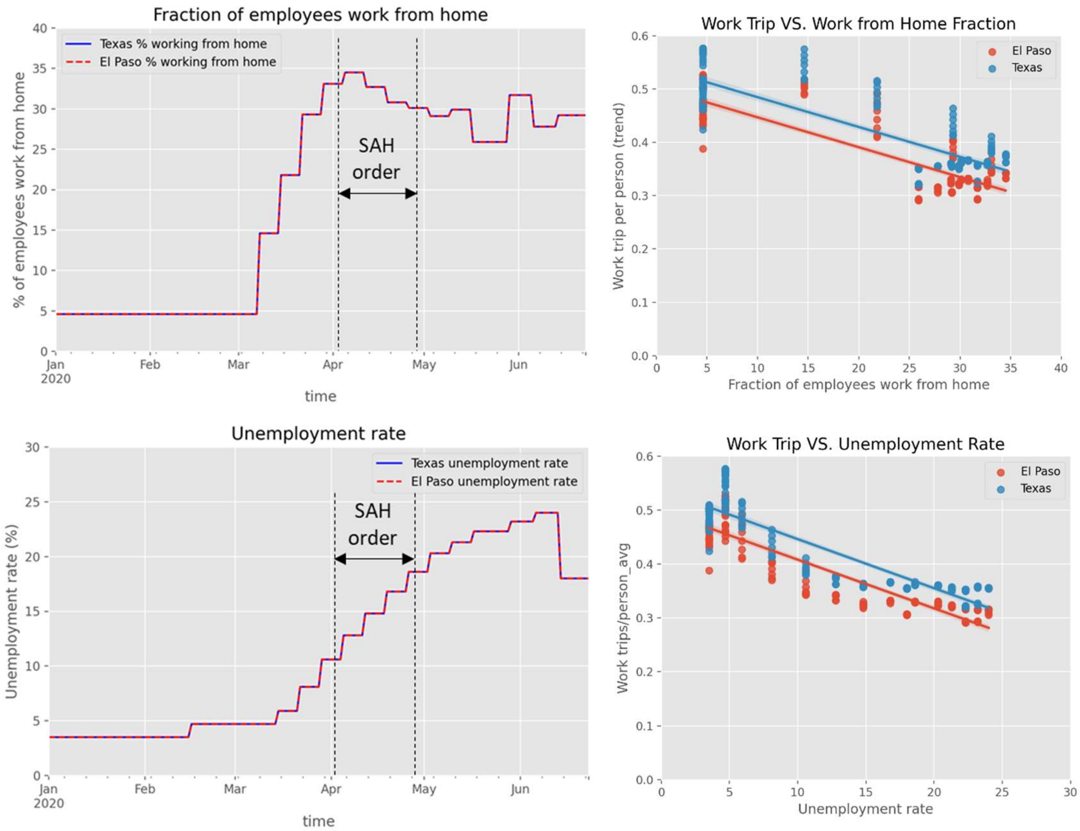


Figure 2. The trend of work-from-home fraction and unemployment rate during COVID-19.

ASSESSMENT OF POST-PANDEMIC EMISSIONS AND AIR QUALITY IMPACTS – CASE STUDY

Overall Approach

A case study was conducted for El Paso, Texas to assess regional emissions, air quality, and related impacts for a plausible post-pandemic scenario. The post-pandemic scenario is simulated using TTI's "Transportation and Emissions Modeling Platform for Optimization" (TEMPO) (https://tempo-dashboard.io/home) (*14*). TEMPO facilitates rapid scenario analysis of the system-wide interactions of transportation strategies. Using the TEMPO platform allowed for the generation of the "full-chain" of impacts, from travel demand, congestion, emission, air quality, and health impacts. A pre-defined baseline scenario based on the most recent travel demand model from the local Metropolitan

Planning Organization (MPO) was used for comparisons with the identified post-pandemic scenarios.

Development of Post-COVID Traffic Scenarios

The number of COVID-19 cases as of July 2020 is still increasing in Texas (*24*) and the ultimate impact on long term traffic patterns remains uncertain. However, some trends have been revealed by preliminary mobility data (*17*, *18*) and can be used to identify plausible post-pandemic traffic scenarios. In this study, TTI attempted to identify a reasonably optimistic traffic scenario to provide a relatively high level of environmental benefits that can be achieved. This can provide insight into whether lasting air quality benefits can be achieved. The following assumptions were used in the development of the plausible, yet optimistic scenarios:

1. The fraction of telecommuting employees remain at the same level as currently seen, i.e. about 30% of the workforce remains working remotely after the pandemic.
2. The economy recovers to the pre-pandemic level. In this case, the unemployment rate is assumed to recover to the pre-pandemic level, i.e. about 3.5% in Texas. Similarly, freight movement will return to the pre-pandemic level to supply the same level of consumer's needs.
3. The frequency and the share of other transportation modes remain the same as pre-pandemic (e.g., transit, bike and walk).
4. The electric vehicle sales will grow relative to other vehicle types, under the sustainable development scenario defined by IEA, and 30% of LDV sales will be EVs by 2030 (*10*).

Based on these assumptions, the post-pandemic scenario primarily considers the impact of telecommuting on passenger travel (not unemployment effects or changes to freight and other modes). Additionally, greater levels of vehicle electrification are considered as an additional potential factor. Thus, the analysis scenarios considered are as follows:

1. **Baseline scenario** – representing pre-COVID traffic patterns
2. **Post-COVID scenario** – representing lasting changes to work travel patterns due to long-term telecommuting in larger numbers

3. **Post-COVID + EV scenario** – the above post-COVID scenario with the additional assumption of increased EVs in the fleet.

As mentioned previously, under the post-COVID scenarios, the reduction in work trips is contributed by an increase in employees who work from home and not from unemployment, which is assumed to return to the pre-pandemic rate of 3.5% (Figure 2). A simple linear regression model was adopted to quantify the contribution of work from home fraction and unemployment rate on work trip trends and predict post-COVID work trip reduction using the UMD data. The fraction of employees work from home and the unemployment rate are used as independent variables to predict weekly moving-average work trip count. The results are provided in Table 2 below.

Table 2. Estimation results of work-trip frequency regression model (R^2 = 0.913)

Variable	Coefficient	Standard error	t-statistic	p-value
Intercept	0.5131	0.003	147.886	0.000
% working from home	-0.0034	0.000	-13.648	0.000
Unemployment rate	-0.0047	0.000	-12.037	0.000

Since the fraction of telecommuting employees stabilized around 30% by the end-of-June without SAH order, we assume 30% is the maximum possible fraction of the telecommuting workforce in Texas in a post-COVID scenario. Thus, the expected work trips per person after the pandemic is predicted to be 0.395 trips/person using the linear regression model estimated in Table 2, which suggests about an 18% reduction of work trips per person compared to pre-pandemic conditions (work trips per person were 0.48 given 5% work from home and the same unemployment rate).

An addition to the post-COVID scenario assumed that EVs will proliferate to a greater extent than conventional vehicles, due to the observations from the COVID-19 period and the expectation that EVs will continue to grow in the future (*10*). This COVID+EV scenario can be viewed as representing a sustainable development case in the post-COVID context. It is assumed that a 30% EV market share is achieved for light-duty vehicles by 2030, with the penetration level of EVs among all registered vehicles rising by year accordingly. In this study, the vehicle purchase and fleet replacement from 2018 to 2030 is simulated using an agent-based fleet simulation model (*25*). With the agent-based model, a fraction of the existing vehicles is replaced by EVs based on current Texas fleet characteristics (vehicle type and model year distribution) and growth of EV sales to reach 30% by 2030. The results of EV sale and market penetration are provided in Figure 3 below. With the EV sales reaching 30% by 2030, the EV penetration level will be around 6%. The 6% EV penetration level will be used in the post-COVID scenario to define the fraction of EVs among all LDVs in the fleet.

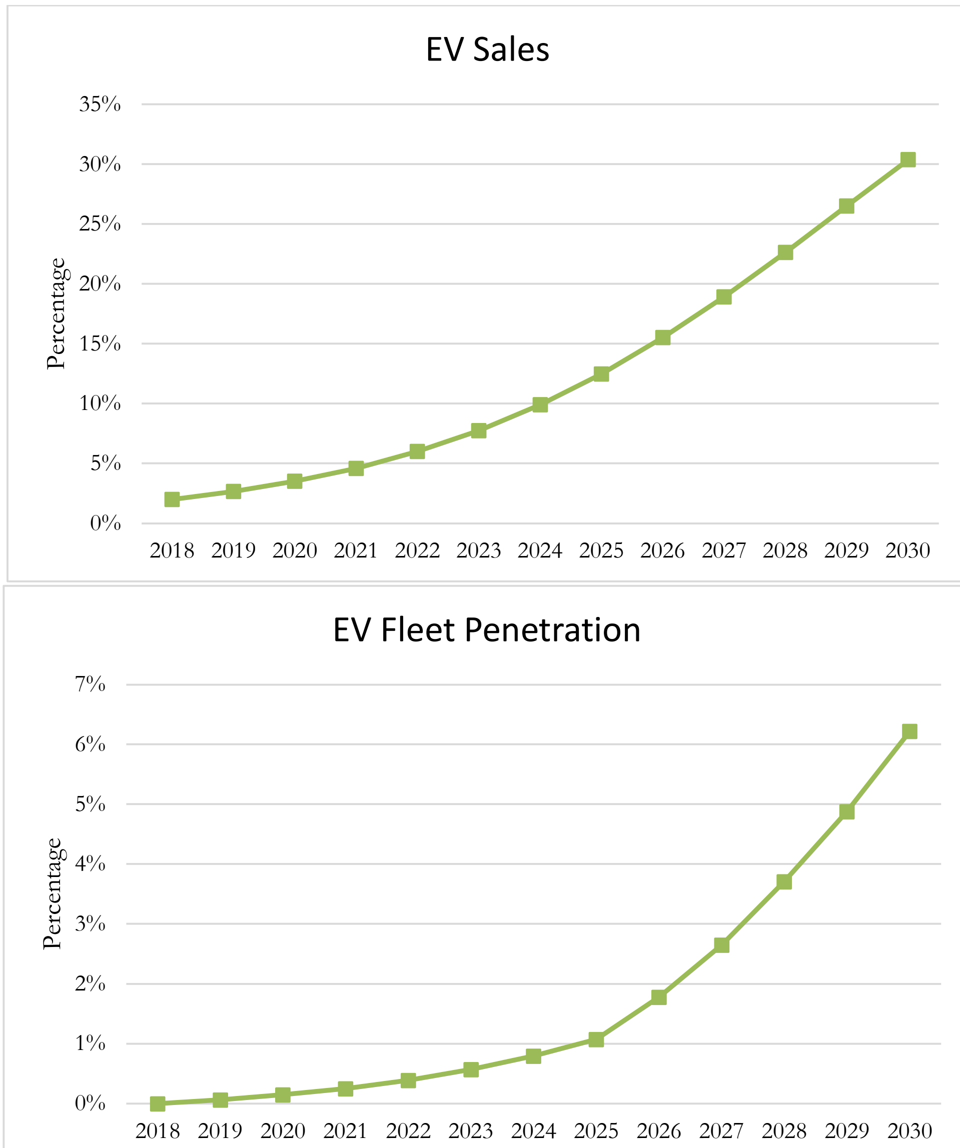


Figure 3. Predicted EV sale and market penetration from 2018 to 2030 for the post-COVID+EV scenario.

Among all the trips in the traffic simulation model, a fraction of trips were randomly assigned to battery-electric vehicles (BEVs) using the EV penetration level defined above.

The BEV fleet was modeled using existing BEV models that are available on the market now. The market share of BEVs is collected using EV sales data from 2011 to 2019 (*26*), and BEV sales were aggregated into three types (100-mile, 200-mile, and 300-mile ranges) based on the electric range of vehicles. For each type of BEV, the BEV model with the highest market share is chosen to represent this type, and the specifications of the three representative models were used for emission modeling in this analysis. In this study, the Nissan Leaf is selected to represent 100-mile BEV, the 2016 Chevrolet Bolt represents 200-mile BEVs and the 2016 TESLA Model S is selected to represent 300-mile BEVs. The vehicle specifications, such as battery capacity and vehicle weight, were retrieved from a full-system vehicle simulator called FASTSim (*27*).

RESULTS

TEMPO was used to analyze the three scenarios (baseline, post-COVID, post-COVID+EV) for El Paso County. The analysis year was 2030 for EV penetration levels, though traffic volume data and emissions rates were used from 2017 for the baseline and adjusted for the post-COVID scenarios. Table 3 summarizes the assumptions and key findings. The remainder of this section provides further details on the various impacts that were analyzed, including travel demand, congestion levels, emissions, dispersion, and health impacts.

Table 3. Summary of Scenario Analysis Assumptions and Results

Type of Impact	Input Data and Assumptions for Assessment	Key Findings
Travel Demand	• Baseline scenario – El Paso travel demand from Travel Demand Model (TDM). Demand from the year 2017 is used as a surrogate for 2030 conditions. • Post-COVID scenario - In the post-COVID scenario, 18% of work trips are randomly removed due to telecommuting, with more rush-hour trips removed; freight trips remain unchanged. • Post-COVID scenario + EVs - 6% of passenger cars are EVs	• About 4% of daily trips were removed under the two post-COVID scenarios. • Higher demand reduction during morning and afternoon peak hours.
Traffic Congestion	• Travel demand changes used as input to the dynamic traffic assignment model.	• Reduced system-level congestion and improved vehicle operation • Total daily VMT reduced by 3.5% (700,000 miles removed per day). • Daily VMT on most links dropped as well due to fewer vehicle throughputs. • The daily total delay reduced by about 10%, with about 23,700 hours of travel time saved in total. • Daily delay on most links decreased within the network, with few exceptions due to changed route choice and increase congestions during some period of the day.
On-Road Vehicle Emissions	• On-road vehicle emissions estimated using traffic inputs and MOVES-Matrix emissions rates. • EV Penetration scenario – 6% of passenger cars are EVs • Zero tailpipe emissions for EVs	• Under the Post-COVID scenario, the daily energy use, CO_2 equivalent, NO_X, and $PM_{2.5}$ emissions reduced by 3.5%, 3.5%, 1.8%, and 1.8%, respectively compared to baseline. • With 6% of LDV fleet replaced by EVs, the daily energy use, CO_2 equivalent, NO_X, and $PM_{2.5}$ emissions drop by 6.2%, 7.3%, 2.7%, and 2.5%, respectively compared to baseline.
Dispersion and Health Impacts	• On-road $PM_{2.5}$ emissions used as input to AERMOD. $PM_{2.5}$ concentration generated by AERMOD used as input to assess health impact.	• The dispersion results suggested that air quality and health improvements are not readily seen at the regional level under the small $PM_{2.5}$ reduction.

Impact on Travel Demand

Although work trips only account for about 20% of all the trips in Texas, they often occur during morning and afternoon rush hours. In this case, the removal of work trips is not flatly distributed within a day and may have a higher impact on rush hour traffic. As the El Paso travel demand provided by MPO from a traditional four-step model does not include any information about the trip purpose, the 2017 National Household Travel Survey (NHTS) data is adopted as a surrogate to investigate the temporal distribution of work trips by the hour (*28*). The NHTS Texas subset contains travel data from 24,464 households, 47,981 vehicles, and 178,579 trips. Among those trips, 101,155 trips are weekday driving trips and about 20% of those trips are work trips (20,294 work trips). In this analysis, the fraction of work trips among all weekday driving trips by each hour is calculated based on NHTS data and used to pre-process the post-pandemic travel demand used in this analysis. For the baseline, a portion of trips is randomly assigned as work trips based on departure time and the work trip fraction in that hour. Among the labeled work trips, the post-pandemic travel demand is generated by randomly removing some trips using the 18% trip reduction rate estimated, assuming those trips are removed due to telecommuting. There is no adjustment on freight movement in this case. The final travel demand inputs are provided in Figure 4. As seen in the figure, more passenger trips were removed around 8:00 am and 5:00 pm (rush hours) under the post-pandemic scenario compared to the rest of the day.

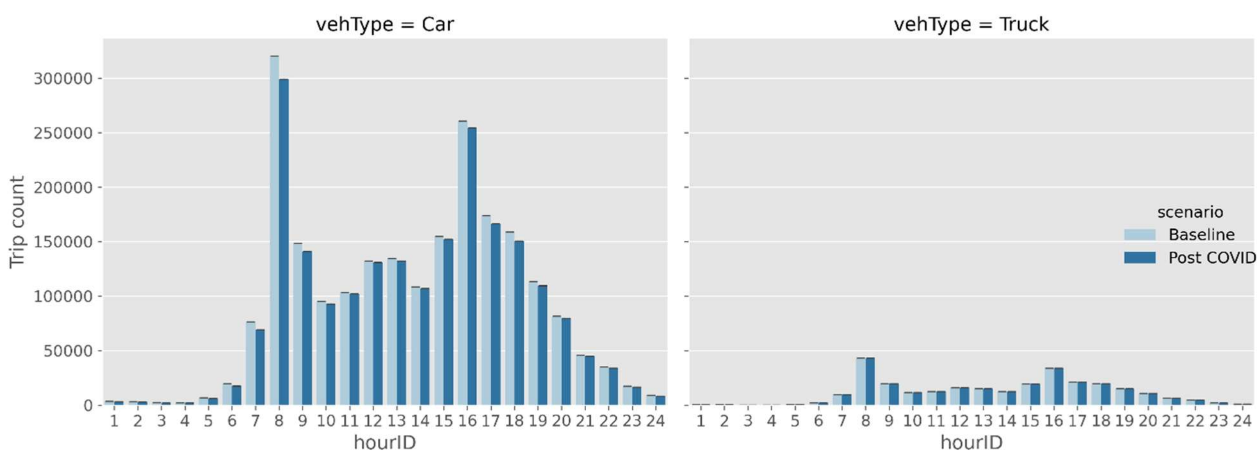
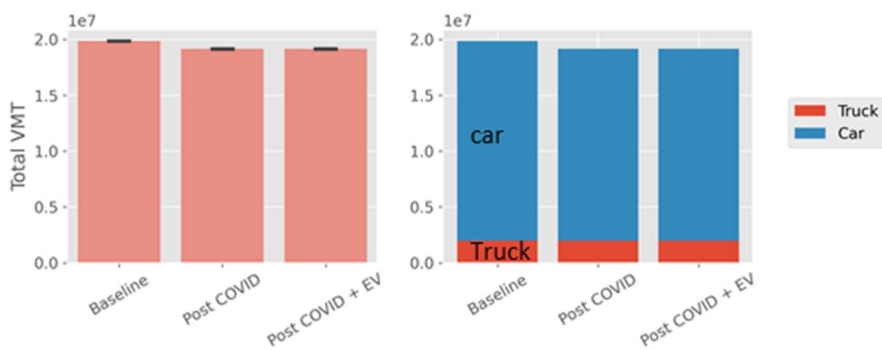


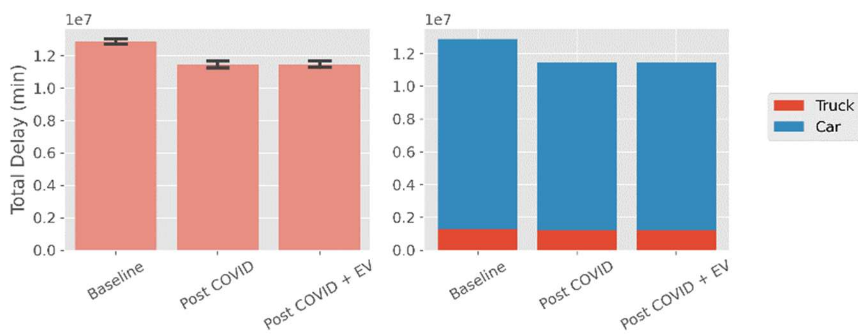
Figure 4. Baseline and post-pandemic travel demand by the hour

Impact on Traffic Congestion

With baseline and post-pandemic travel demand serving as input, the traffic congestion is simulated using a mesoscopic dynamic traffic assignment (DTA) model called DynusT (*29*). To measure the stochasticity of the model, five simulation runs were performed for each scenario in DynusT. The DynusT model adopts an iterative approach to simulate individual travel behavior under varying traffic conditions within a day and generate vehicle trajectories as output. It can generate performance metrics such as minute-by-minute VMT and delay within a day. The simulated VMT and delay by scenario are summarized in Figure 5. Under the same demand, there is no difference in the congestion level between the two post-COVID scenarios. With work trips removed throughout the day due to telecommuting, total daily VMT reduced by 3.5% (700,000 miles removed per day). Daily VMT on most links dropped as well due to lower vehicle throughput. The daily total delay reduced by about 10%, with about 23,700 hours of travel time saved in total. Daily delay on most links decreased within the network, with few exceptions due to changed route choice and increased congestion during some period of the day. At the network-level, with 18% of work trips removed due to telecommuting, the reduction in total VMT and total delay are both significant, suggesting reduced congestion levels system-wide and improved vehicle operation.



Daily Total VMT by Scenario
(error bars - 95% confidence interval)



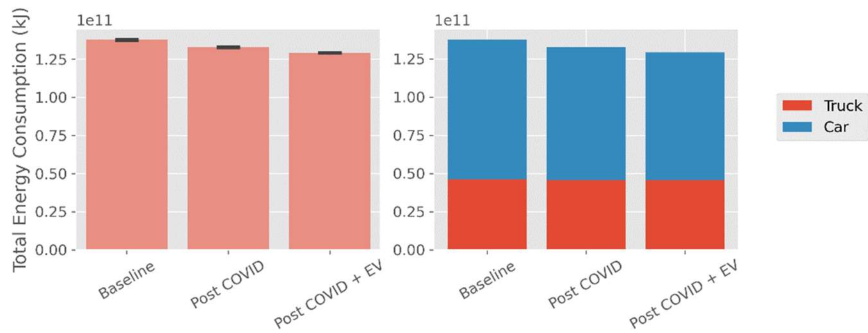
Daily Total Delay by Scenario
(error bars - 95% confidence interval)

Figure 5. Comparison of post-pandemic and El Paso baseline traffic congestion

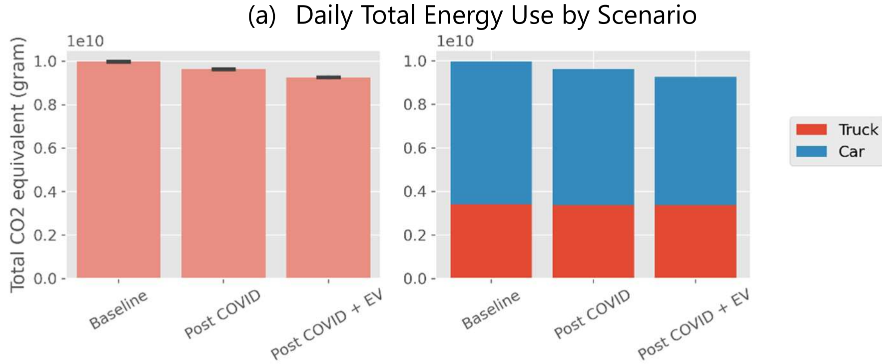
On-Road Vehicle Emissions

The link-level on-road emissions from conventional vehicles were estimated using MOVES-Matrix, a multidimensional MOVES emission rate database which produces results identical to MOVES 2014a (*30*). In this study, the hourly link-level VMT and speeds from DynusT output and vehicle type distributions from county-level registration data were used to match the emission rates generated under default fuel composition, inspection and maintenance (I/M) program and average weather from July in El Paso. The total emissions on each link and each hour, including energy consumption, greenhouse gas (GHG) emissions, and air pollutants, were generated by multiplying link VMT and corresponding emission rates. To simulate the environmental impact of the EV penetration scenario, an activity-based modeling approach is used to simulate the energy use of EVs (*31*), and the running exhaust emissions from EVs are assumed as zero. The link-level speed and VMT from selected EV trajectories are used to calculate the energy use of EVs at the regional level. The total emissions were calculated assuming conventional vehicle trips for the remainder of the fleet.

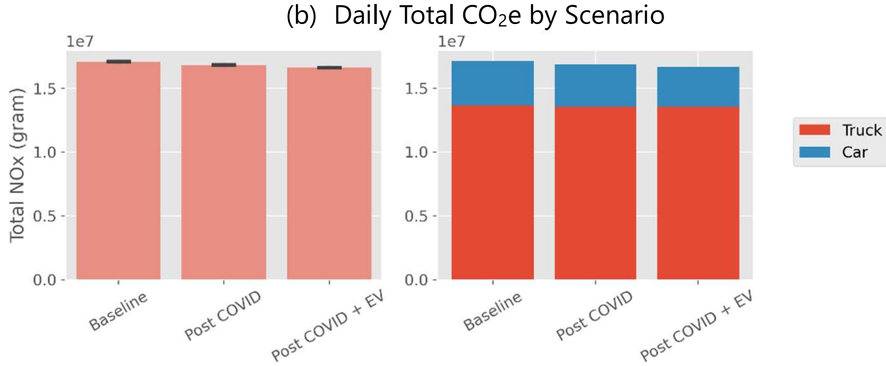
The daily total energy use (in kilojoules, kJ), carbon dioxide (CO_2) equivalent, NO_X, and particulate matter ($PM_{2.5}$) emissions under three scenarios, as well as the error bars representing 95% confidence interval, are provided in Figure 6. Under the post-COVID scenario of 18% of work trips removed due to telecommuting, the daily energy consumption, CO_2 equivalent, NO_X, and $PM_{2.5}$ emissions reduced by 3.5%, 3.5%, 1.8%, and 1.8%, respectively compared to the baseline. With the additional assumption of 6% of the light-duty vehicle (LDV) fleet replaced by EVs, the daily energy consumption, CO_2 equivalent, NO_X, and $PM_{2.5}$ emissions drop by 6.2%, 7.3%, 2.7%, and 2.5%, respectively compared to El Paso baseline. As trucks contribute disproportionally high criteria pollutant emissions, and truck VMT remains the same as the baseline, the reductions in air pollutants relatively less than reductions in energy use and GHG emissions. The total emissions from trucks are slightly decreased under the post-pandemic scenario due to the traffic improvements.



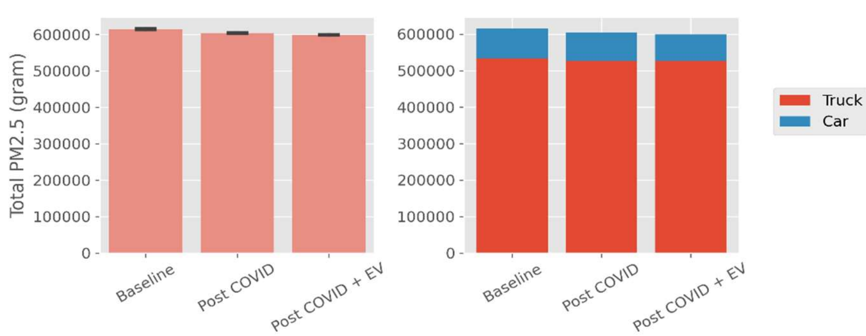
(a) Daily Total Energy Use by Scenario



(b) Daily Total CO_2e by Scenario



(c) Daily Total NO_X by Scenario



(d) Daily Total $PM_{2.5}$ by Scenario

Figure 6. Comparison of post-pandemic and El Paso baseline emissions and energy consumption.

To provide a clearer picture of the differences from the baseline, the emission reductions under each post-COVID scenario as well as the 95% confidence interval of the emission reduction is shown in Figure 7. It is seen that the energy use reductions, GHG emissions, and air pollutant emissions reductions were all increased by nearly 50% in the post-COVID+EV scenario. This indicates that if vehicle electrification continues to grow in addition to work trip reduction, higher mobile source emission reduction benefits can be achieved at the regional level.

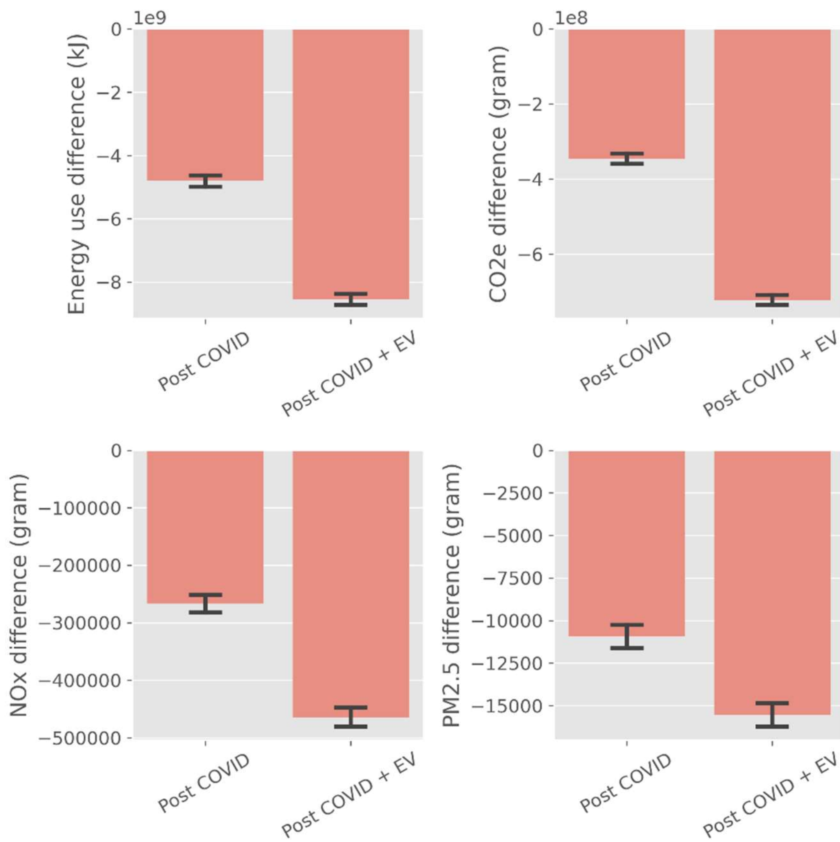
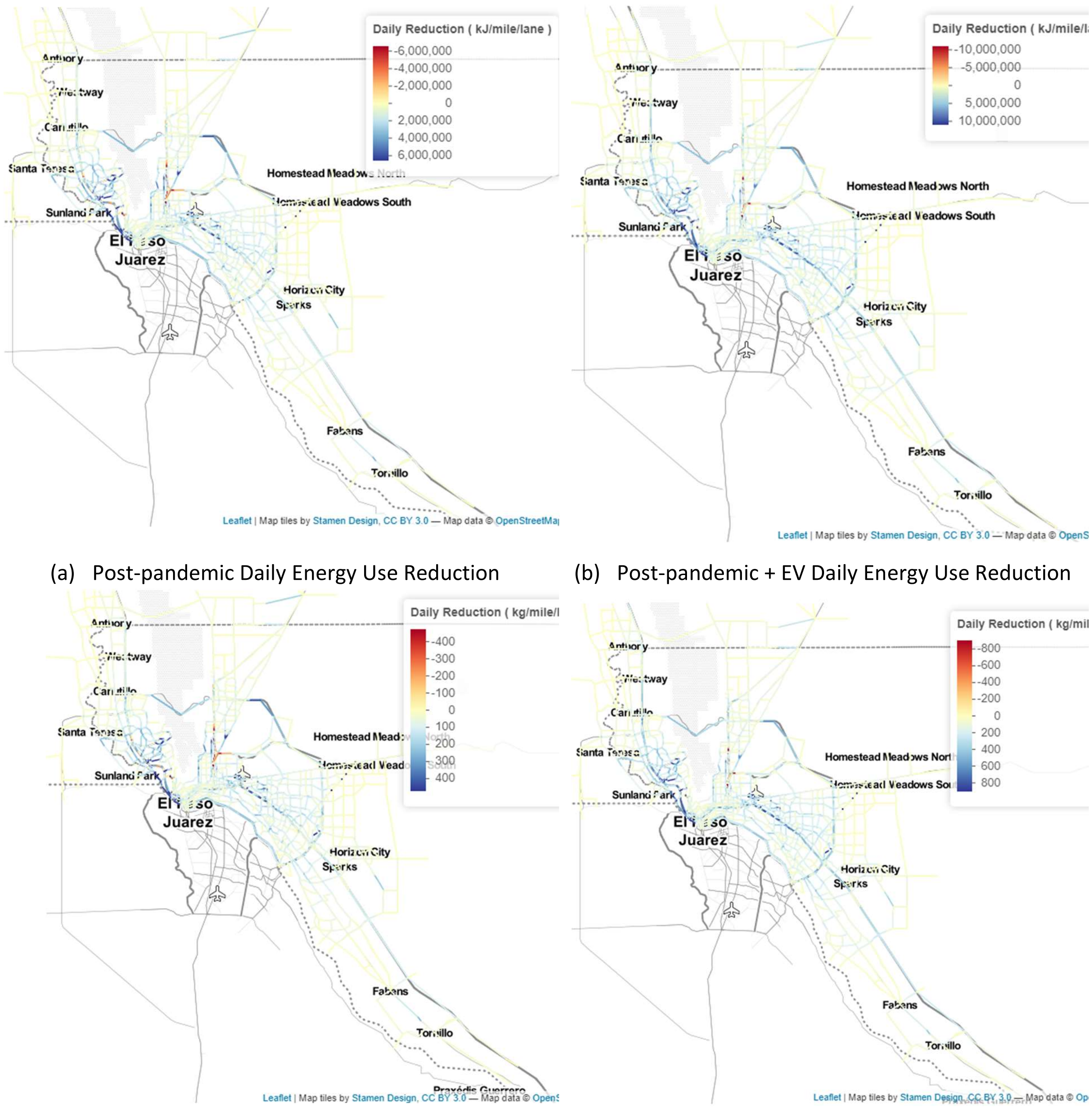


Figure 7. Emission reduction under post-COVID and post-COVID with EV scenarios

The TEMPO platform also provided the ability to assess the spatial distribution of energy use and GHG emission reductions (illustrated in Figure 8) below and air pollutant emissions (illustrated in Figure 9). On most network links, daily energy use, emissions, and air pollutants were reduced due to the improved traffic conditions under the post-pandemic scenario. The results are consistent with the traffic conditions, with higher reductions occurring on major highways and corridors, and smaller benefits were observed on local streets and outside of downtown areas. By introducing 6% EVs in the LDV fleet, the air pollutant reductions are slightly higher than the 100% conventional vehicle case. In general, with less traffic under post-pandemic scenarios, the regional-level GHG emissions and air pollutions reduced moderately.



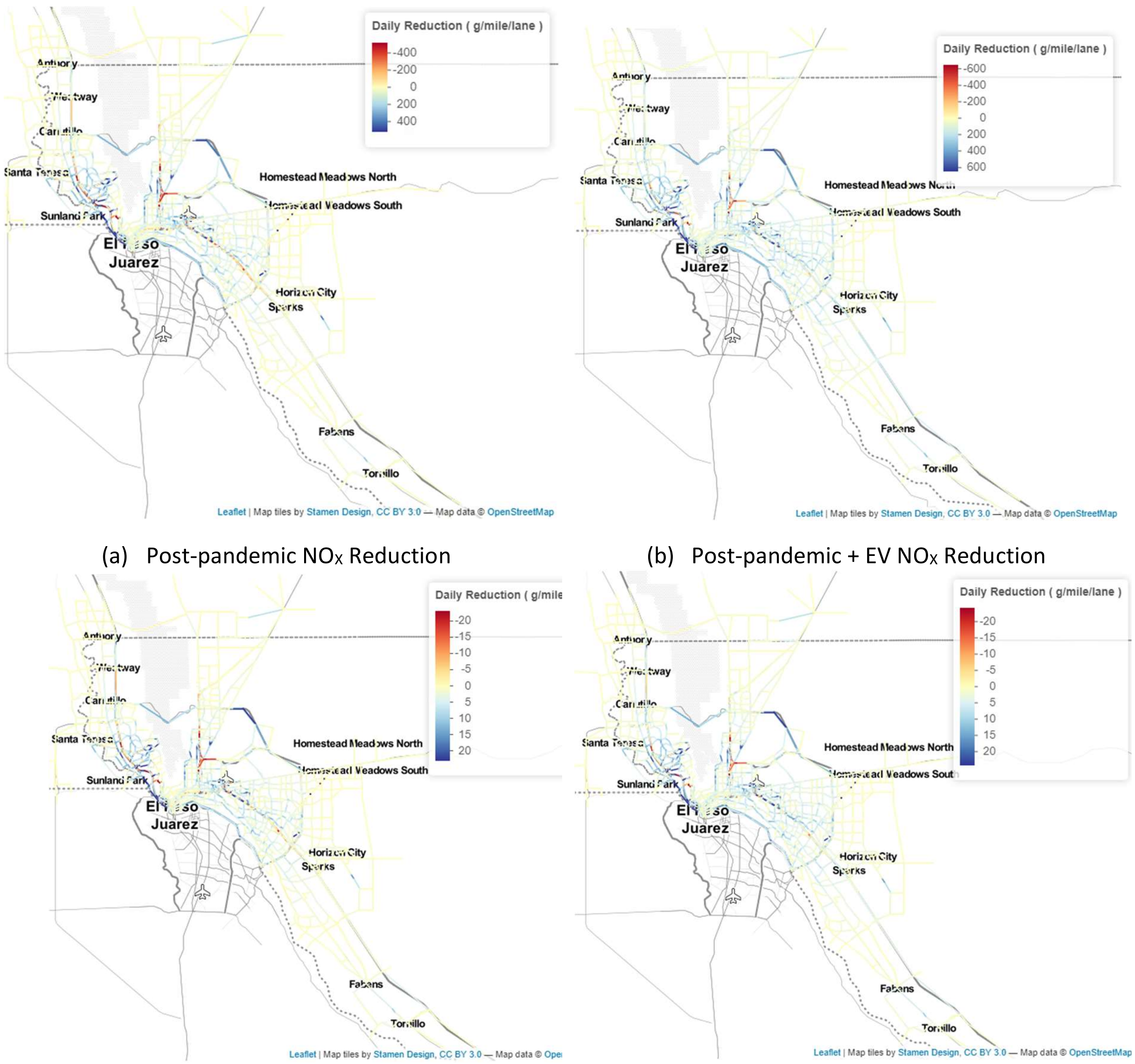
(a) Post-pandemic Daily Energy Use Reduction

(b) Post-pandemic + EV Daily Energy Use Reduction

(c) Post-pandemic Daily CO_2e Reduction

(d) Post-pandemic + EV Daily CO_2e Reduction

Figure 8. Spatial distribution of reductions in energy use and GHG emissions under the post-pandemic scenarios



(a) Post-pandemic NO_X Reduction

(b) Post-pandemic + EV NO_X Reduction

(c) Post-pandemic Daily $PM_{2.5}$ Reduction

(d) Post-pandemic + EV Daily $PM_{2.5}$ Reduction

Figure 9. Spatial distribution of air pollutant reductions under the post-pandemic scenarios

Air Quality and Health Impacts

The air quality impact of post-pandemic traffic is evaluated for $PM_{2.5}$ in TEMPO using the dispersion generated by US EPA's regulatory model AERMOD (*32*). The daily $PM_{2.5}$ emissions for each link in the emissions analysis above are used as major model inputs. An indicator of health impacts of the exposure to $PM_{2.5}$ pollution was then estimated in TEMPO using a previous study on transportation-related health problems (33), where the fraction of childhood asthma cases directly attributable to traffic-related air pollution (TRAP) was determined to vary exponentially with the average $PM_{2.5}$

concentration. Given the small $PM_{2.5}$ reduction demonstrated above, the annual average $PM_{2.5}$ concentrations appear to decrease mildly in most areas, except for the links along some major corridors with higher delay and $PM_{2.5}$. However, the differences in $PM_{2.5}$ concentrations are very small in magnitude, and most of the receptor-level changes are not statistically significant. In addition, there appear to be minimal differences between the post-COVID and post-COVID+EV scenarios. These results suggested that air quality improvements are not readily seen at the regional level under the small $PM_{2.5}$ reduction. Due to this, the percentage of asthma cases attributable to TRAP follows a similar pattern to $PM_{2.5}$ concentrations, with no significant changes in the potential of traffic-related asthma cases under both post-pandemic scenarios. The improvement in air quality and health may not be large enough to reduce the health risk of residents and potentially reduce the vulnerable populations to a potential upcoming disease outbreak. However, with a large fraction of people who work from home, people are less exposed to in-vehicle and outdoor air pollution, which may have some indirect health benefits.

CONCLUSIONS

This study provided an overview of currently observed trends in traffic patterns in Texas due to the COVID-19 pandemic, and assessed impacts of a plausible post-pandemic travel pattern in Texas. The potential impact of COVID-19 pandemic on travel patterns, especially the impact of working culture shift due to pandemic on work trips, were investigated using observed traffic data collected by UMD, along with assumption regarding plausible long-lasting trends of increased working from home and increased EV market shares.

Overall, the results suggested with 30% of employees working from home, 18% of work trips would be removed, translating to less congestion and emissions at the regional level. With 6% of the LDV fleet being electrified, the emission benefits can also rise further. However, these emissions changes are not shown to impact PM2.5 dispersion and consequently, potential health impacts, likely due to only light-duty vehicle activity being changed in the post-COVID scenarios. The results suggest that working from home can be a viable pathway to reduce congestion and emissions, but further air quality improvement strategies including those targeted at non-passenger vehicles are still needed to yield meaningful air quality and health impact.

The results from this study provide the TWG stakeholders with information to consider on potential travel patterns and fleet changes that may occur under the 'new normal' that emerges from the COVID-19 pandemic.

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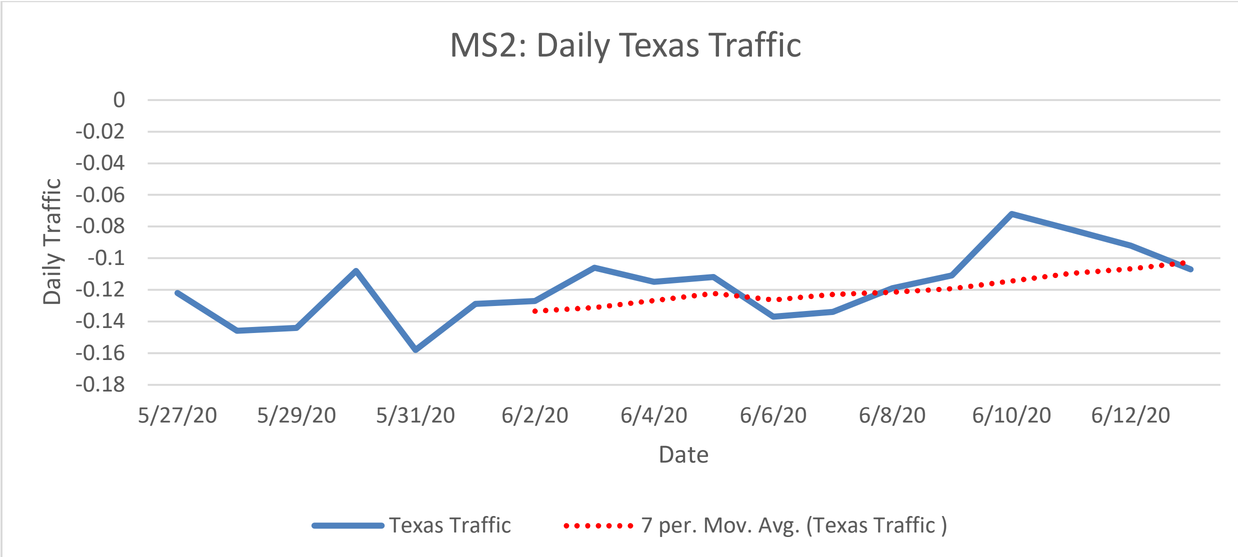
APPENDIX A. TRAVEL TRENDS FROM OTHER DATA SOURCES DURING COVID-19



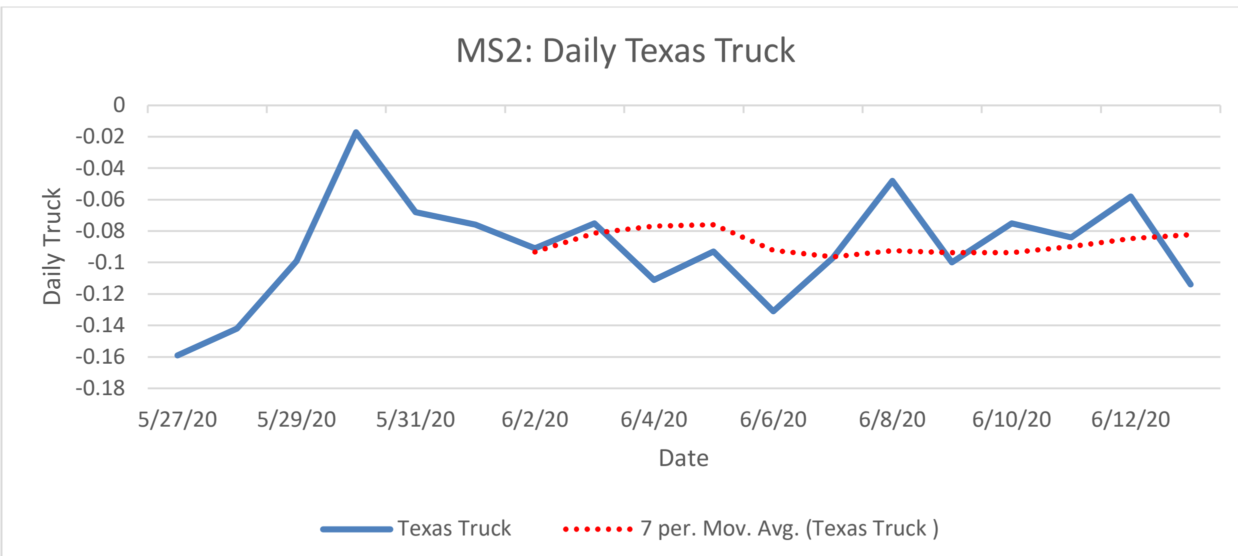


Figure 10. Travel Trends based on MS2 Data

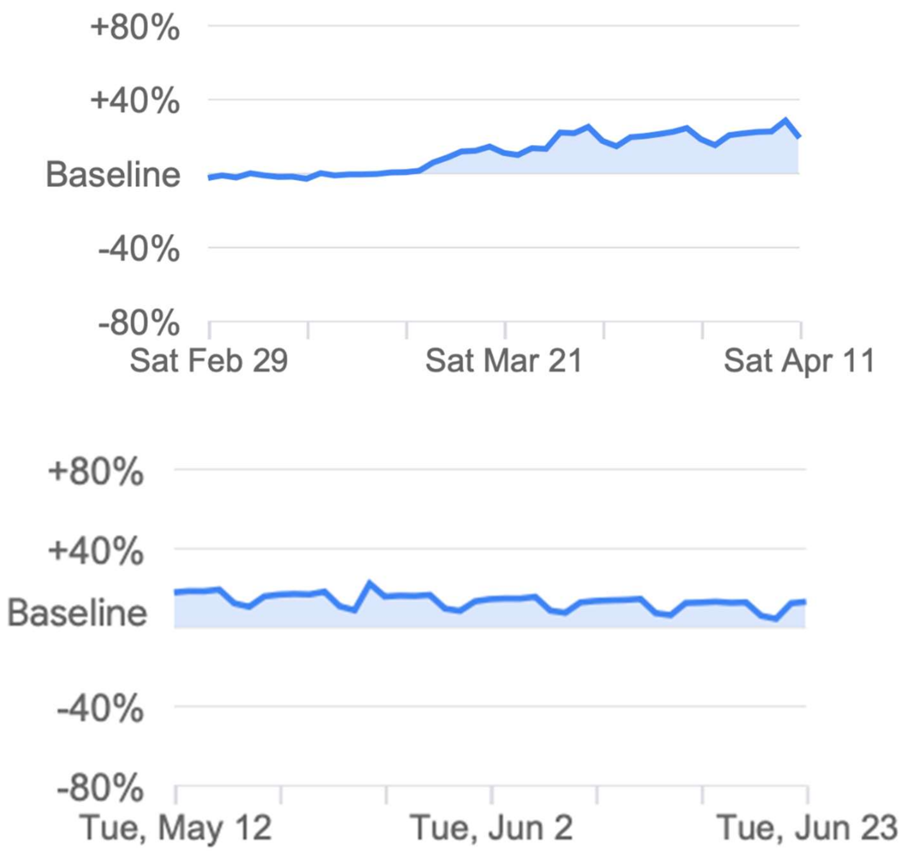


Figure 11. Google Mobility Data: El Paso County, Residential from April and June

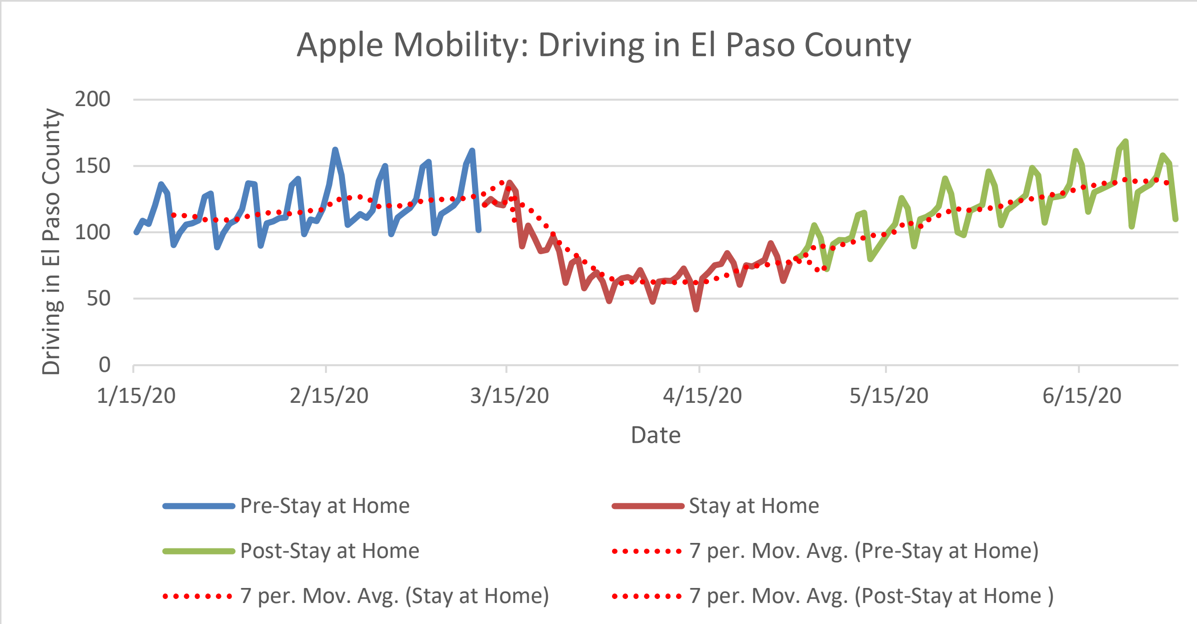


Figure 12: Travel Trends based on Apple Mobility Data