Analysis of Impact of COVID-19 Travel Behavior Change and Air Quality Impacts

Prepared by the Capital Area Council of Governments – October 26, 2021

EXECUTIVE SUMMARY

During the early days of the COVID-19 pandemic in March and April 2020, the Austin area witnessed sharp decreases in vehicle traffic across the region, and one of the questions this raised for people interested in transportation and air quality issues was how much of an impact this reduction in traffic had on air quality. From a policy perspective, such an analysis can be helpful to understanding the environmental impacts of transportation demand management (TDM) policies and programs, as well as other transportation policies and investments targeted at reducing traffic or congestion. One topic of special interest has been to assess the extent to which sustaining higher levels of telecommuting that occurred during the pandemic could be beneficial in reducing air pollution. This study was designed to help provide an understanding of:

- How transportation activity and regional/local air quality in 2020 differed from recent years and existing forecasts;
- How much of an emissions impact higher levels of telecommuting can have both directly (by eliminating "home-to-work" trips) and indirectly (by reducing congestion and thereby improving emission rates for vehicles in-use); and
- How much of an impact on ambient air pollution concentrations increases in local telecommuting can have.

Major findings of this study include the following:

- There were significant reductions in vehicle activity within the region that translated into significant reductions in emissions of criteria pollutants and greenhouse gas emissions, though the region actually saw an increase in truck activity.
- A significant share of the reduction in on-road emissions that occurred in 2020 is related to telecommuting, but other changes in driving activity related to reductions in other types of trips (i.e., dropping kids off at schools, driving to restaurants and stores) and unemployment/withdrawing from the labor force and appear likely to have accounted for a majority of the reduction in emissions.
- Due to significant improvements in the average emissions rates of criteria pollutants from passenger vehicles, the biggest impacts of sustained higher levels of telecommuting would be in closer-in years, since the air quality benefit per worker will diminish over time.
- The vast majority of the air pollution benefit of telecommuting is attributable to the direct reduction in emissions from the vehicles that are not going to be used, but there are notable "bonus" indirect emission reductions that occur across the entire transportation network as a result of reduced congestion/improved vehicle speeds.
- Higher levels of telecommuting will help reduce the impact of the region's transportation activity on regional air pollution concentrations, but they will have a much more substantial impact in reducing the region's greenhouse gas emissions. Light duty vehicles remain by far the largest share of on-road GHG emissions but a decreasing share of "criteria" pollutant emissions that contribute to regional air quality.

The first section of the report provides an introduction/background to the study. The second section includes an analysis of changes in on-road vehicle activity in 2020 relative to 2017-2019 and existing projections for 2020. Section 3 includes analysis of ambient air pollution data, including analysis of the extent to which various factors other than changes in local on-road emissions might have affected air pollution in 2020. Section 4 includes an analysis of the impact of telecommuting on reducing on-road emissions, while Section 5 provides an analysis of how these emissions reductions may translate into reductions in ambient air pollution concentrations. Section 6 provides conclusions and summaries of findings.

One take-away from this study is that there is no one policy or investment that can address the region's concerns about air pollution, even within the share of it that can be attributed to transportation. Telecommuting provides one way to reduce emissions and improve ambient air pollution within the region, but policies and investments targeted at reducing emissions from trucks and from other types of trips from light-duty vehicles are going to need to be an important part of reducing the impact of on-road activity on regional air pollution and greenhouse gas emissions moving forward. Maximizing telecommuting is a good way to reducing a significant share of on-road emissions, encouraging people to shop at stores within walking/biking distance or chaining trips to avoid unnecessary additional VMT might be just as important in reducing air pollution moving forward.

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1 INTRODUCTION

One of the many ways in which the COVID-19 pandemic changed our lives has been to reduce personal vehicle usage starting in March 2020. The City of Austin, the Texas Department of Transportation (TxDOT), and the Central Texas Regional Mobility Authority (CTRMA) all reported traffic reductions of as much as 50% shortly after businesses started shifting to telecommuting and local governments started enacting "stay at home" orders and limitations on business operations. Traffic picked up again in May 2020, but remained well below pre-pandemic levels for the remainder of 2020. Two key policy questions that these changes in transportation behavior pose for local policy-makers are: 1) how much of an impact did these reductions in transportation have on air quality? and 2) how much of an impact on air quality can we have in the future by sustaining some of the expanded telecommuting that occurred as a result of the pandemic? This study seeks to help answer these questions.

In April 2020, following numerous inquiries from around the region, CAPCOG conducted a preliminary review of ambient air quality data at regional air pollution monitors for March and April 2020 compared to similar weeks in 2017, 2018, and 2019, to evaluate whether there was any evidence that the reductions in traffic resulted in noticeable improvements in ambient air pollution concentrations in the region.[1] CAPCOG's analysis showed lower O_3 and NO_2 concentrations, but higher concentrations of CO and $PM_{2.5}$. This analysis only covered a short period of time, and as CAPCOG noted in the memo, "it would require complex regional air quality modeling to get a more definitive idea of the exact extent this impact, or to differentiate the impact of local changes in traffic from the impact of changes in traffic across the state and country." We also noted that we didn't know what share of the reduction in traffic could be attributed to telecommuting versus other factors, and that telecommuting has both direct benefits from reduced vehicle usage and indirect benefits from improvements in emissions rates from other vehicles remaining on the road operating at higher vehicle speeds.

City of Austin contracted with CAPCOG later in 2020 to conduct a more thorough analysis for there region, and this report is the result. The study includes:

- Analysis of on-road vehicle activity and emissions trends;
- Analysis of data that can help characterize the extent to which changes in vehicle activity could have been attributed to telecommuting versus other factors (unemployment, virtual learning, fewer personal trips);
- Analysis of how the region's vehicle activity changes compare to the rest of the state and the rest of the country;
- Analysis of ambient air pollution concentrations;
- Analysis of meteorology and emissions data from other sources that need to be taken into account; and
- Estimation of the impact of permanent increased in telecommuting on future emissions.

[1] Memorandum from Andrew Hoekzema, CAPCOG Director of Regional Planning and Services, to Clean Air Coalition and Clean Air Coalition Advisory Committee Members RE: Analysis of Potential Impacts of COVID-19 Crisis on Regional Air Quality. April 24, 2020.

In analyzing whether "air quality was better" in 2020, one of the key questions that needs to be answered is "better than what?" Air pollution levels can vary significantly year to year, month to month, day to day, and hour to hour, and long-term reductions in emissions associated with federal engine standards for mobile sources would have resulted in air quality improvements year over year regardless of whether vehicle usage had also decreased. Almost all of the National Ambient Air Quality Standards (NAAQS) set by the U.S. Environmental Protection Agency (EPA) are based on the most recent three years' of data in order to smooth out year-to-year variations in pollution levels. Therefore, many of the analyses in this report compare averages from 2017-2019 to 2020. However, the Austin-Round Rock-Georgetown Metro area remains the fastest-growing large metro area in the country, and federal emissions standards are estimated to have large impacts on emissions even within this four-year window, so CAPCOG also includes some comparisons to what "business as usual" for 2020 might have been if the pandemic had not occurred, since we would have expected higher vehicle each year. Finally, for the analyses of the extent to which future air quality can be improved through sustained telecommuting, CAPCOG compared 2023 air pollution levels in a "business as usual" scenario to various scenarios with reduced personal vehicle usage. These general analysis parameters were agreed to between City of Austin and CAPCOG staff prior to its initiation.

In order to assist with key parts of this study related to on-road emissions modeling and ambient air pollution modeling, CAPCOG sub-contracted with the Teas Transportation Institute (TTI) and the Alamo Are Council of Governments (AACOG), respectively. CAPCOG then conducted secondary analyses of this modeling and incorporated these analyses into this report.

Section 2 of this report includes analyses of on-road vehicle emissions and activity trends, along with other data sources that shed light on the extent to which observed reductions in vehicle activity may have been related to telecommuting versus other factors and how the Austin area's changes compare to the rest of the country.

Section 4 includes comparisons of ambient air pollution data, meteorological data, and emissions data from 2017-2019 to 2020.

Section 5 includes a detailed analysis of on-road emissions benefits from telecommuting based on TTI's modeling, and Section 6 includes analysis of the ambient air quality benefits of these emission reductions.

CAPCOG's conclusions and key findings from the study are summarized in Section 6.

Appendices A and B are deliverables from CAPCOG's vendors, and are being submitted separately from this document.

2 Analysis of On-Road Vehicle Activity Changes

CAPCOG reviewed data from a number of sources to evaluate the extent to which on-road vehicle activity changed within the region and beyond as a result of the pandemic, and generally how these changes would be expected to relate to air quality improvements.

2.1 Annual VMT Data and On-Road Emissions Trends

In 2015, the Texas A&M Transportation Institute (TTI) developed on-road emissions inventory "trends" data for every year from 1999 to 2050 for every county of the state. The following table summarizes the total on-road criteria pollutant emissions inventories.

Table 2-1. Austin-Round Rock-Georgetown MSA On-Road Emissions Trends Estimates 2017-2020 (tpy).

Pollutant or Activity	2017	2018	2019	2017-2019	2020	Difference 2017-2019 to 2020	% Difference
CO (tpy)	76,568	74,353	72,568	74,497	70,380	-4,116	-6%
NO_X (tpy)	11,452	10,176	9,152	10,260	8,308	-1,952	-19%
PM_{10} (tpy)	1,128	1,115	1,110	1,118	1,102	-15	-1%
$PM_{2.5}$ (tpy)	422	397	380	400	360	-40	-10%
SO_2 (tpy)	61	61	61	61	61	0	0%
VOC (tpy)	5,839	5,483	5,222	5,515	4,947	-567	-10%

Despite the decreases in emissions, vehicle miles traveled (VMT) was projected to be 4% higher in 2020 than the annual averages for 2017-2019. This is because of federal vehicle emissions standards and the continued replacement of older, higher-emitting vehicles with newer, cleaner vehicles.

The following figure shows a comparison of actual average daily VMT compared to the projected VMT in the trends inventory, as well as the auto VMT and truck VMT components.[2] These data show that overall VMT within the region was 16% below both the 2017-2019 average and the projection for 2020, but this reduction was entirely attributable to a reduction in auto VMT – truck VMT was actually 3% higher compared to both the 2017-2019 average and the 2020 projection. This suggests that any decrease in emissions would likely be smaller than the VMT reduction would indicate, since trucks emit much more per VMT than autos. Across the state, auto VMT was 8% lower in 2020 than the average for 2017-2019 and truck VMT was 2% lower, so the region had both a more pronounced trends in both directions.

One potential explanation for the increase in truck VMT while auto VMT declined would be an increase in package deliveries due to people shifting buying from in-person to online. For example the U.S. Postal Service (USPS) reported a 32% increase in package volume in 2020 compared to 2019.[3] However, county-level data within the region and within other metro areas does not provide much clarity as to this potential explanation. Within the region, truck VMT decreased in Williamson County and Caldwell County but increased in Bastrop, Hays, and Travis County, but auto VMT decreased by 9-22%.

[2] Actual VMT data are from TxDOT's Roadway Inventory Data summary for 2005-2020. Available online at: https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html.
[3] https://www.gao.gov/products/gao-21-261

Figure 2-1. Projected v. Actual VMT-Total (millions of VMT per day)

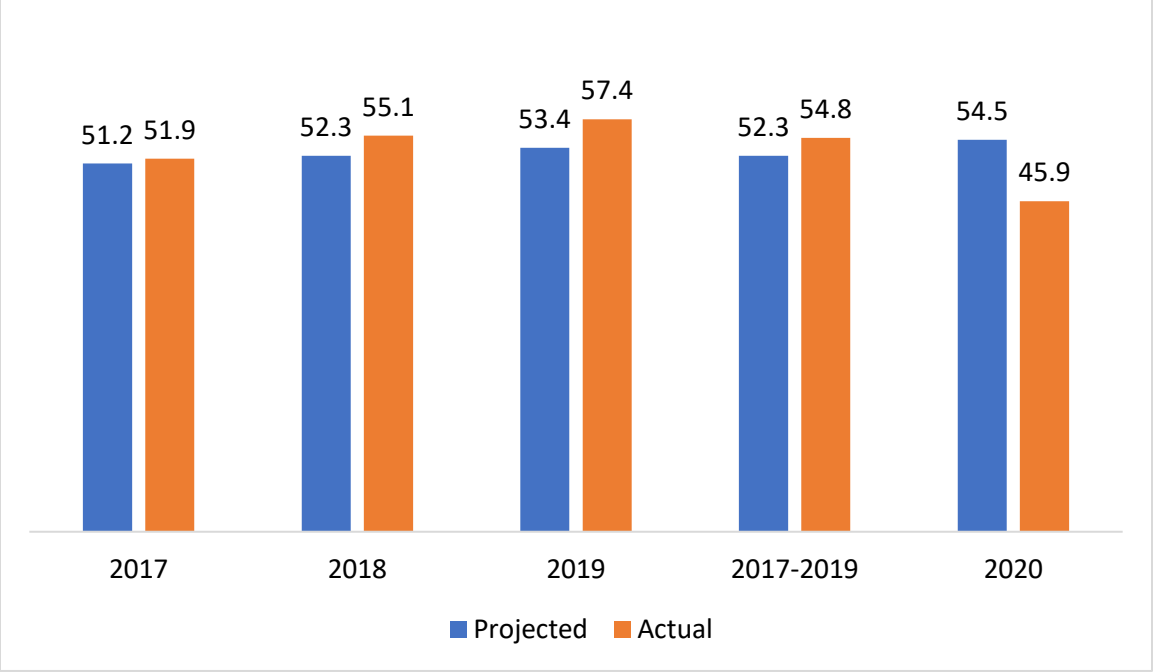


Figure 2-2. Projected v. Actual VMT-Auto (millions of VMT per day)

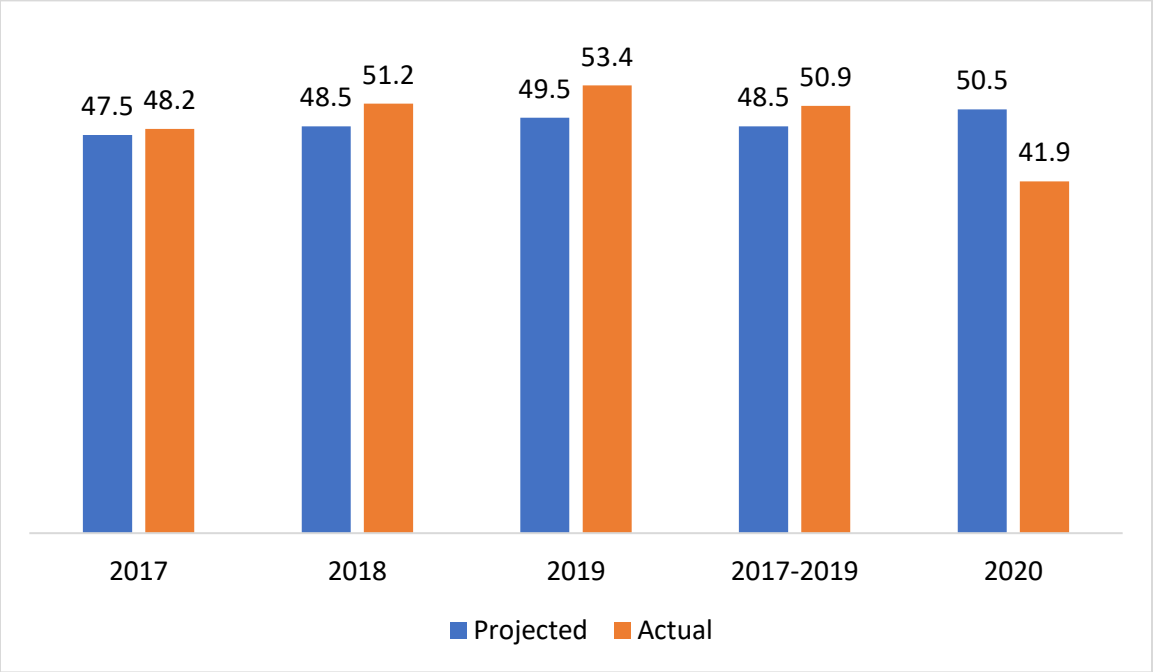
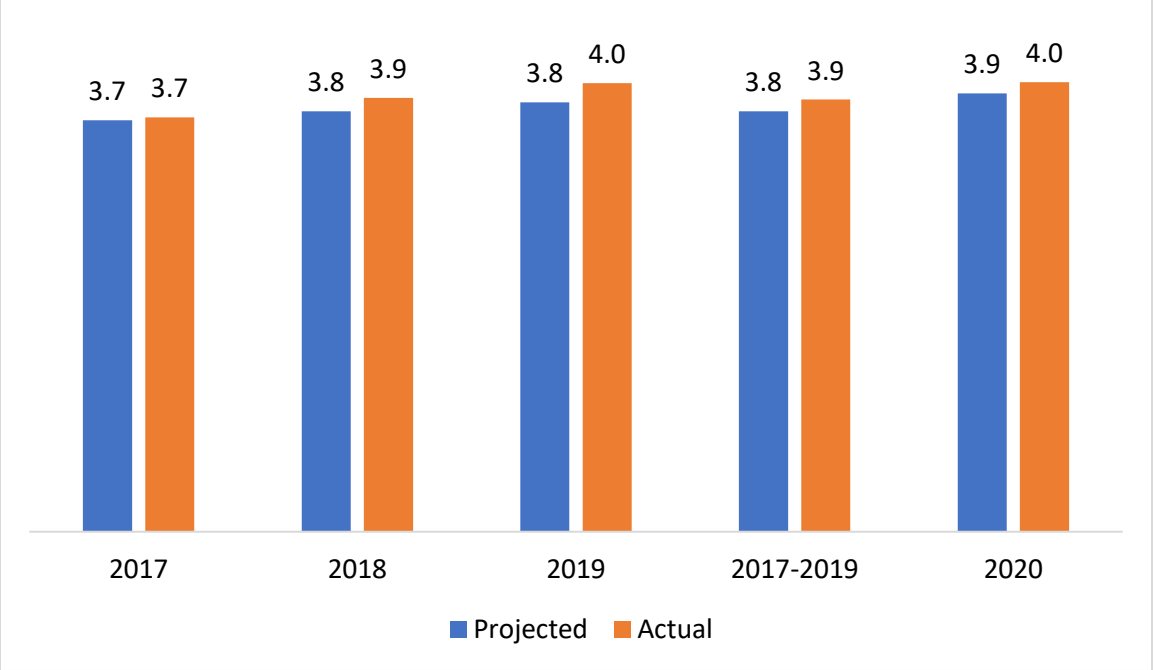


Figure 2-3. Projected v. Actual VMT-Truck (millions of VMT per day)



These data show that actual VMT in 2020 was 16.1% below the average for 2017-2019, and 15.7% below the total projected by TTI for 2017-2019. However, the decrease in VMT from 2017-2019 to 2020 and from expected 2020 levels did not occur equally across all vehicle types.

So, while "auto" VMT (which includes all light-duty vehicles except possibly motorcycles) were down by 18% from 2017-2019 levels and 17% from projected 2020 levels, "truck" VMT (which includes all heavy-duty vehicles) were 4% higher than 2017-2019 levels and 3% higher than were projected for 2020.

Depending on the pollutant and year, average emissions rates for heavy-duty vehicles were between 15 and 300 times higher per VMT than passenger vehicles. Therefore, on-road emissions would have declined less, relative to what was expected for 2020, than the overall decrease in VMT might suggest, since this decrease in VMT was as a result of decreases in auto VMT. The ratios of heavy duty to passenger vehicle emission rates are shown in the table below for 2017-2019 and 2020.

Table 2-2. Ratios of Average Heavy-Duty Vehicle Emission Rates to Passenger Vehicle Emission Rates for 2017-2019 and 2020

Pollutant	2017-2019	2020
CO	15.29	14.54
NO_X	228.00	225.43
PM_{10}	124.60	107.57
$PM_{2.5}$	267.65	212.01
SO_2	72.54	75.05
VOC	20.79	18.89

CAPCOG recalculated the heavy-duty and light-duty emissions using the actual 2017-2020 VMT data to compare the actual change in on-road emissions from 2017-2019 to 2020 to the expected change from the trends inventory. The table below shows this summary.

Table 2-3. Comparison of Expected Changes in On-Road Emissions from 2017-2019 to 2020 to Estimated Actual Changes

TOTAL	Expected Change	Approximate Actual Change	Difference	Difference as Share of Total
CO	-5.5%	-24.3%	-18.8%	77.2%
NO_X	-19.0%	-28.3%	-9.3%	32.8%
PM_{10}	-1.4%	-16.2%	-14.9%	91.5%
$PM_{2.5}$	-9.9%	-20.6%	-10.6%	51.7%
SO_2	-0.3%	-16.8%	-16.5%	98.1%
VOC	-10.3%	-28.1%	-17.8%	63.3%

This analysis shows reductions in on-road emissions ranging from 16% to 28%, with the change in VMT from 2017-2019 to 2020 responsible for 33 – 98% of those decreased depending on the pollutant. Considering the changes observed in ambient air pollution concentrations of O_3 and NO_2 from 2017-2019 to 2020 (discussed in section 4), this analysis would suggest that about 1/3 of improvements in ambient air pollution could be attributable to the reduction in VMT in 2020 relative to 2017-2019 to the extent those improvements were driven by local reductions.

2.2 Census Pulse Survey Data

Since April 2020, the U.S. Census Bureau has conducted the "Household Pulse Survey," which it describes as "designed to quickly and effectively deploy data collected on how people's lives have been impacted by the coronavirus pandemic." Phases 2 (8/9/2020 – 10/26/2020) and 3 (10/28/2020 – 3/29/2021) included the following questions relevant to telework:

"Q13a: Working from home is sometimes referred to as telework. Did any adults in this household substitute some or all of their typical in-person work for telework because of the coronavirus pandemic, including yourself?

(1) Yes, at least one adult substituted some or all of their typical in-person work for telework
(2) No, no adults substituted their typical in-person work for telework
(3) No, there has been no change in telework"[4]

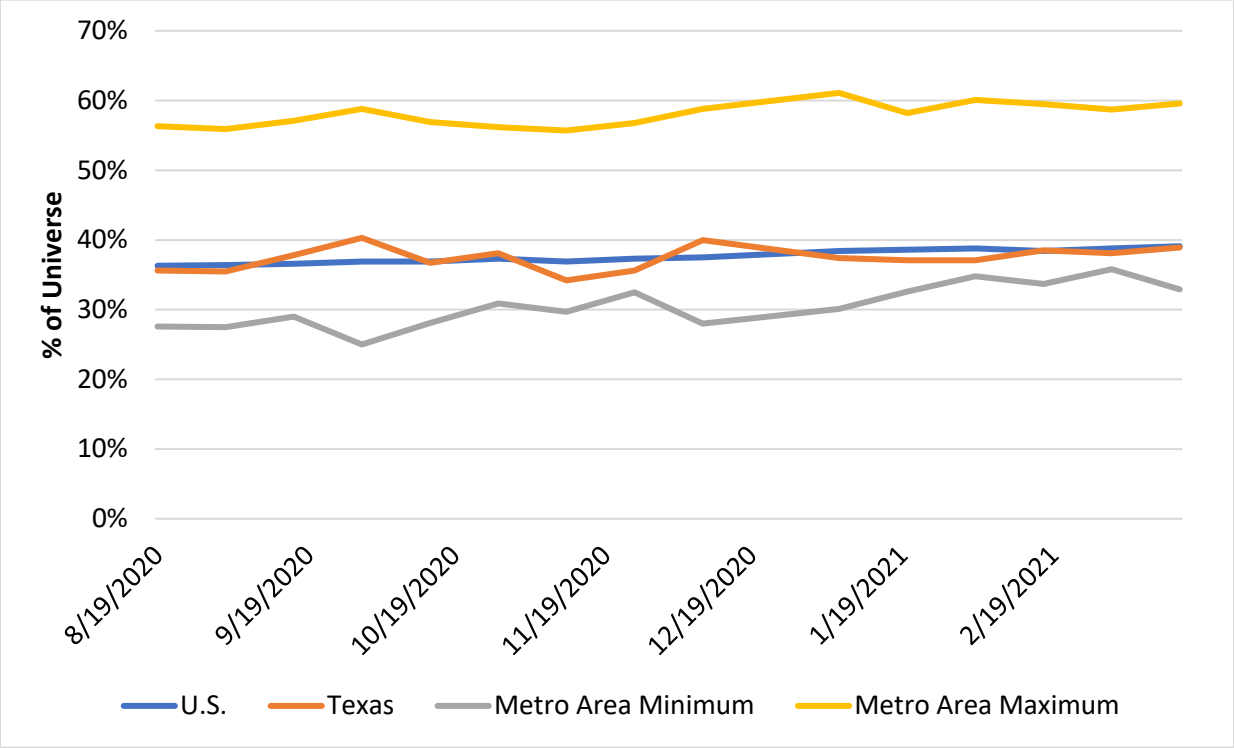
Results are available at the national and state level, and for the following metro areas:

- Atlanta-Sandy Springs-Alpharetta, GA Metro Area
- Boston-Cambridge-Newton, MA-NH Metro Area
- Chicago-Naperville-Elgin, IL-IN-WI Metro Area
- Dallas-Fort Worth-Arlington, TX Metro Area
- Detroit-Warren-Dearborn, MI Metro Area

[4] https://www2.census.gov/programs-surveys/demo/technical-documentation/hhp/Phase_2_Questionnaire_11_2_20_Updated_English.pdf

- Houston-The Woodlands-Sugar Land, TX Metro Area
- Los Angeles-Long Beach-Anaheim, CA Metro Area
- Miami-Fort Lauderdale-Pompano Beach, FL Metro Area
- New York-Newark-Jersey City, NY-NJ-PA Metro Area
- Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area
- Phoenix-Mesa-Chandler, AZ Metro Area
- Riverside-San Bernardino-Ontario, CA Metro Area
- San Francisco-Oakland-Berkeley, CA Metro Area
- Seattle-Tacoma-Bellevue, WA Metro Area
- Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area

Figure 2-4. Adults in households where at least one adult has substituted some or all of their typical in-person work for telework because of the coronavirus pandemic, U.S., Texas, and selected Metro Area Minimums and Maximums, 8/19/2020 – 3/29/2021



Phase 3.1 included changes to the questions as follows:

"Q13a: Working from home is sometimes referred to as telework. In the **past 7 days**, have any adults in this household teleworked? [emphasis in original]

(1) Yes
(2) No

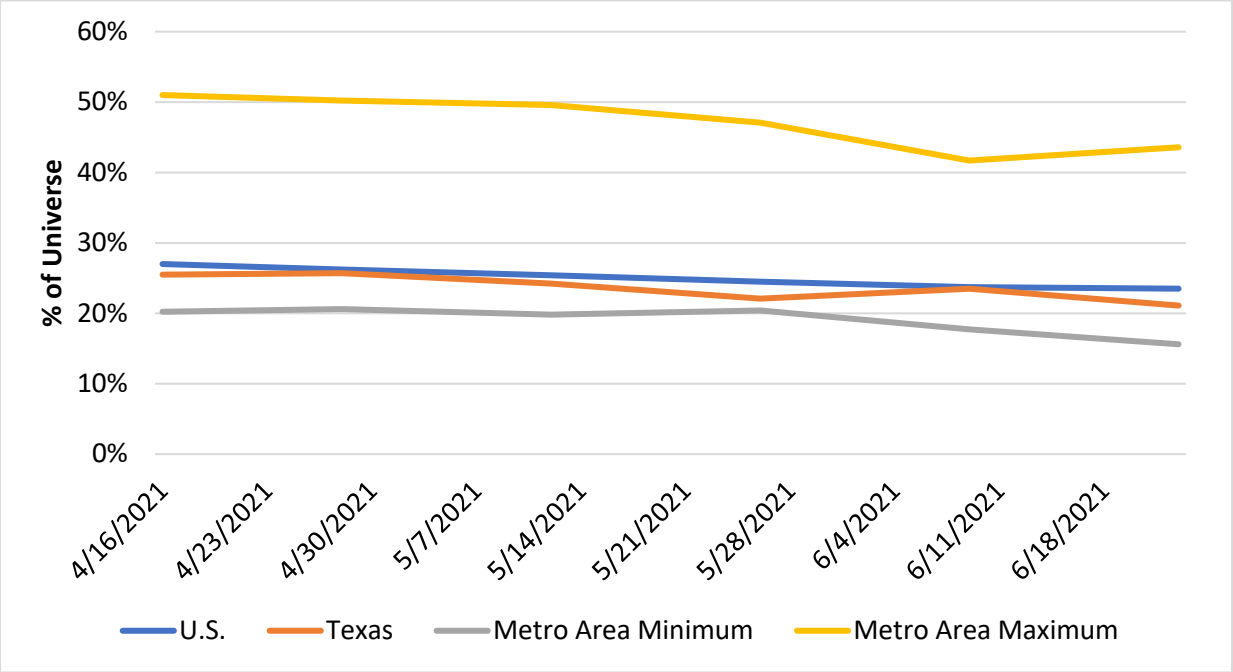
Q13b: Have any adults teleworked **because of** the coronavirus pandemic? [emphasis in original]

(1) Yes
(2) No

Q13c: Since **January 1, 2021**, have you worked or volunteered **outside your home**? [emphasis in original]

(1) Yes
(2) No"[5]

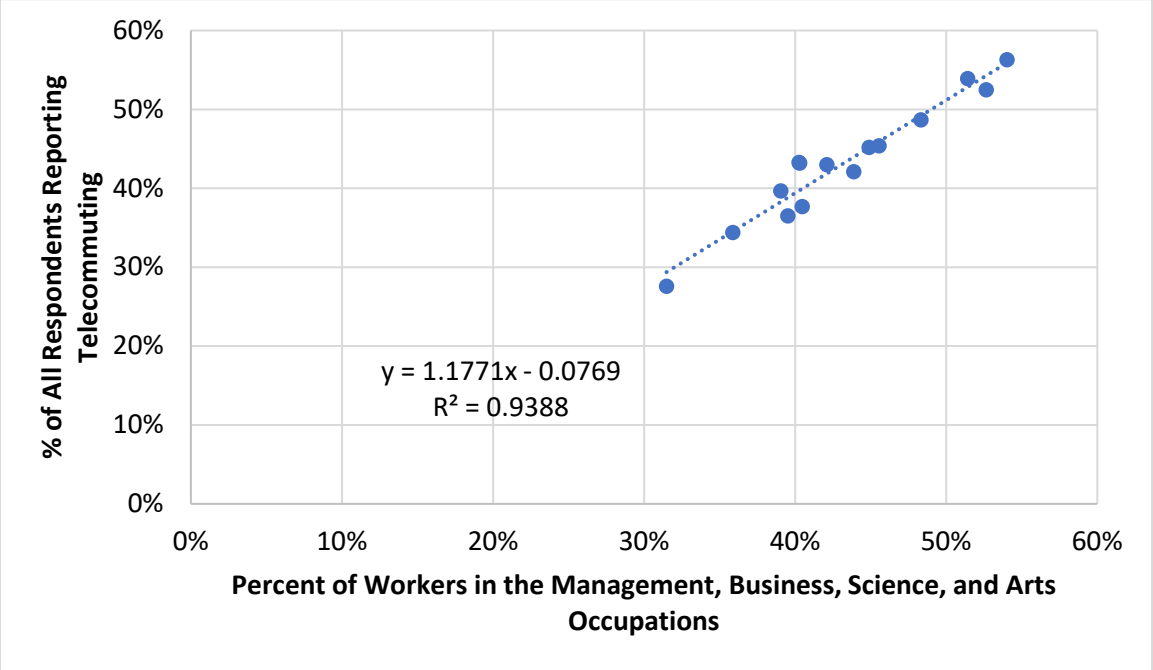
Figure 2-5. Adults in households where at least one adult has teleworked because of the coronavirus pandemic in the past 7 days, U.S., Texas, and selected Metro Area Minimums and Maximums, 4/16/2021 – 7/5/2021



The areas with the highest percentages of adults telecommuting in the first survey were the Washington D.C. (56.3%), Boston (53.9%), San Francisco (52.5%) metro areas. These three metro areas also had the highest percentage of workers in the "Management, business, science, and arts" occupations in 2019: 54.0%, 51.4%, and 52.6%, respectively.[6] This data point has a high degree of correlation to the percentage of people who had indicated telecommuting related to the pandemic, as the following figure shows.

[5] https://www2.census.gov/programs-surveys/demo/technical-documentation/hhp/Phase3_1_Questionnaire_05_05_21_English.pdf
[6] U.S. Census Bureau. 2019 American Community Survey, Table S2401: Occupation by Sex for the Civilian Population 16 Years and Over.

Figure 2-6. Metro Area Telecommuting Due to Pandemic Compared to % of Workers in Management, Business, Science, and Arts Occupations



In the Austin-Round Rock-Georgetown Metro area, 49% of workers held an occupation in the management, business, science, and arts occupations, which suggests that it would be towards the higher end the range for telecommuting. Using the trendline equation, CAPCOG could assume that if the Austin metro area had been included, the percentage that would have reported some extra telecommuting as a result of the pandemic would have been about 50%.

Since the Household Pulse survey did not collect transportation-related data from earlier in the pandemic, it isn't possible to use this dataset to determine how much different it might have been. Anecdotally, there are a variety of ways employers responded even among Clean Air Coalition (CAC) member organizations. For example, City of Austin pretty much remained fully remote throughout the year, while City of Round Rock was back in the office most if not all of the time relatively soon after the initial surge in March and April. While CAPCOG came back in June 2020 half-time, CAPCOG returned to full telecommuting after the 2nd surge until October, and then CAPCOG returned to half-time again until June 2021.

It's important to note that these data only reflect whether or not there was any telecommuting at all, not whether the respondents were fully telecommuting. Assuming that some portion of the workforce that would have responded "yes" to this question is going to their place of work at least once a week, it would be reasonable to assume that the actual extent of reduced commuting trips would be 10% - 40%. The 10% level would be equivalent to the 50% of the workforce, that reported increased telecommuting, was telecommuting one extra day a week. However, the higher end of that range would assume that most people, who were doing any extra telecommuting as a result of the pandemic, were telecommuting every day of the week with a smaller share of workers telecommuting only a few extra days a week.

The Austin-Round Rock-Georgetown MSA actually already had quite high percentages of workers who *primarily* telecommuted in 2019 before the pandemic. The estimated 126,055 workers who primarily telecommuted in 2019 represented 10.47% of all workers living in the MSA, a higher percentage than any other large metro area (those with at least 1 million workers living within the region).[7]

2.3 Movability Surveys

Movability, the region's Transportation Management Association (TMA), conducted surveys during the pandemic that can be useful in assessing the extent of teleworking prior to the start of the Census Household Pulse Survey.[8] While the survey respondents aren't necessarily representative of all employers region-wide, they do represent a significant share of large employers and the responses provide some insight into the extent to which telecommuting may have been higher prior to the start of the Household Pulse Survey. The survey included 45 employers (i.e, employers with about 9,000 employees) with an average number of employees of 200 per organization responding to the survey. Movability's survey showed that 30% of respondents planned to start having employees return to the office in some capacity in May – August 2020. Among these respondents, 50% indicated that they did not plan to allow extra telecommuting after the return to the office. While not all of the employees at these companies would necessarily have been telecommuting prior to this period, it is certainly reasonable to think based on these results that perhaps an additional 10-15% of all employees beyond the estimated 50% in August-December would have had access to added telecommuting at least one day a week between March 2020 and August 2020.

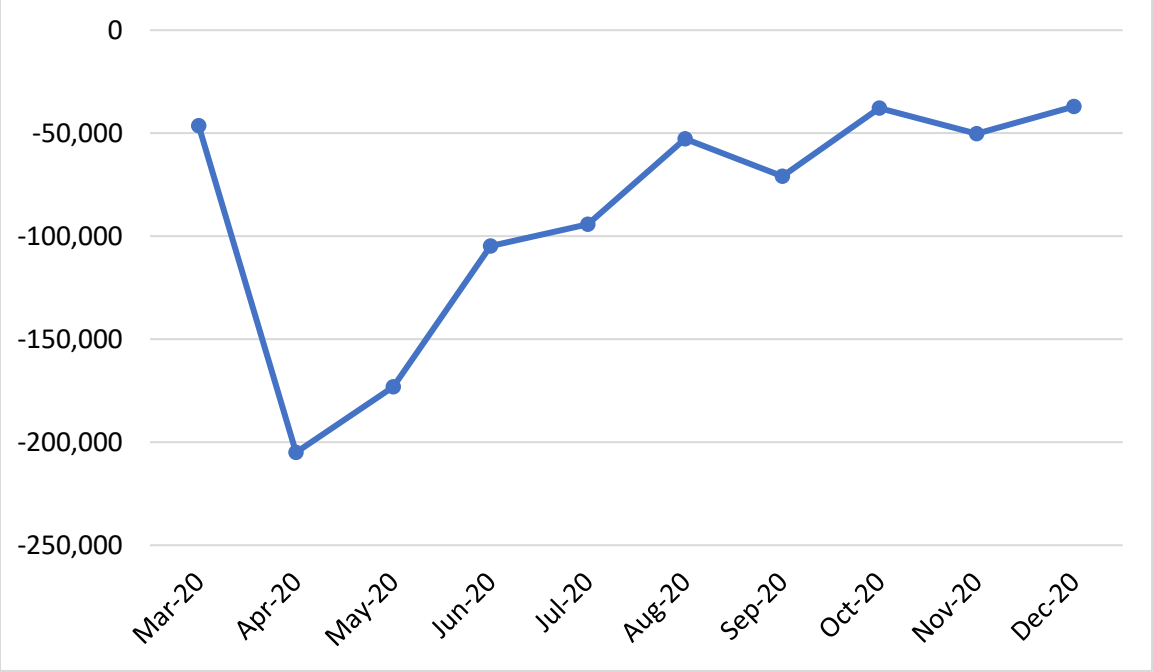
2.4 Unemployment and Withdrawal from the Labor Force

While increases in telecommuting is one potential explanation for reduced commuting, job loss also eliminates home-to-work commutes. The sharp increase in unemployment and people leaving the labor force entirely that coincided with the start of the pandemic can be seen in the monthly employment figures from the Texas Workforce Commission, shown below. Unemployment accounted for about 2/3 of the reduction in employment, while withdrawal from the labor force entirely accounted for the other third. It was only in July 2021 that the labor force count finally reached pre-pandemic levels. However, unemployment still remains higher than pre-pandemic levels at 4.23% in July 2021 compared to 2.62% in April 2020 when unemployment was at its worst. The overall unemployment rate was 11.82%.

[7] U.S. Census Bureau. 2019 American Community Survey, Table B08006: Sex of Workers by Means of Transportation to Work. Universe: Workers 16 years and over.

[8] https://movabilitytx.org/lets-go-news-blog/return-to-work-survey-results

Figure 2-7. Number of People Employed Relative to February 2020



Assuming the same 13.23 mile per commute in Capital Area Metropolitan Planning Organization's (CAMPO's) 2015 travel demand model, the reduction in employment relative to February 2020 would have meant about 2.3 million fewer VMT per day than was occurring pre-pandemic. Since the 2020 VMT numbers do include January and February, the impact of the reduction in employment is a bit less during the pandemic – about 1.9 million fewer VMT per day for the annual average.

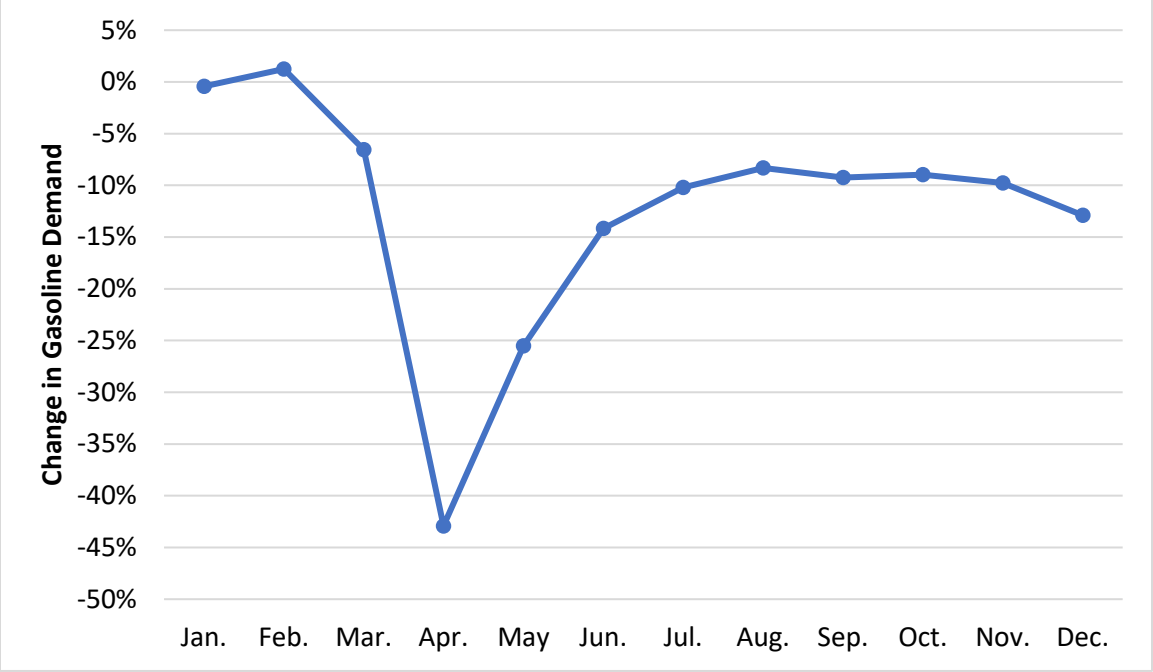
The actual reduction in VMT from 2019 to 2020 was 11.5 million VMT per day, which means that the reduction in employment levels accounted for approximately 17% of the reduction in average daily VMT from 2019 to 2020.

2.5 Analysis of Gasoline Consumption Data

While regional gasoline consumption data is not readily available, the Energy Information Administration (EIA) does make weekly gasoline consumption available at the national level. These data showed a 43% reduction in gasoline consumption in April 2020 relative to the average for April 2017-2019. Gasoline consumption rebounded significantly in May 2020 but remained at least 9% below demand each month for the remainder of the year, with the difference widening again in December 2020 as the pandemic resurged.[9]

[9] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=WGFUPUS2&f=W

Figure 2-8. Change in Gasoline Demand in 2020 Relative to 2017-2019 Nationwide



Overall for 2020, total gasoline demand was about 12% below 2017-2019 demand levels. This difference is less than the 18% drop in VMT that the region experienced, but CAPCOG believes that the overall month-to-month pattern at the national level is likely similar for the Austin area.

3 Analysis of Air Pollution

CAPCOG's analysis of ambient air monitoring for this analysis indicated the following:

- NO_2 concentrations were statistically lower in 2020 than they were in 2017-2019, consistent with both a reduction in VMT and a reduction in average NO_X emissions rates from vehicles.
- O_3 concentrations in 2020 were lower than they were in 2017-2019, although the difference was only statistically significant at two of the five monitoring stations analyzed. This is consistent with both a reduction in VMT and a reduction in average NO_X emissions rates from vehicles.
- CO and $PM_{2.5}$ concentrations and were not statistically different in 2020 compared to 2017-2019 concentrations, including at the region's near-road monitor. This suggests that the concentrations of these pollutants were not substantially impacted by the reduction in VMT or average emission rates that occurred within this timeframe.
- PM_{10} concentrations were substantially higher in 2020 compared to 2017-2019 levels, but this appears to be related to large-scale weather conditions rather than any behavior change related to COVID-19 or any other local increase in emissions.

3.1 Air Pollution Monitoring Data

The following table summarizes air pollution monitoring data from the region in terms comparable to EPA's NAAQS.[10]

Table 4-1. Summary of Comparison of 2020 Air Pollution Levels to 2017-2019 Levels

Pollutant	CAMS	Statistic	Units	2017-2019 Avg.	95 % Confidence Interval (+/-)	2020	2020 Outside of Confidence Interval?
CO	1068	1-Hour Avg., 2nd-highest	ppm	2.2	0.1	2.2	No
CO	1068	8-Hour Avg., 2nd highest	ppm	1.5	0.3	1.6	No
NO_2	1068	1-Hour Avg., 98th percentile	ppb	45.9	1.0	43.0	Lower
NO_2	1068	Annual mean	ppb	12.6	0.6	11.6	Lower
O_3	38	8-Hour Avg., 4th-highest daily	ppb	66.7	4.0	63	No
O_3	614	8-Hour Avg., 4th-highest daily	ppb	66.7	2.8	66	No
O_3	690	8-Hour Avg., 4th-highest daily	ppb	68.7	1.7	64	Lower
O_3	1604	8-Hour Avg., 4th-highest daily	ppb	64.7	3.6	59	Lower
O_3	1675	8-Hour Avg., 4th-highest daily	ppb	66.7	7.2	62	No
$PM_{2.5}$	171	24-Hour Avg., 98th percentile	$\mu g/m^3$	22.9	2.2	23.0	No
$PM_{2.5}$	1068	24-Hour Avg., 98th percentile	$\mu g/m^3$	22.3	1.2	22.5	No
$PM_{2.5}$	171	Annual mean	$\mu g/m^3$	9.8	0.4	9.5	No
$PM_{2.5}$	1068	Annual mean	$\mu g/m^3$	9.3	0.2	9.4	No
PM_{10}	38	24-Hour Avg., 2nd-highest	$\mu g/m^3$	48.0	33.3	81	No
PM_{10}	171	24-Hour Avg., 2nd-highest	$\mu g/m^3$	41.3	5.6	91	Higher

The following sub-sections provide more detailed analyses of each pollutant.

[10] https://www.epa.gov/criteria-air-pollutants/naaqs-table

3.1.1 Carbon Monoxide

The region's only CO monitor is at CAMS 1068, which is the "near-road" monitor located along IH-35 just north of the interchange with US-183. The first figure shows peak 8-hour CO concentrations, while the 2nd figure shows peak 1-hour concentrations. The bar for the 2017-2019 represents a 95% confidence interval given the 2017, 2018, and 2019 data.

Figure 3-1. 2nd-Highest 8-hour CO (ppm)

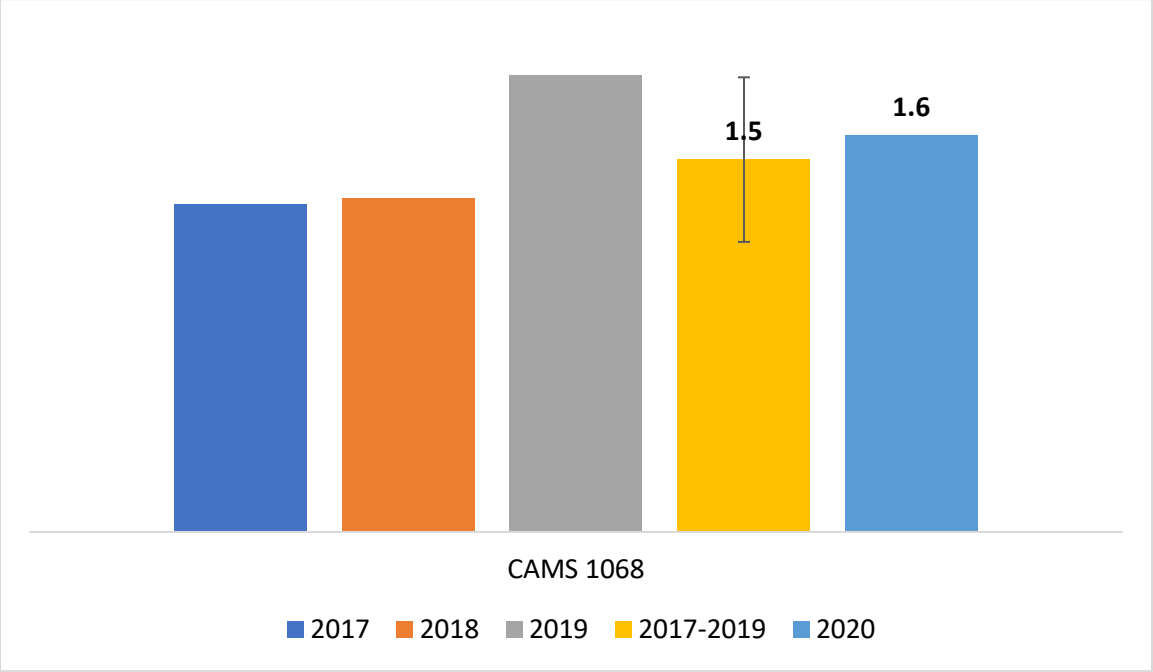
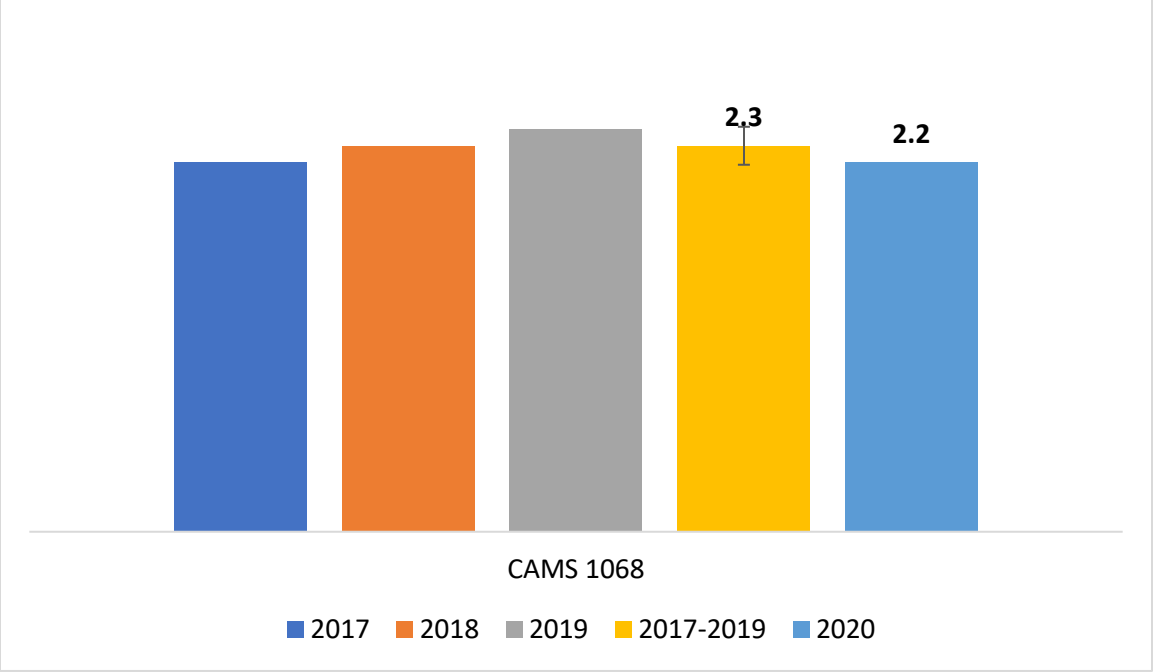


Figure 3-2. 2nd-Highest 1-hour CO (ppm)

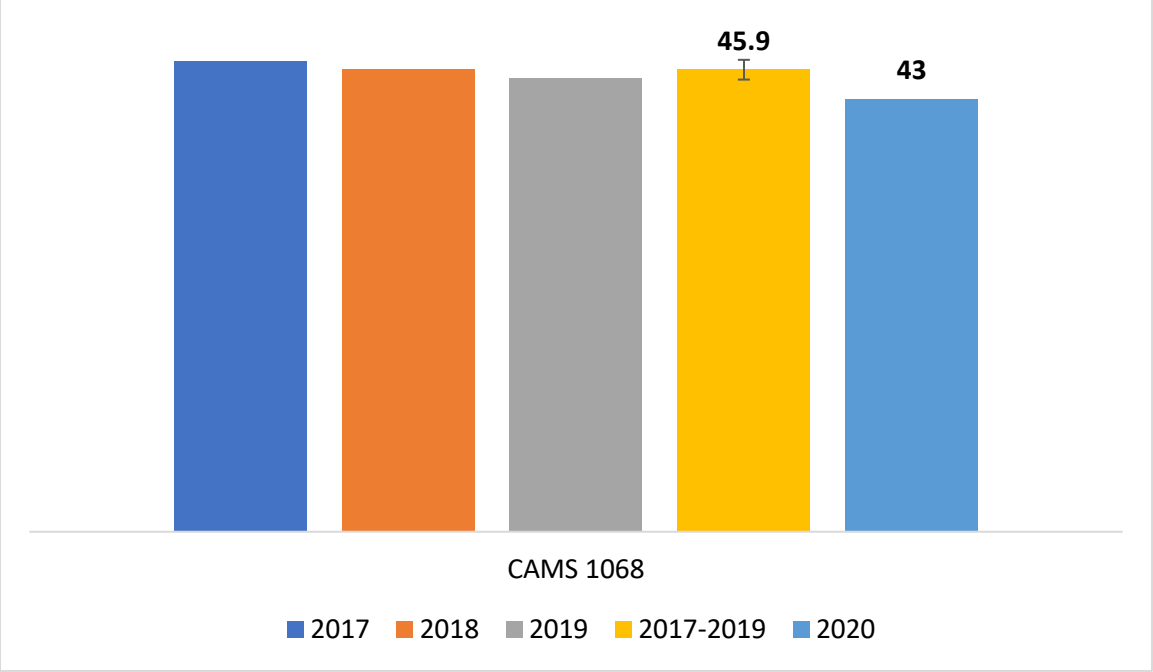


These data show higher peak 8-hour concentrations but lower 1-hour concentrations, but concentrations within the 95% confidence interval for 2017-2019 in any event. For context, the 8-hour CO NAAQS is 9 ppm and the 1-hour NAAQS is 35 ppm. As will be discussed later, there are no readily available explanations for the lack of much difference in the CO concentrations despite large decreases in vehicle activity since vehicles account for more than ½ of the region's CO emissions.

3.1.2 Nitrogen Dioxide

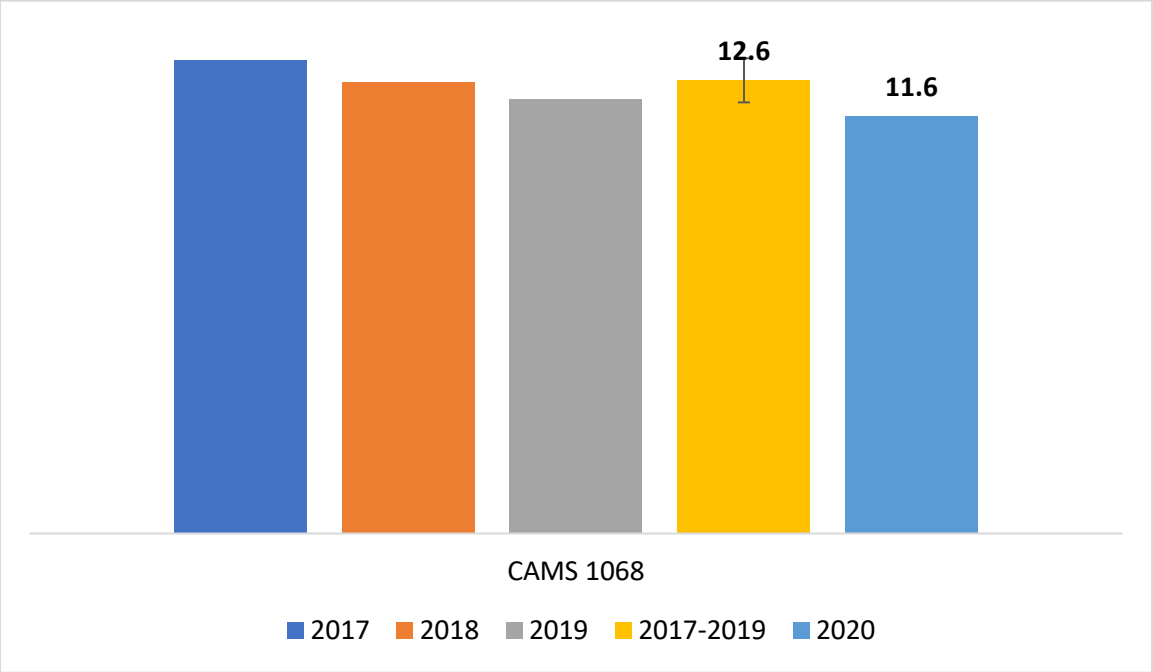
The region's only NO_2 monitor in operation throughout all of 2020 was also at CAMS 1068. The first figure shows peak 1-hour CO concentrations, while the 2nd figure shows annual average concentrations.

Figure 3-3. 98th Percentile of Daily 1-Hour NO_2 (ppb)



The 98th percentile of daily maximum 1-hour NO_2 concentration in 2020 was 2.9 ppb lower than the 2017-2019 average, a 6% reduction, and statistically lower than the 95% confidence interval.

Figure 3-4. Annual Mean NO_2 (ppb)



The annual mean NO_2 concentration in 2020 was 1 ppb lower than the 2017-2019 average, a 8% reduction, and statistically lower than the 95% confidence interval.

These results are consistent with the analysis CAPCOG conducted in April 2020, when average near-road concentrations of NO_2 in the last two weeks of March 2020 were 35% lower than average concentrations during the same two weeks from the prior 3 years, but vehicle activity was also at or beyond 50% lower as well, versus 18% on an annual basis.

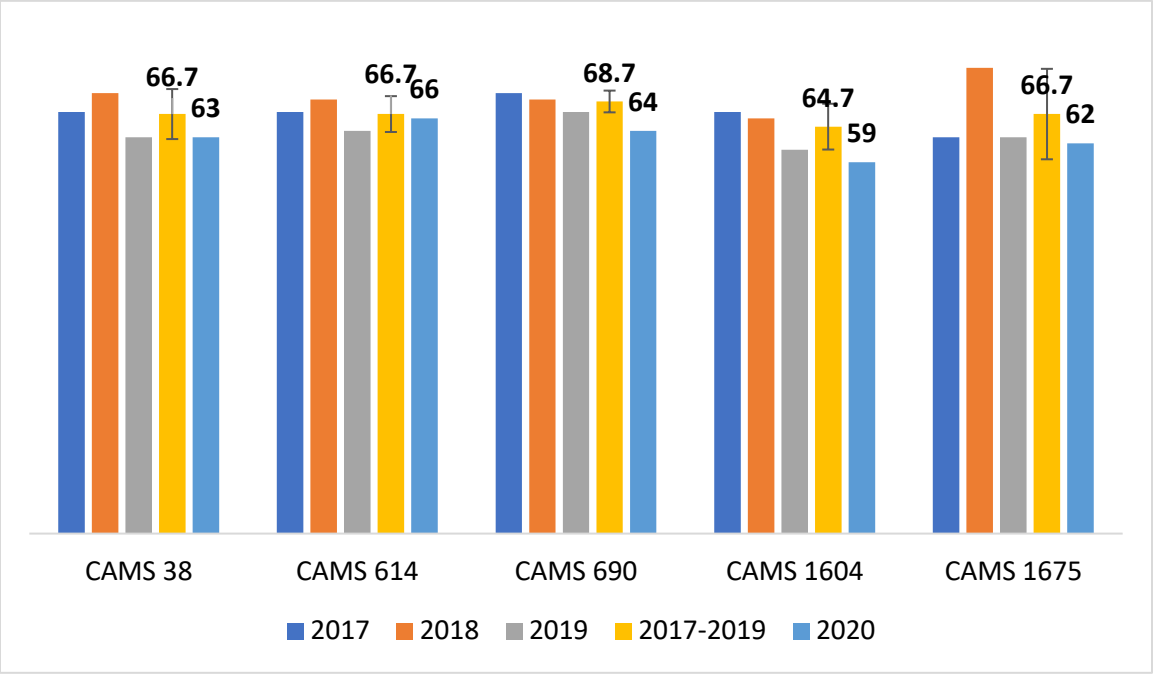
The 1-hour NAAQS is 100 ppb and the annual NAAQS is 53 ppb, so overall levels were well below the maximum allowable even before the pandemic.

3.1.3 Ozone

O_3 has long been the main focus of regional air pollution planning efforts due to how close the region has been to violating the O_3 NAAQS. The region's 2017-2019 O_3 design value was 69 parts per billion (ppb), which was just narrowly in compliance with the 70 ppb O_3 NAAQS. Since the monitor that has tended to show the highest O3 concentrations (CAMS 3) was shut down for almost all of 2020 due to the need for TCEQ to relocate it to accommodate construction on the property by its owners, comparisons of 2020 data to 2017-2019 for this monitor are not useful. However, TCEQ's other regional O_3 monitor (CAMS 38 in northwest Travis County) has data for all four years, and CAPCOG has an additional four monitors that collected data for all four of these years (another four monitors have been relocated within this timeframe). CAMS 614 is located in Dripping Springs, CAMS 690 is located in Georgetown, CAMS 1604 is located in Lockhart, and CAMS 1675 is located in San Marcos.

A comparison of the 4th-highest maximum daily 8-hour O_3 concentration at each monitoring station is shown at each station in the figure below.

Figure 3-5. 4th Highest Maximum 8-Hour O_3 2017-2020 by Site (ppb)



This analysis shows lower O_3 levels in 2020 at all monitoring stations compared to 2017-2019. 2020 MDA8 O_3 values were 0.7 – 5.7 ppb lower than the 2017-2019 averages. For CAMS 690 (Lake Georgetown) and CAMS 1604 (Lockhart), these changes represented statistically significantly lower

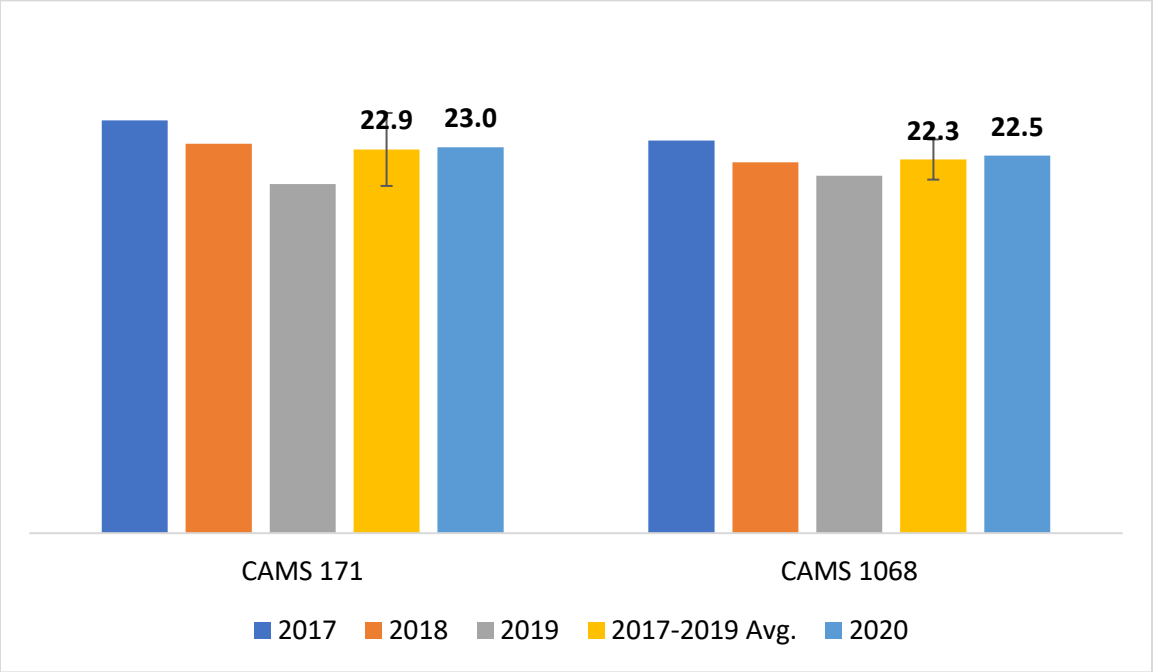
MDA8 O_3 at a 95% confidence level. The average difference between 2017-2019 averages and 2020 across all five sites was 3.9 ppb.

3.1.4 Particulate Matter

There are three monitoring stations in the region that collected particulate matter (PM) data from 2017-2020: CAMS 38, CAMS 171 in East Austin and CAMS 1068, the near-road monitor that also collects CO and NO_2 data. CAMS 171 collects data on both particles smaller than 10 micrometers in diameter (PM_{10}) and particles smaller than 2.5 micrometers in diameter ($PM_{2.5}$), while CAMS 1068 only collects $PM_{2.5}$ data and CAMS 38 only collects PM_{10} data.

The following figure shows an analysis of 24-hour $PM_{2.5}$ concentrations.

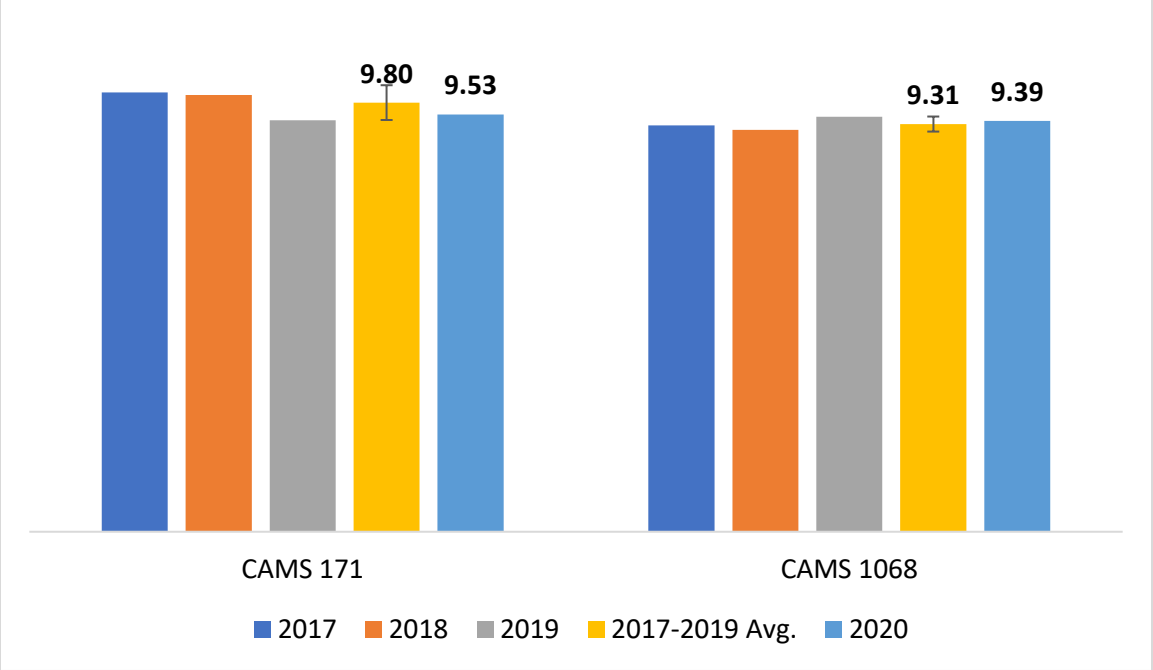
Figure 3-6. 98th Percentile 24-Hour $PM_{2.5}$ Average 2017-2020 by Site (µg/m³)



As the figure above shows, the 98th percentile of 24-hour $PM_{2.5}$ concentrations at CAMS 171 and CAMS 1068 were both slightly higher than the three-year average for 2017-2019: 0.2 µg/m³ at CAMS 1068 (the near-road monitor located along IH-35) and 0.1 µg/m³ for CAMS 171 (Austin Webberville Rd.), both of which were well within a 95th percent confidence interval for the 2017-2019 data.

The following figure shows a comparison of annual $PM_{2.5}$ concentrations.

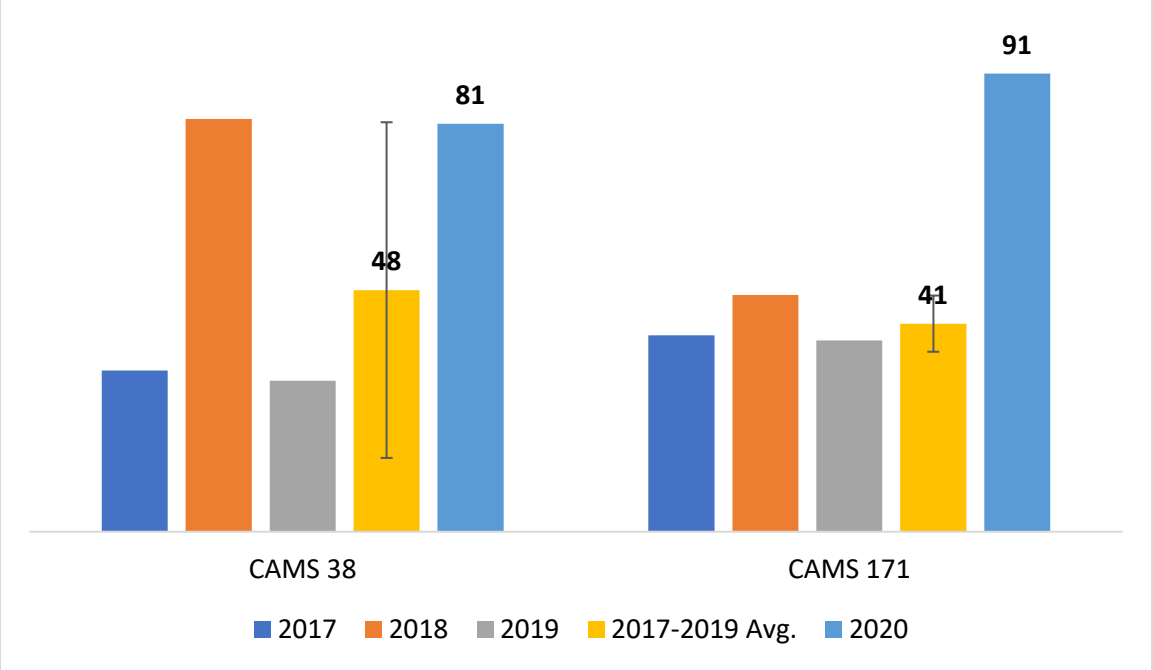
Figure 3-7. Annual Mean $PM_{2.5}$ Average 2017-2020 by Site (µg/m³)



The 2020 annual mean $PM_{2.5}$ concentration at CAMS 171 was 0.27 µg/m³ lower than the 2017-2019 average at CAMS 171, but the 2020 mean was 0.08 µg/m³ higher at CAMS 1068. Both of these values were within the confidence interval for the 2017-2019 data.

The following figure shows an analysis of PM_{10} concentrations.

Figure 3-8. 2nd-Highest 24-hour PM_{10} Concentrations 2017-2020 by Site (µg/m³)



Uniquely among the pollutants monitored within the region, PM_{10} is monitored using 24-hour samples collected once every six days, meaning there were only 61 samples collected in all of 2020, versus thousand of hourly samples for all of the other pollutants. Since compliance with the PM_{10} NAAQS is based an area's 2nd-worst day staying at or below 150 µg/m³, it is also very susceptible to extreme swings, as can be seen in the data for CAMS 38.

CAPCOG reviewed the dates PM_{10} concentrations exceeded 50 µg/m³ at each monitoring station in 2020 and compared them to TCEQ's air quality forecast for those days to determine whether any large-scale weather conditions coincided with these events.

- June 26, 2020: (63 µg/m³ at CAMS 171, 51 µg/m³ at CAMS 38): "Heavy amounts of African dust will continue to expand across most of the state… The associated PM10 AQI due to the African dust could also reach the upper end of the "Moderate" range or possibly higher in parts of the Austin [area]"
- July 2, 2020: (91 µg/m³ at CAMS 171, 81 µg/m³ at CAMS 38): "Moderate to heavy amounts of African dust will continue from the slightly more intense dust cloud on Wednesday… The associated PM10 AQI due to the African dust could also reach the…lower end of the "Moderate" range in parts of the Austin [area]."
- July 8, 2020: (53 µg/m³ at CAMS 171, 45 µg/m³ at CAMS 38): "Light to moderate amounts of African dust associated with the arrival of a new slightly more intense dust cloud will spread into the state to cover portions of the eastern half of the state generally along and east of a Del Rio to Wichita Falls line… The associated PM10 AQI due to the African dust could also possibly reach …the upper end of the "Good" range (perhaps with an isolated low "Moderate" or two) in parts of the Austin [area]"

- October 12, 2020: (98 µg/m^3 at CAMS 171, 89 µg/m^3 at CAMS 38): "Suspended blowing dust generated the previous night over the Texas Panhandle through the Permian Basin could be transported South along the leading edge of the advancing cold front into portions of Central and North Central Texas. The intensity and duration of the possible blowing dust however is not expected to be enough to raise the daily PM10 AQI beyond the "Good" range throughout most of the impacted regions, which primarily includes parts of the Dallas-Fort Worth, Midland-Odessa, and Waco-Killeen areas."

Based on this review of the data and the associated weather conditions, CAPCOG does not believe the elevated PM_{10} concentrations observed in 2020 were related to any behavior change connected to COVID-19, but rather true outliers associated with specific large-scale meteorological events.

3.2 Analysis of Meteorological Data

One of the potential explanations for changes in ambient air pollution concentrations year to year is differences in meteorology. Generally, the following factors are associated with lower ground-level O_3 concentrations:

- Higher wind speeds
- Lower temperatures
- Higher relative humidity
- Lower solar radiation

CAPCOG used data from CAMS 38 in Northwest Travis County for wind speed, temperature, and solar radiation. Since CAMS 38 lacks relative humidity data, CAPCOG used relative humidity data from CAMS 5002 (Camp Mabry).

CAPCOG's analysis of meteorological data collected from within the region from 2017-2020 suggests that the reduced O_3 concentrations observed in 2020 relative to 2017-2019 would not be explainable by any of these factors.

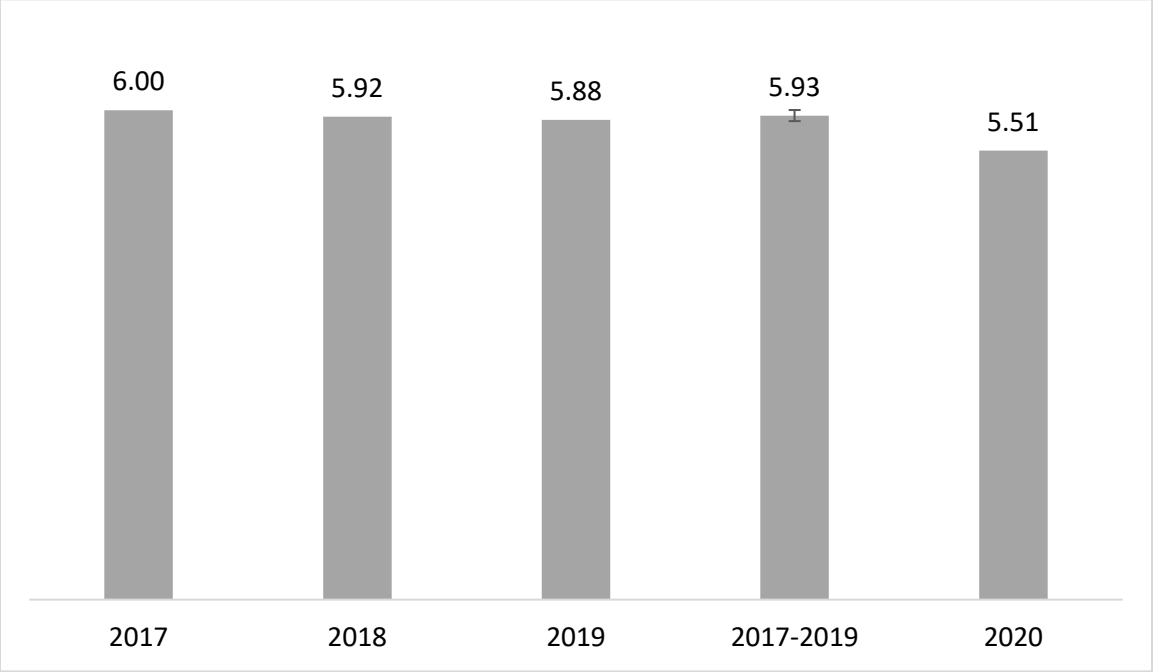
- There were not statistically significant differences in average temperature or average solar radiation.
- There were differences in the overall distribution of relative humidity, but average relative humidity was not statistically different. 2020 had fewer hours with humidity below 50% and above 90%, and more hours in the 70-90% range. There was no significant difference in the number of hours in the 50-70% range. Since the highest O_3 concentrations tend to occur when humidity is at its lowest, the reduction in the number of hours at the lower end of the scale would actually lead to higher O_3 concentrations, which is contrary to what was observed. This suggests that O_3 levels might have dropped further from 2017-2019 concentrations if humidity levels had remained comparable.
- There were statistically significant differences in average wind speeds, with lower average wind speeds in 2020 relative to 2017-2019. This suggests that O_3 levels would have fallen more from 2017-2019 concentrations if wind speed had been comparable.

3.2.1 Wind Speed

For O_3, lower wind speed is generally associated with higher peak air pollution concentrations. This is because emissions continue to add to the concentrations of the same mass of air for a longer period of time under slower wind conditions. If wind speeds in 2020 tended to be higher than they had been in 2017-2019, that would be one potential explanation for the lower O_3. CAPCOG analyzed wind speed in two ways: 1) CAPCOG calculated the average hourly wind speed at CAMS 38 for all hours available in 2020 and compared it to the 3-year average for 2017-2019, and 2) CAPCOG calculated the percentage of hourly averages that fell into four bins: < 5 miles per hour (mph), 5-10 mph, 10-15 mph, and 15+ mph.

The following figure shows a comparison of the average hourly wind speed for each year, as well as the 2017-2019 average.

Figure 3-9. Comparison of 2020 Avg. Hourly Wind Speed to 2017-2019 Avg. Hourly Wind Speeds (miles per hour)



Average wind speeds were statistically significantly lower in 2020 than the averages for 2017-2019, which would have tended to cause pollution levels to be higher.

The following table shows the analysis of the distribution of hourly wind speed data into the four speed bins, along with whether the 2020 data was outside of the confidence interval for the 2017-2019 data.

Table 4-2. Analysis of Distribution of Average Hourly Wind Speeds 2017-2020

Avg. Wind Speed (mph)	% of Hourly Observations, 2017-2019	% of Hourly Observations, 2020	2020 Relative to 2017-2019 95% Confidence Interval
<5	39.08%	43.03%	High
5 – 10	54.53%	52.04%	Low
10 – 15	6.17%	4.86%	Low
≥ 15	0.23%	0.08%	Within

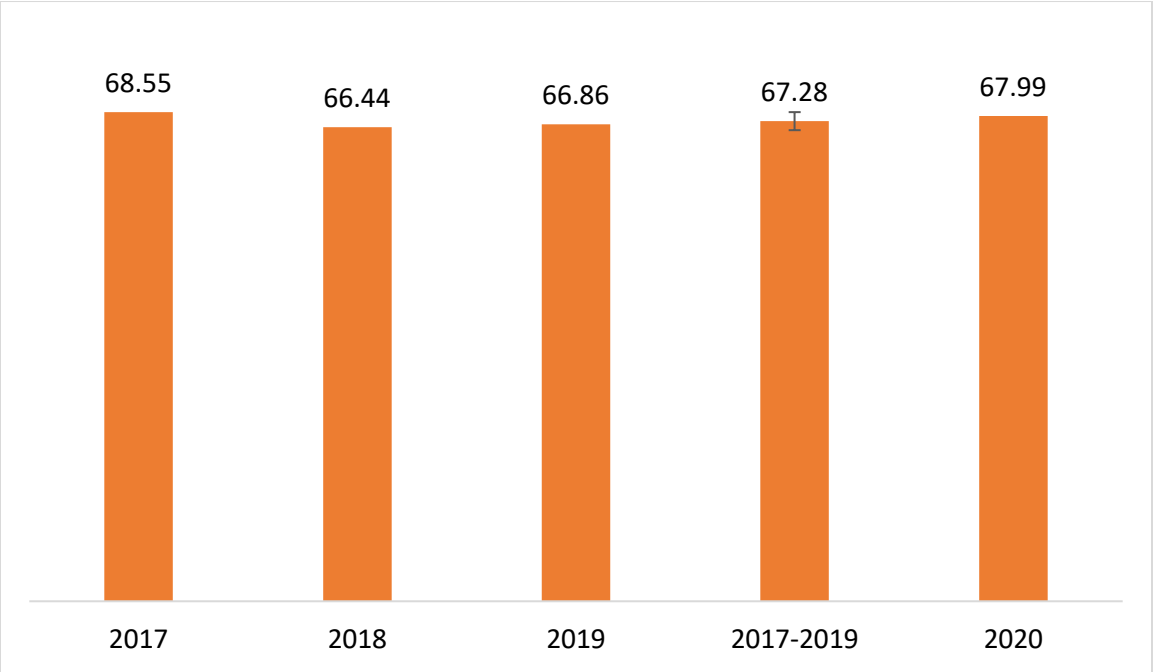
These data show that to the extent there were differences between 2020 wind speeds and 2017-2019 wind speeds, there were more days with low wind speeds, which would have been conductive to higher pollution concentrations.

3.2.2 Temperature

Higher temperatures are generally associated with higher peak O_3 air pollution concentrations. CAPCOG analyzed temperature in two ways: 1) CAPCOG calculated the average temperature at CAMS 38 for all hours available in 2020 and compared it to the 3-year average for 2017-2019, and 2) CAPCOG calculated the percentage of hourly averages that fell into 10-degree Fahrenheit bins ranging from 30 degrees to 90 degrees.

The following figure shows a comparison of the average hourly temperatures.

Figure 3-10. Comparison of 2020 Avg. Hourly Temperature to 2017-2019 Avg. Hourly Temperatures (F)



The average hourly temperature for 2020 was within the range of the 95% confidence interval for the 2017-2019 average.

The following table shows the analysis of the distribution of hourly temperature data into ten-degree bins.

Table 4-3. Analysis of Distribution of Average Hourly Temperature 2017-2020

Avg. Temperature (F)	% of Hourly Observations, 2017-2019	% of Hourly Observations, 2020	2020 Relative to 2017-2019 95% Confidence Interval
<30	0.96%	0.08%	Low
30-40	4.18%	3.10%	Within
40-50	10.84%	10.20%	Within
50-60	15.19%	15.03%	Within

60-70	19.90%	23.03%	Within
70-80	28.01%	27.44%	Within
80-90	14.78%	15.18%	Within
90+	6.14%	5.96%	Within

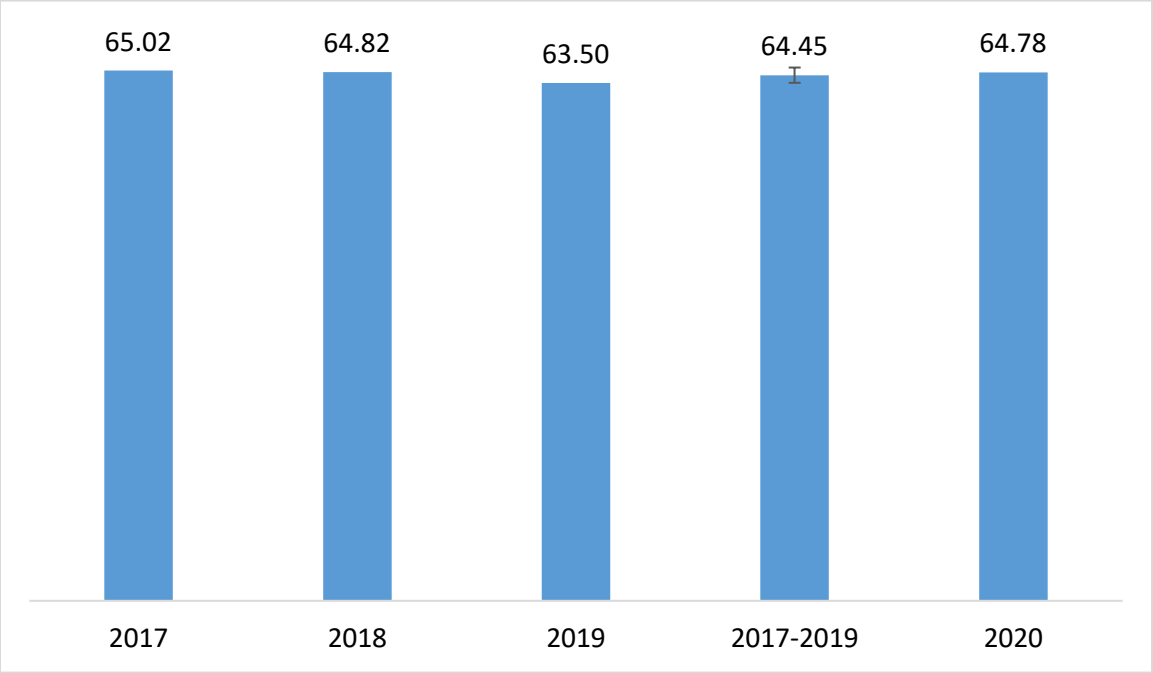
These data suggest that 2020 temperatures were consistent with what was observed in 2017-2019 and would not likely have contributed to pollution levels being either higher or lower than observed 2017-2019. The very low number of observations at below 30 degrees do not coincide with "ozone season," and the difference at that range would not explain the reduction in O3 pollution levels observed in 2020 relative to 2017-2019.

3.2.3 Relative Humidity

Lower relative humidity is generally associated with higher peak O_3 air pollution concentrations. CAPCOG analyzed relative humidity in two ways: 1) calculation of average relative humidity at CAMS 5002 for all hours available in 2020 and compared it to the 3-year average for 2017-2019, and 2) CAPCOG calculated the percentage of hourly averages that fell into each 10% bin.

The following figure shows a comparison of the average relative humidity levels for each year.

Figure 3-11. Comparison of 2020 Avg. Hourly Relative Humidity to 2017-2019 (%)



Average hourly relative humidity in 2020 was within the 95% confidence interval for 2017-2019, and was therefore not statistically significantly different.

The following table shows the analysis of the distribution of hourly relative huidity

Table 4-4. Analysis of Distribution of Average Hourly Relative Humidity 2017-2020

Avg. Relative Humidity	% of Hourly Observations, 2017-2019	% of Hourly Observations, 2020	2020 Relative to 2017-2019 95% Confidence Interval
<10%	0.0%	0.0%	Within
10%-20%	0.8%	1.3%	High
20%-30%	5.2%	4.5%	Low
30%-40%	10.1%	7.8%	Low
40%-50%	11.4%	11.5%	Within
50%-60%	13.2%	13.6%	Within
60%-70%	13.5%	13.5%	Within
70%-80%	15.9%	19.7%	High
80%-90%	20.1%	21.4%	High
90+%	9.9%	6.7%	Low

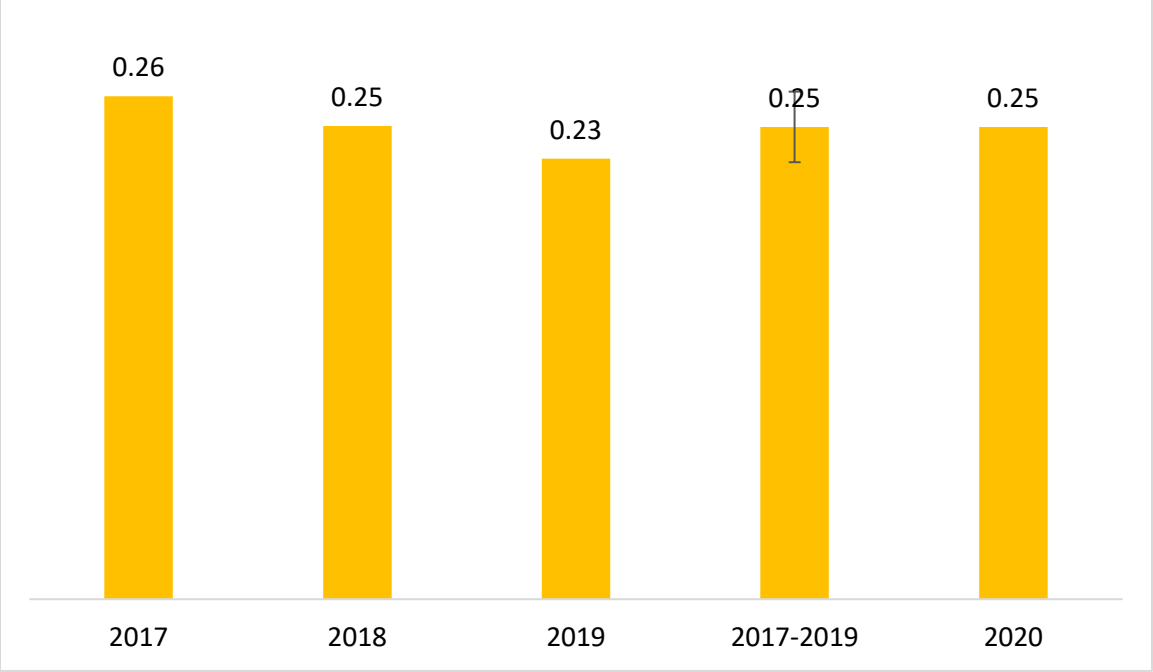
These data provide amore mixed picture, but broadly, there were statistically significantly fewer observations when relative humidity was below 50% and above 90% and more observations in the 70-90% range. In general, this smaller number of hours when relative humidity was low would be expected to lead to higher O_3 levels in 2020 than in prior years.

3.2.4 Solar Radiation

O_3 is "photochemically" generated when NO_X and VOC react in the presence of sunlight, so higher average solar radiation leads to higher O_3 concentrations. As with the other meteorological analyses, CAPCOG analyzes average solar radiation for each year and analyzed the distribution of hourly observations into several "bins" to gain additional insight into the extent to which meteorology in 2020 may have differed from meteorology 2017-2019.

The following figure shows a comparison of the average hourly wind speed for each year, as well as the 2017-2019 average.

Figure 3-12. Comparison of 2020 Avg. Hourly Solar Radiation to 2017-2019 Avg. Hourly Temperatures (langleys/m²)



This analysis did not show any statistically significant difference in solar radiation.

The following table shows the analysis of the distribution of hourly solar radiation observations.

Table 4-5. Analysis of Distribution of Average Hourly Solar Radiation 2017-2020

Avg. Solar Radiation (langleys/m²)	% of Hourly Observations, 2017-2019	% of Hourly Observations, 2020	2020 Relative to 2017-2019 95% Confidence Interval
0 – 0.25	68.2%	68.5%	Within
0.25 – 0.50	9.3%	9.0%	Within
0.50 – 0.75	8.2%	8.5%	Within
0.75 – 1.00	8.0%	8.3%	Within
1.00 – 1.25	4.9%	3.8%	Within
1.25 – 1.50	1.4%	1.9%	Within

This analysis also does not show any difference in solar radiation in 2020 compared to 2017-2019.

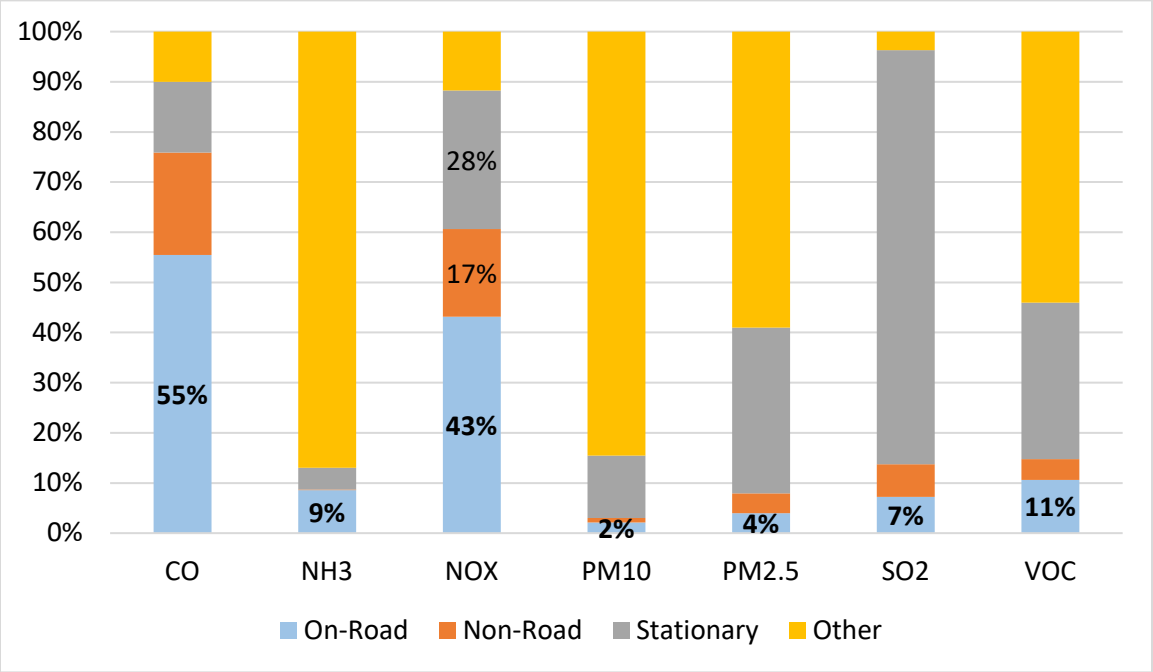
3.3 Analysis of Other Emissions Sources

While this study's focus is on on-road emissions, it is necessary to evaluate the extent to which on-road emissions contribute to overall emissions within the region and whether there were any significant changes in emissions from other source types from 2017-2019. This section shows the share of criteria pollutant emissions attributable to each source type and 2020 emissions data on point sources and non-road mobile sources compared to 2017-2019 emissions for context.

3.3.1 On-Road Emissions as a Share of Total Emissions

In order to properly understand the extent to which changes in transportation behavior can influence ambient air concentrations, it is important to understand how much on-road emissions contribute to total emissions within the region. Data from the 2017 National Emissions Inventory (NEI) shows that on-road sources contributed between 2% and 55% of total emissions of all criteria pollutants, depending on the pollutant. Non-road sources like construction equipment, tractors, lawn equipment, and trains accounted for 1% - 20% of total emissions, stationary sources accounted for 4% - 83%, and other sources such as biogenic emissions, dust, agriculture, and fires accounted for 4% - 87% of total emissions. The figure below shows the percentages for each pollutant. NO_X emissions are highlighted due the reductions in ambient NO_2 and O_3 concentrations noted earlier in this section.

Figure 3-13. Share of Austin-Round Rock-Georgetown MSA 2017 NEI Emissions Totals by Source Type



3.3.2 Point Source Emissions Data

TCEQ compiles annual point source emissions inventories for the state from annual emissions data reported by facilities that emit more than a minimum threshold of criteria air pollutants or hazardous air pollutants (HAPS). While 2020 data has been reported by the facilities to TCEQ, this data is not yet available from TCEQ, which has to quality-assure/quality-check the data before it is considered finalized. However, data from the 2014-2019 summary file available on TCEQ's website can be helpful in identifying trends. The extent to which certain pollutants may have been trending up or down in recent years may be helpful in assessing the extent to which 2020 point source emissions were likely to be higher or lower than they were in 2017, 2018, and 2019. The following table summarizes the 2014-2019 data, along with the trend coefficient (i.e., the tons per year of the pollutant that emissions would be expected to be increasing or decreasing), along with the trendline "goodness of fit" statistic (R^2), which ranges from 0 (no trendline) to 1 (perfect trendline).

Table 4-6. Austin-Round Rock-Georgetown MSA Point Source Emissions 2014-2019 and Trendline Analysis (tpy)

Pollutant	2014	2015	2016	2017	2018	2019	Trend	Trendline R^2
CO	5,672	5,532	5,737	5,729	5,943	5,953	+75	0.75
NO_X	5,081	5,271	5,319	4,810	5,375	5,670	+79	0.26
PM_{10}	953	1,017	958	980	890	892	-19	0.51
$PM_{2.5}$	538	597	568	527	528	509	-11	0.43
SO_2	2,032	1,789	1,846	1,918	1,756	1,743	-42	0.50
VOC	730	805	841	744	770	819	+7	0.09

This analysis shows show small positive trends in CO, NO_X, and VOC emissions from point sources, with small negative trends in PM_{10}, $PM_{2.5}$, and SO_2. The low R^2 values and coefficients for the trends in NO_X and VOC means do not provide much of a basis for making a 2020 projection. Therefore, notwithstanding other data, reductions in 2020 point source emissions of these pollutants relative to 2017-2019 data would not be expected.

For the 2019 point source inventory, the emissions by industrial sector are summarized below.

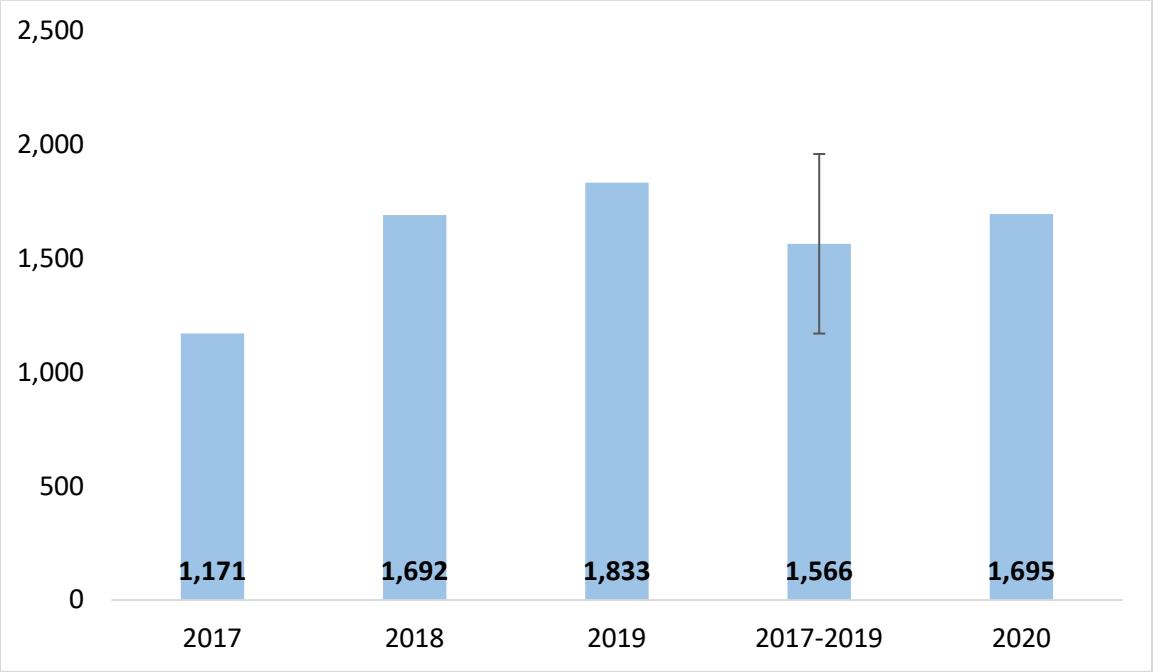
Table 4-7. 2019 Point Source Emissions by Industry

SIC Code	Description	CO	NO_X	Pb	PM_{10}	$PM_{2.5}$	SO_2	VOC
2951	PAVING MIXTURES AND BLOCKS	0.23%	0.05%	0.00%	0.28%	0.06%	0.02%	0.62%
3241	CEMENT, HYDRAULIC	59.09%	38.43%	34.17%	37.24%	28.73%	83.95%	22.00%
3251	BRICK AND STRUCTURAL CLAY TILE	2.20%	0.76%	33.33%	7.87%	1.90%	7.20%	0.85%
3274	LIME	1.46%	8.90%	0.00%	8.87%	6.68%	0.08%	0.69%
3674	SEMICONDUCTORS AND RELATED DEVICES	1.37%	2.28%	0.00%	6.94%	0.81%	0.12%	16.28%
3821	LABORATORY APPARATUS AND FURNITURE	0.03%	0.04%	0.00%	0.67%	1.13%	0.00%	1.50%
4619	PIPELINES, NEC	0.39%	0.67%	0.00%	0.19%	0.33%	0.01%	0.85%
4911	ELECTRIC SERVICES	26.13%	38.76%	32.50%	26.00%	44.81%	1.59%	23.55%
4922	NATURAL GAS TRANSMISSION	2.02%	8.14%	0.00%	2.83%	4.96%	0.02%	9.24%
4953	REFUSE SYSTEMS	7.00%	1.59%	0.00%	8.87%	10.17%	7.00%	12.49%
5171	PETROLEUM BULK STATIONS & TERMINALS	0.09%	0.04%	0.00%	0.01%	0.01%	0.00%	9.62%
8731	COMMERCIAL PHYSICAL AND BIOLOGICAL RESEARCH	0.01%	0.35%	0.00%	0.23%	0.41%	0.01%	0.29%
9999	NONCLASSIFIABLE ESTABLISHMENTS	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.02%

Among the region's point sources, Austin White Lime (which is the only Lime plant in the region), Texas Lehigh Cement Company (which is the only cement plant in the region), and power plants accounted for more than 80% of the CO, NO_X, $PM_{2.5}$, and SO_2 emissions, 72% of the PM_{10} emissions, 67% of the region's lead emissions, and 46% of the region's VOC emissions.

2020 emissions data for NO_X and SO_2 are available from EPA for power plants because they are required to report their hourly emissions data to EPA each quarter as part of the acid rain program and other pollutant trading programs. The following figure shows the 2017-2020 NO_X emissions from regional power plants.[11]

Figure 3-14. Power Plant NO_X Emissions 2017-2020 (tpy)

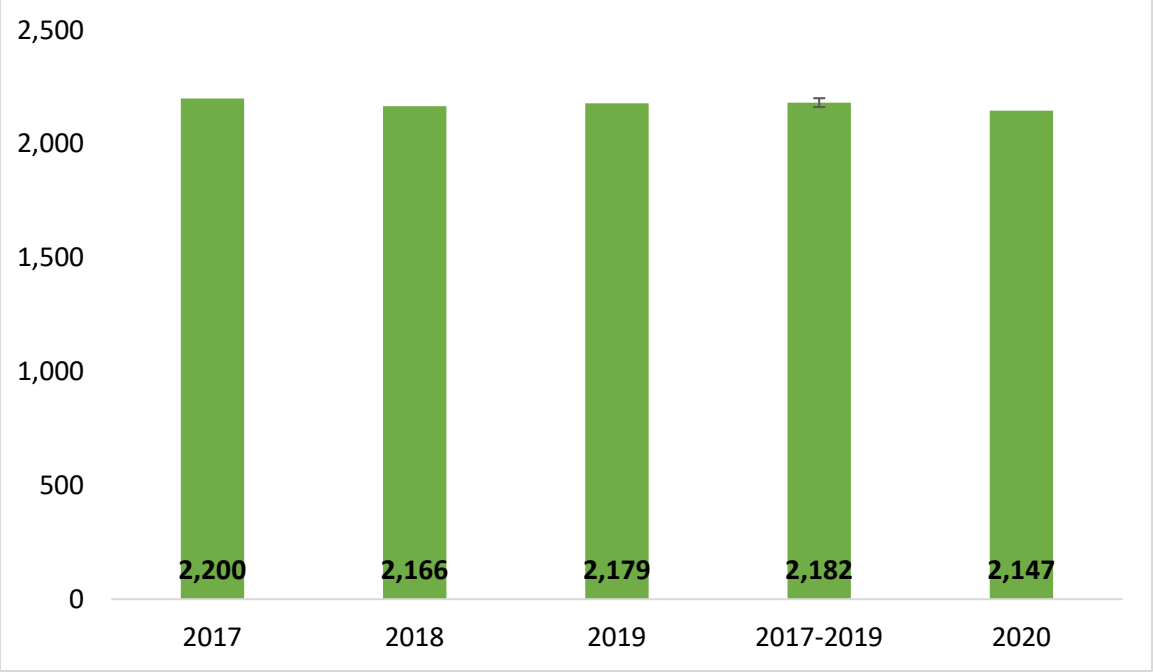


These data show that power plant NO_X emissions were about 8% higher in 2020 than they averaged for 2017-2019. This increase in emissions would have led to higher, rather than lower, O_3 and NO_2 concentrations, all else being equal.

While TCEQ's 2020 point source summary file is not yet available, Texas Lehigh and Austin White Lime provided the data from their submission to CAPCOG. The following tables compare these facilities' 2020 emissions to emissions reported for 2017-2019.

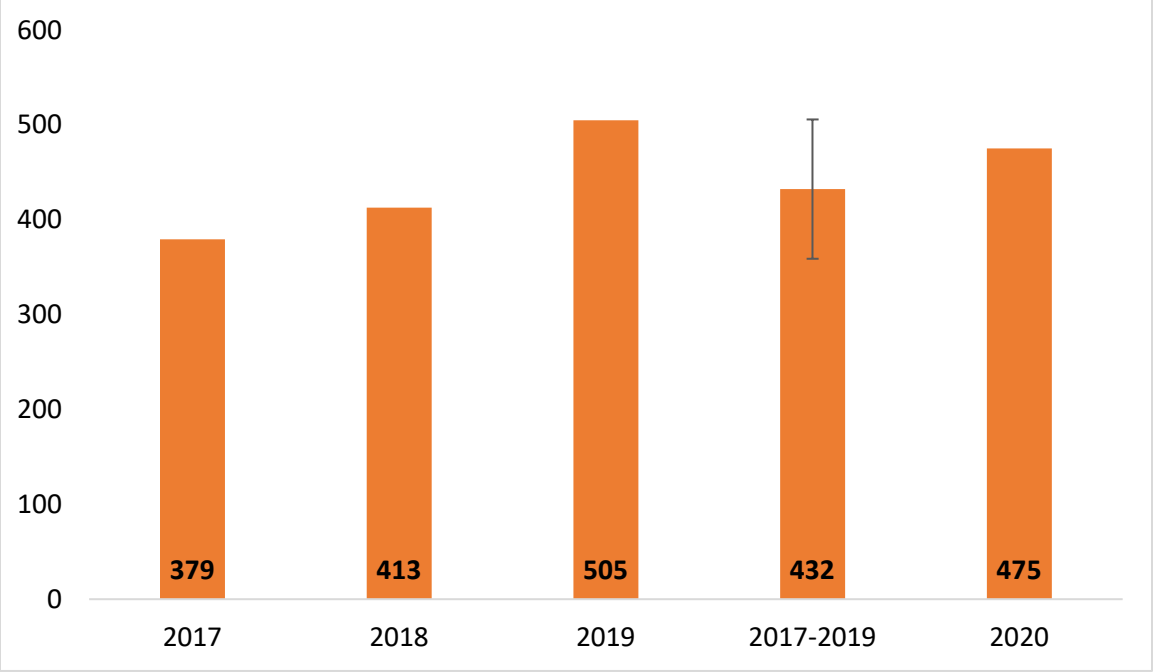
[11] CAPCOG excluded emissions data from the turbine units at Decker Creek power plant from this analysis due to a significant difference between the emissions data that Austin Energy reports to TCEQ and the "worst case scenario" emissions rates that Austin Energy is required to use for reporting to EPA that are about five times higher than the emissions reported to TCEQ. The totals in EPA's database for 2014-2020 range from 140 – 356 tpy NO_X, with 2020 having the lowest total at 140 tpy. Actual emissions would have ranged from about 25-75 tpy.

Figure 3-15. Texas Lehigh NO_X Emissions 2017-2020 (tpy)



Texas Lehigh's NO_X emissions in 2020 were 2% below the average for 2017-2019, which was enough that it was outside of the 95% confidence interval. This reduction in NO_X emissions from the region's largest point source certainly could have contributed to O_3 reductions within the region to some extent, but since Texas Lehigh already operates their NO_X controls at maximum efficiency on predicted high O3 days, it is unlikely that this 2% reduction in annual NO_X emissions would have meant a comparable reduction in hourly NO_X emissions on high-O_3 days during the key period from 9 am – 3 pm when they implement this control measure.

Figure 3-16. Austin White Lime NO_X Emissions 2017-2020 (tpy)



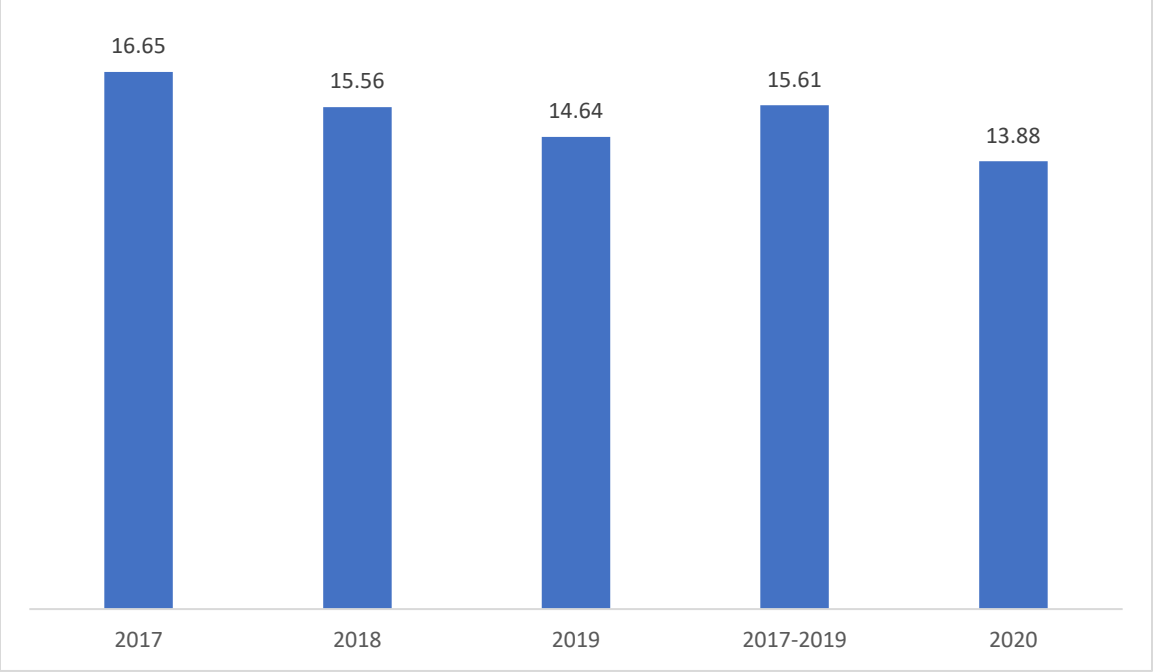
Austin White Lime's NO_X emissions in 2020 were 10% above the average for 2017-2019, but the high degree of year-to-year variation from 2017-2019 meant that this value fell within the 95% confidence interval. Nevertheless, this increase NO_X emissions from a large point source located relatively close to the urban core would have tended to increase rather than decrease O_3 concentrations in 2020 relative to 2017-2019.

CAPCOG's analysis of the region's 2020 point source emissions data compared to 2017-2019 data indicate that NO_X emissions from power plants (+8%) and Austin White Lime (+10%) were higher in 2020 than they were from 2017-2019, although the increases were within the normal year-to-year variation observed across those three years. Nevertheless, these higher NO_X from point sources within the region would tend to lead to higher O_3 and NO_2 concentrations within the region, so to some extent, they may have muted the impact of the decrease in O_3 associated with reduced mobile source emissions.

3.3.3 Non-Road Emissions Data

The "non-road" source category includes a wide range of mobile sources including construction equipment, trains, airplanes, agricultural equipment, lawn and garden equipment, generators, and many others. EPA has established engine exhaust standards for non-road sources that are expected to continue to reduce emissions in the future even as equipment counts are expected to increase. The figure below shows the estimated average O_3 season weekday NO_X emissions from non-road sources from 2017-2020.

Figure 3-17. Non-Road Ozone Season Weekday NO_X Emissions 2017-2020 (tpd)



The 1.73 tpd reduction in non-road NO_X emissions from the 2017-2019 average represents about 25% of the 6.93 tpd in mobile source NO_X reductions expected from 2017-2019 to 2020, with on-road sources accounting for the other 75% under a "business as usual" scenario.

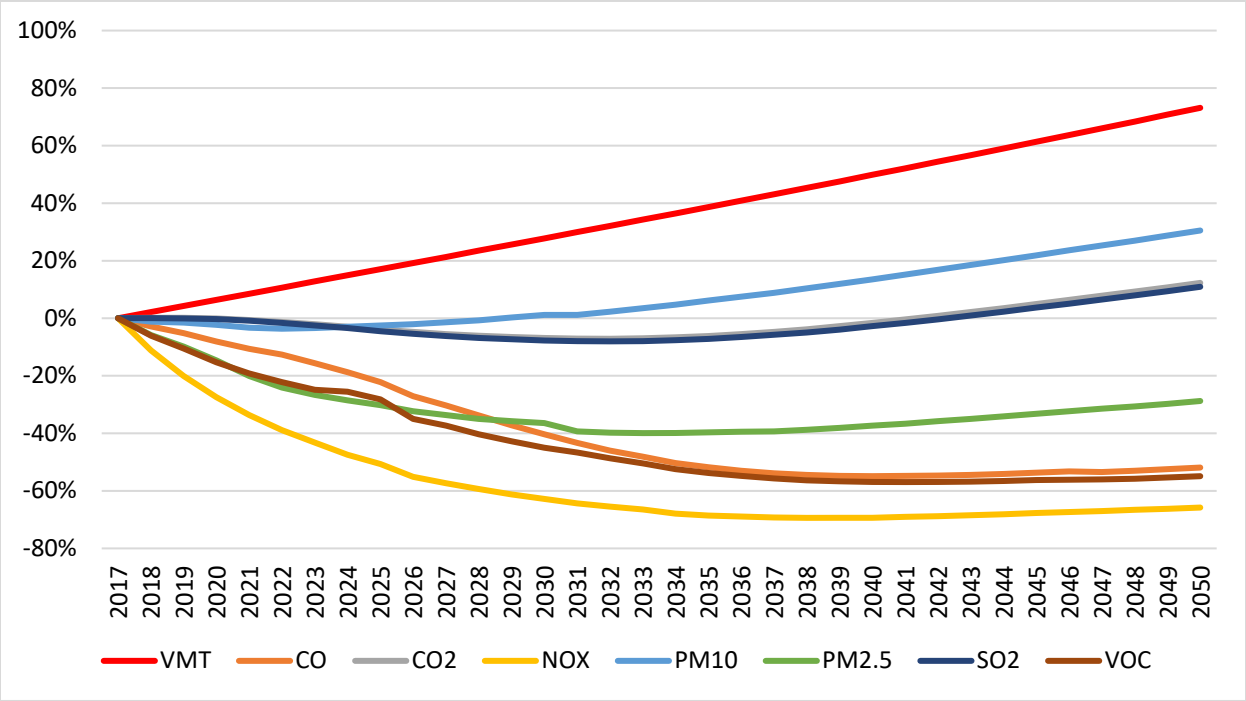
4 Analysis of On-Road Emissions Benefits of Telecommuting

Beyond the preliminary analysis in section 3, CAPCOG conducted a more detailed analysis of the on-road emission benefits from telecommuting that is detailed in this section. One component of this analysis was on-road emissions modeling conducted by the Texas Transportation Institute (TTI), which is included as an appendix to this report.

4.1 Trends in On-Road Emissions

Since this study is concerned with understanding both a retrospective understanding of how regional air quality in 2020 compared to air quality in recent years/air quality in a "business as usual" scenario, and a prospective understanding of how more extensive telecommuting could affect air quality in the future, an analysis of TCEQ's existing "trends" emissions inventories for the region is useful. These inventories were developed in 2015 by TTI to provide emissions estimates for every county in the state for 1990 and 1999-2050. These trends inventories provide both a point of comparison for the retrospective analysis and an estimate of future on-road emissions and emissions rates. The following figure shows VMT and on-road emissions for each year relative to 2017 levels.

Figure 4-1. Projected VMT and On-Road Emissions, 2017-2050



For criteria pollutants, especially NO_X, there are significant reductions that were expected to occur even within the first few years of this time frame. 2020 NO_X emissions were projected to be 27% lower than 2017 NO_X emissions, and 2025 NO_X emissions were projected to be less than half the 2017 totals. These reductions are expected to occur despite the projected increases in VMT because of federal emissions standards. What this means for this study is that significant decreases in criteria air pollution emissions from on-road sources would have been expected to occur anyway from 2017-2019 to 2020 even if there had been an increase in VMT. Except for PM_{10}, which is heavily influenced by brakewear and tirewear, reductions continue to occur all the way into the 2030 to 2040 timeframe, despite the VMT increases, before starting to increase again.

One of the implications of these trends is that the marginal benefit of measures to reduce vehicle activity shrinks over time since each additional vehicle that is taken off the road would have been emitting less per hour or per mile on average than the year before.

4.2 On-Road Emissions by Process

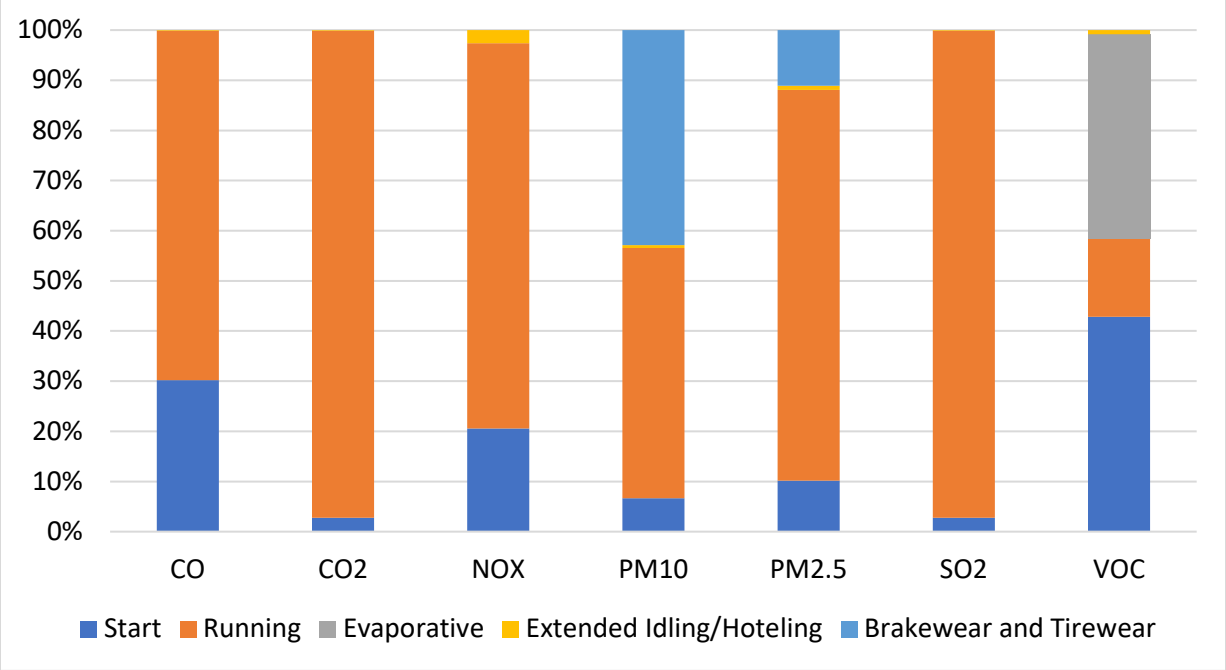
On-road emissions can be broken down into various types of processes, not all of which would be expected to be affected by telecommuting. These include:

- Start exhaust: a fixed amount of emissions that occurs every time a vehicle is started associated with bringing the vehicle from a state of “rest” to operating status;
- Running exhaust: exhaust emissions that are related to the extent of engine use;
- Evaporative emissions: VOC emissions from fuel leakage and gas tank permeation;

- Extended idling/hoteling: only associated with long-haul combination trucks, and reflects overnight use of the truck or auxiliary power to sleep in a truck; and
- Brakewear and tirewear: PM emissions from degradation of brake pads and tires arising from on-road use.

Since extended idling/hoteling activity would not be affected by telecommuting, it was not analyzed for this project. The relationship between evaporative emissions and vehicle use is complex since it is affected by vehicle temperature and how long a vehicle is parked versus in-use. Due to this complexity, CAPCOG did not evaluate potential impacts of telecommuting on evaporative emissions. The following figure shows the share of total on-road emissions by process.

Figure 4-2. Share of on-road emissions by emissions process, 2020



For this analysis, the significant share of emissions attributable to "start" processes is notable because these emissions would be expected to occur regardless of the distance of the trip. To the extent that employers are interested in analyzing the emission reduction benefits of their telecommuting efforts, it useful to separately analyze the extent to which these efforts would reduce start emissions versus VMT/running emissions. In some cases, if employees live close to the office, a majority of the emission reduction benefit could be as a result of the reduction in "start" emissions rather than the reduction in VMT.

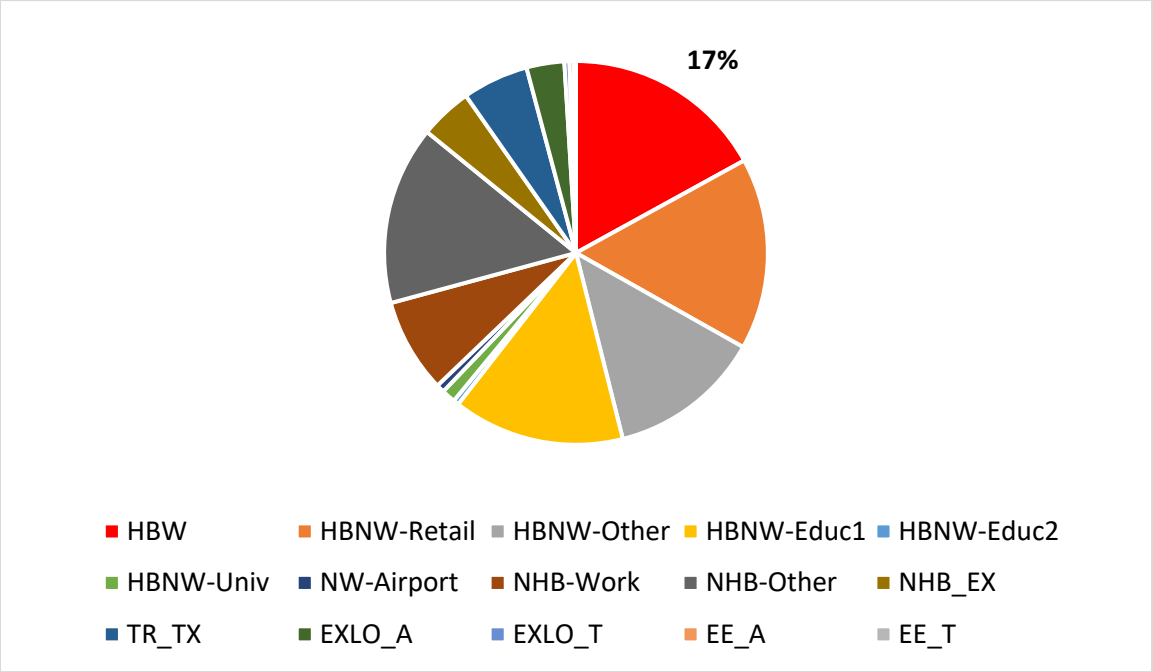
4.3 Estimating Commuting Trips and VMT Using CAMPO's Travel Demand Model Data

The latest travel demand model for the region was developed by the Capital Area Metropolitan Planning Organization (CAMPO), which covers the five-county MSA plus Burnet County with a 2015 base year. The travel demand model estimates the number and length of vehicle trips within the region by trip purpose. Trip types include:

- Home-Based Work (HBW)
- Home-Based Non-Work – Retail (HBNW-Retail)
- Home-Based Non-Work – Other (HBNW-Other)
- Home-Based Non-Work – K-12 education (HBNW-Educ1)
- Home-Based Non-Work – Higher education except for University of Texas (HBNW-Educ2)
- Home-Based Non-Work – University of Texas (HBNW-Univ)
- Non-Work Airport (NW-Airport)
- Non-Home-Based Work (NHB-Work)
- Non-Home-Based Other (NHB-Other)
- Non-Home-Based – External (NHB_EX)
- Truck/Taxi (TR_TX)
- External-Local – Auto (EXLO_A)
- External-Local – Trucks (EXLO_T)
- External-External – Auto (EE_A)
- External-External – Truck (EE_T)

HBW trips represent commuting between a home and a workplace, and they are the primary focus of this study. The following figure shows the percentage of trips from each type.

Figure 4-3. Trips by Type in 2015 Travel Demand Model



"Autos" represent 94.86% of all vehicle trips generated within the region and 95.22% of vehicle miles traveled within the region in CAMPO's travel demand model.

There was a total of 1,341,268 HBW person-trips per day, which CAPCOG calculated translated into 1,226,440 HBW vehicle trips in autos. This represented 26.48% of all auto trips (i.e., excluding trucks), which is higher than its share of person-trips because other types of trips, such as dropping children off at school or going to retail establishments, tend to have a higher number of occupants per trip. These

HBW trips translated into 16,225,801 VMT per day. This represented 38.34% of all auto VMT (42,315,493 VMT per day) and 32.92% of all VMT (49,281,299 VMT per day). This suggests that while a large share of the steep reduction in vehicle activity in March and April 2020 when "stay at home" orders were in effect were attributable to reduced commuting. Additionally, major reductions in other types of trips were likely significant contributors to this reduction in VMT, and those types of trips would not likely be affected (or would not be expected to be much affected) by changes in telecommuting patterns.

For the emissions and photochemical modeling analyses later on this report, CAPCOG evaluated the impact of 10% and 25% reductions in HBW trips on emissions and ambient air pollution concentrations. These changes would represent a reduction in personal vehicle use, which is a smaller universe than "autos," since "autos" include light-duty vehicles used for commercial purposes such as work vans and taxis. Based on data in the 2017 NEI, passenger vehicles (passenger cars (PC) and light-duty passenger trucks (PT) like SUVs) account for 97.54% of all light-duty vehicle trips and 95.97% of all light-duty vehicle VMT. The following table summarizes how the 10% and 25% reductions in HBW trips translated into changes to personal vehicle activity.

Table 5-1. How 10% and 25% reductions in HBW trips affects total passenger vehicle trips and VMT

Metric	10% Reduction in HBW Trips	25% Reduction in HBW Trips
% Change in PC + PT Trips	-2.46%	-6.14%
% Change in PC + PT Trips	-4.03%	-10.06%

This study also involves an analysis of how the reductions in HBW VMT affects the emissions from other vehicles on the road as a result of speed improvements. For this analysis:

- The 10% reduction in HBW trips represented a 3.29% reduction in total VMT region-wide
- The 25% reduction in HBW trips represented a 8.23% reduction in total VMT region-wide

4.4 On-Road Emissions Modeling

CAPCOG contracted with TTI to model the effects the 10% and 25% reductions in HBW trips on on-road emissions in Travis County in 2023. CAPCOG and City of Austin agreed on 2023 as the analysis year since it would be more useful in characterizing the benefits of additional permanent telecommuting in the future, rather than trying to further parse the extent of the benefit in changes to 2020 emissions levels relative to "business as usual" or 2017-2019 levels. The analysis area was limited to Travis County rather than the entire MSA due to resource limitations. However, the analysis should be comparable for other analysis years from a relative perspective (i.e., % reductions) and for the region at large (i.e., ratios for Travis County should be close to what they would have been for the region as a whole).

TTI's report and accompanying spreadsheet are included as appendices to this report. The following table summarizes the emission reductions that TTI estimated for each scenario and how these compare to baseline summer weekday emissions in Travis County in 2023. For the 10% telecommuting scenario, on-road emissions were 1.2% - 4.3% lower, while for the 25% telecommuting scenario, on-road emissions were 3.1% - 11.0% lower.

Table 5-2. Estimated 2023 Travis County On-Road Emission Reductions from 10% and 25% Telecommuting Scenarios

Pollutant	Baseline On-Road Emissions (lbs/day)	Emission Reduction Benefit (lbs/day) – 10% Telecommute	% Benefit-10% Telecommute	Emission Reduction Benefit (lbs/day) – 25% Telecommute	% Benefit-25% Telecommute
CO	221,348	7,459	3.37%	18,623	8.41%
CO_2	30,570,737	959,798	3.14%	2,403,210	7.86%
NH_3	1,676	57	3.42%	142	8.50%
NO_X	18,271	342	1.87%	848	4.64%
PM_{10}	3,613	155	4.28%	397	10.98%
$PM_{2.5}$	952	31	3.30%	80	8.35%
SO_2	199	6	3.19%	16	8.00%
VOC	14,251	177	1.24%	445	3.12%

The following two tables summarize the share of the emission reductions that came from each component of the analysis/process. Note that for NH_3, there was actually a disbenefit from the speed improvements, which is why the percentage associated with direct reductions from VMT reductions exceeds 100% in these tables.

Table 5-3. Share of 10% telecommuting benefit from direct VMT and start reductions and indirect improvements in speed

Pollutant	Direct Emission Reductions from VMT Reductions	Direct Emissions Reductions from Start Reductions	Indirect Emission Reductions from Speed Improvements
CO	80.45%	15.31%	4.24%
CO_2	90.73%	1.46%	7.81%
NH_3	102.87%	0.00%	-2.87%
NO_X	69.59%	26.52%	3.89%
PM_{10}	66.33%	1.00%	32.67%
$PM_{2.5}$	67.83%	4.35%	27.82%
SO_2	90.91%	1.47%	7.63%
VOC	27.86%	66.19%	5.94%

Table 5-4. Share of 25% telecommuting benefit from direct VMT and start reductions and indirect improvements in speed

Pollutant	Direct Emission Reductions from VMT Reductions	Direct Emissions Reductions from Start Reductions	Indirect Emission Reductions from Speed Improvements
CO	88.71%	6.75%	4.53%
CO_2	91.39%	0.59%	8.02%
NH_3	103.40%	0.00%	-3.40%
NO_X	83.71%	12.76%	3.52%

Pollutant	Direct Emission Reductions from VMT Reductions	Direct Emissions Reductions from Start Reductions	Indirect Emission Reductions from Speed Improvements
PM_{10}	46.17%	0.60%	53.23%
$PM_{2.5}$	59.08%	2.30%	38.62%
SO_2	91.57%	0.59%	7.84%
VOC	45.87%	43.58%	10.55%

These data indicate that except for NH_3, increased telecommuting would cause indirect emission reduction benefits related to speed improvements. For CO, CO_2, NO_X, SO_2, and VOC, this amounts to an extra 3-12% reduction in emissions beyond the direct emission reductions from elimination of those commuting trips.

For the PM emission reductions, a large share of the benefits are related to these indirect benefits. 28-39% of the $PM_{2.5}$ reductions and 33-53% of the PM_{10} reductions related to telecommuting are a result of the indirect emission reductions from network-wide speed improvements.

5 Estimated Impact of Increased Telecommuting Related to COVID-19 on Ambient Air Pollution Levels

Due to the complex way in which emissions, meteorology, land use, and ambient air quality interact with one another to, the only way to assess the extent to which reductions in emissions from telecommuting can translate into improvements in ambient air pollution is to photochemically model these changes. This involves modeling a “business as usual” scenario, modifying the emissions inputs for personal vehicles to represent the increased telecommuting, and comparing the results.

5.1 Scenarios Modeled

CAPCOG contracted with the Alamo Area Council of Governments (AACOG) to conduct photochemical modeling to approximate the impact that the direct emission reductions associated with 10% and 25% shifts towards telecommuting would have on ambient air pollution concentrations. The model was run a total of four times, reflecting the following scenarios:

1. Base case for 2023
2. 10% shift toward telecommuting
3. 25% shift towards telecommuting
4. 25% reduction in commuting trip length

Scenarios 2 and 3 involved applying adjustment factors to the start and running exhaust emissions of all pollutants for passenger vehicles and passenger trucks to represent 10% and 25% reductions in HBW trips. Scenario 4 was identical to scenario 3, except without the reduction in start emissions. The inclusion of this scenario enables a comparison of the relative importance of reducing trips versus reducing VMT in reducing ambient air pollution concentrations.

Due to time and resource constraints, this modeling was run simultaneous to the on-road emissions modeling, but since the relationships are roughly linear, it is possible to simulate the impact of many different levels of telecommuting on ambient air pollution.

5.2 Emission Reductions

The following table represents the average weekday NO_X, VOC, and CO emission reductions that would be expected to occur in 2023 region-wide for each scenario.

Table 6-1. Average Weekday Emission Reductions for Each Scenario, 2023 (tons per day)

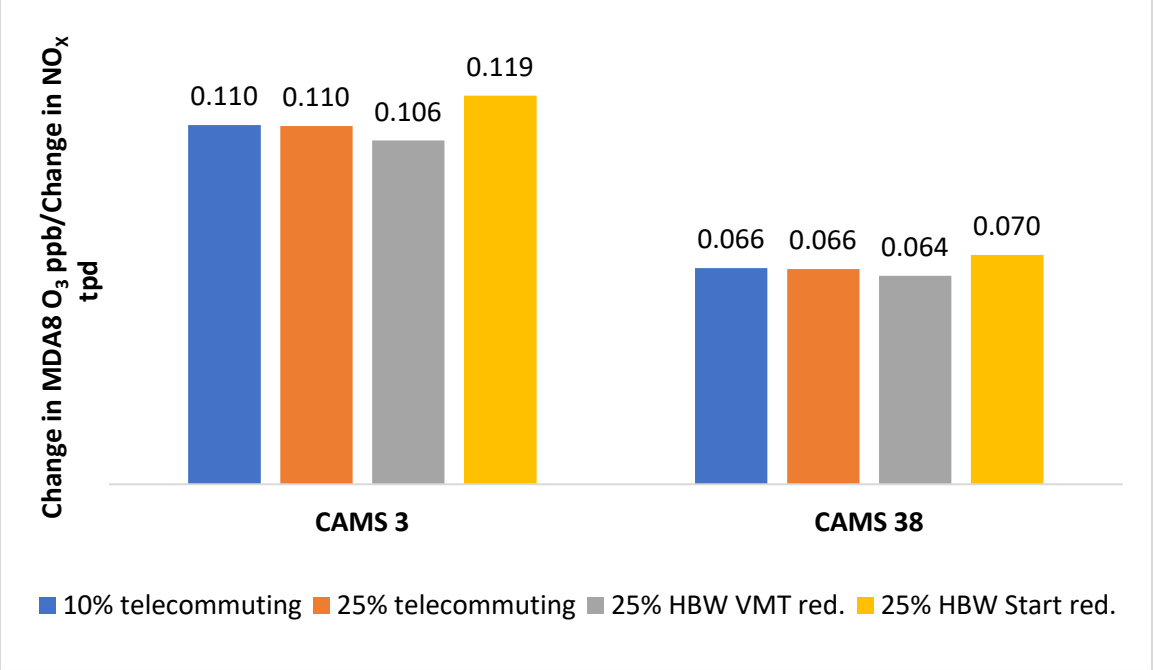
Scenario	NO_X	VOC	CO
10% Shift to Telecommuting	0.2926	0.1423	5.3480
25% Shift to Telecommuting	0.8506	0.7250	13.0847
25% Shift in HBW VMT	0.3266	0.4104	3.9794

5.3 Impact on Maximum Daily O_3 Concentrations

Analysis of prior photochemical modeling for the region tells us that 99% or more of locally-generated O_3 is attributable to NO_X emissions. Therefore, changes in maximum daily 8-hour O_3 concentrations can be compared to the NO_X emission reductions for each scenario in order to calculate ppb O_3/tpd NO_X response ratios. These ratios for each of the grid cells containing regulatory O_3 monitors are shown below. The fourth scenario identified in the chart represents the difference between the 25% telecommuting scenario and the 25% HBW VMT reduction scenario, and it was simply calculated from the modeling results for these two scenarios.[12]

[12] These reflected the average change in MDA8 O_3 concentrations for any days where baseline MDA8 O_3 at the monitor was >=60 ppb divided by the average NO_X emissions reduction per weekday, regardless of whether the baseline MDA8 O_3 value of 60 ppb or more occurred on a weekday.

Figure 5-1. Change in MDA8 O_3 ppb to Change in NO_X tpd ratios

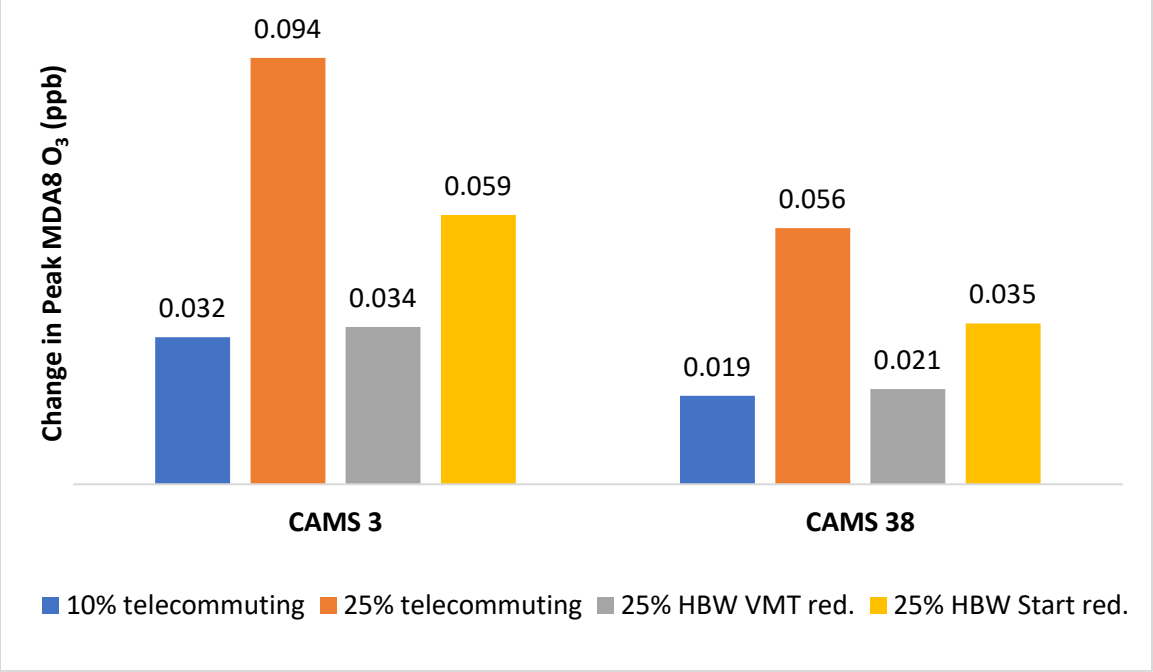


These results show several things:

1. The relationship between MDA8 O_3 reductions and NO_X reductions from personal vehicles is basically linear at these monitoring stations;
2. The impact of the reductions is higher at CAMS 3 than CAMS 38, which makes sense given CAMS 3's closer proximity to the urban core of Austin; and
3. Personal vehicle starts (i.e., trips, regardless of length) have 10-15% higher impact per ton of emissions than reducing personal vehicle VMT.

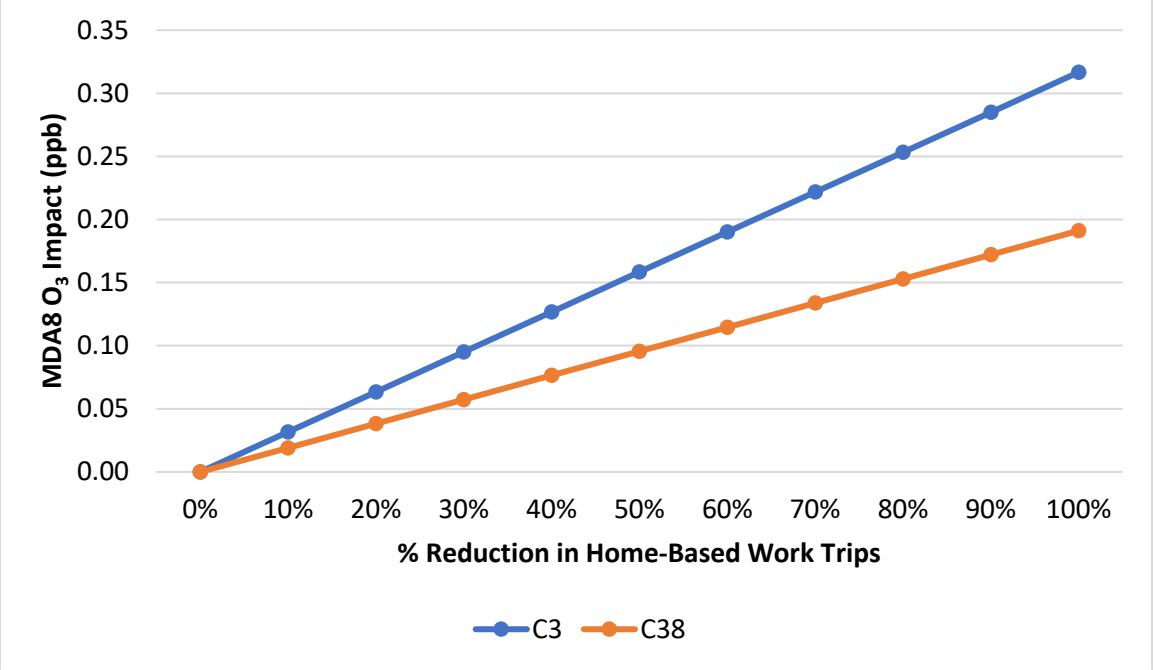
Using these ratios along with the calculated direct personal vehicle NO_X emission reductions from the TTI project yields the following O_3 impacts for 2023.

Figure 5-2. Modeled 2023 Impacts of Each Scenario



Since the relationships appear linear, it is possible to use these results to estimate a range of impacts at different levels of telecommuting. The following chart shows that at the theoretical limit of 100% telecommuting peak 8-hour O_3 levels at CAMS 3 would be reduced by 0.32 ppb and at CAMS 38 by 0.19 ppb.

Figure 5-3. Peak MDA8 O_3 Impact at CAMS 3 and CAMS 38 from Telecommuting, 2023



TTI's "Trends" inventories showed 2020 NO_X emissions from passenger vehicles were 27% higher than the projection for 2023, which suggests that the O_3 impacts at these monitors would also be 27% higher from telecommuting at any level. At the theoretical limit of 100% telecommuting, this would translate into O_3 reductions of 0.40 ppb and 0.24 ppb at CAMS 3 and 38, respectively.

5.4 Impact on Average Ground-Level CO and NO_2 Concentrations

The modeling output also provided concentrations for CO and NO_2. Since transportation is a major contributor to CO and NO_X emissions within the region, reductions in personal vehicle use should result in decreases in ambient concentrations of CO and NO_2. The following two figures show the ratios of changes in average ambient concentrations for the modeling period to the changes in weekday CO and NO_X emissions that were modeled.

Figure 5-4. Ratios of Average CO concentration changes to CO emissions changes

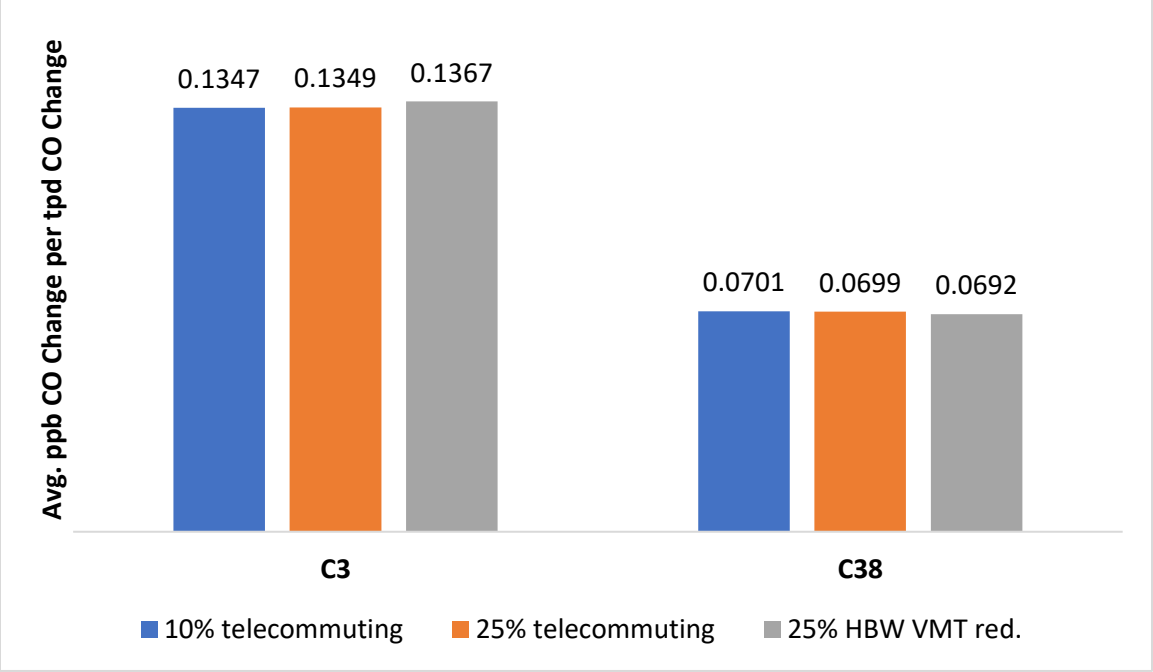
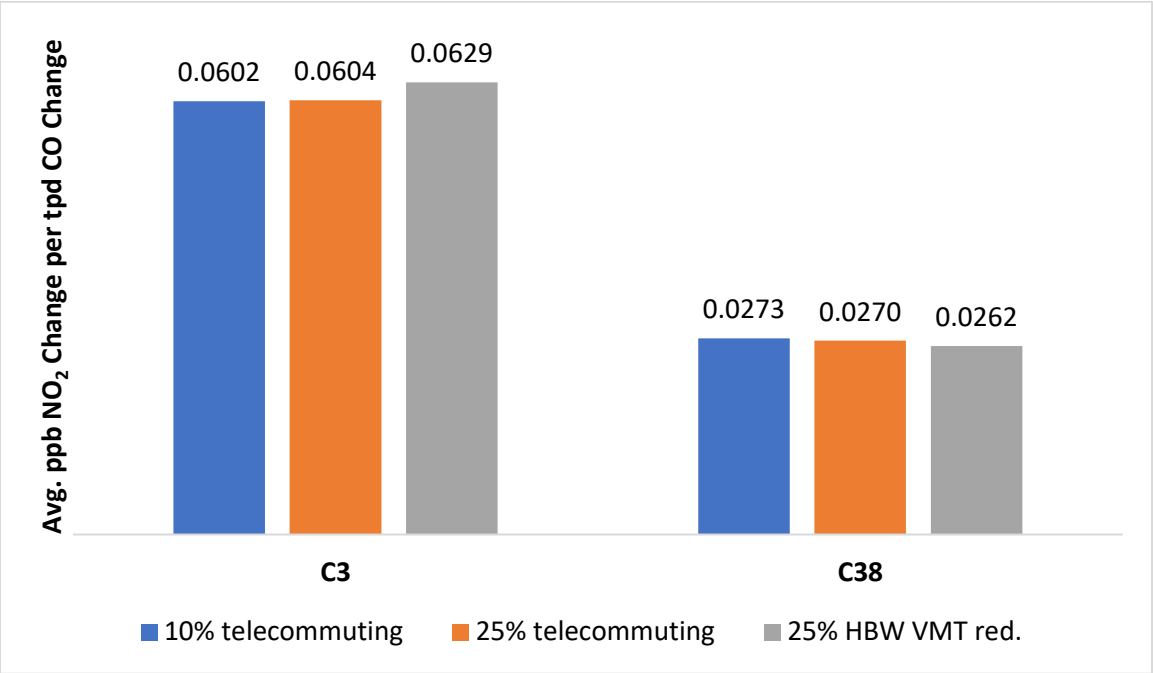


Figure 5-5. Ratios of Average NO_2 concentration changes to NO_X emissions changes



6 CONCLUSION

The overarching conclusion of this study is that the significant reductions in personal vehicle usage within the Austin area in 2020 due to the COVID-19 pandemic did improve regional air quality, but the impact of increases in telecommuting specifically was more limited than might be expected. O_3 and NO_2 concentrations would have occurred anyway even with grown in vehicle as a result of federal emissions standards, and a large share of the improvement in pollution levels in 2020 compared to 2017-2019 is attributable to these standards. Nevertheless, the 18% decrease in personal vehicle use within the region and 12% drop in gasoline usage nation-wide between 2017-2019 and 2020 led to decreases in both locally-generated and "background" air pollution levels coming into the region. There were some factors actually working in the opposite direction: NO_X emissions from power plants and Austin White Lime were higher, and wind speeds and relative humidity were lower, all of which would have led to higher O_3 formation. These factors likely dampened the air quality improvements could have otherwise occurred due to the reduced personal vehicle usage.

To the extent that O_3 quality improvements can be attributed to changes in personal vehicle use, local increases in telecommuting are likely only responsible for less than 0.1 ppb of that improvement. This may seem like a surprising conclusion, but it is important to keep in mind the following points: 1) regional emissions account for less than half of the region's peak O_3 concentrations, 2) on-road sources make up less than half of the region's NO_X emissions, 3) personal vehicles make up about half of the region's on-road NO_X emissions, 4) commuting trips account for only about 1/3 of all personal vehicle usage, 5) a large number of the reduction in home-based work trips that occurred in 2020 can be attributable to the decrease in employment due to layoffs and people leaving the labor force, and 6) the region already has the highest percentage of workers who primarily telecommuted among major metro areas prior to the pandemic. Moving forward, the relative impact of each additional telecommute on regional pollution will continue to decrease as cars continue to get cleaner.

Nevertheless, personal vehicles use and commuting still make up a large share of the region's greenhouse gas emissions, telecommuting can yield significant CO_2 emission reductions. A 10% increase in telecommuting should result in a 3% reduction in on-road CO_2 emissions, while a 25% increase in telecommuting would result in an 8% reduction in CO_2. This study showed that in addition to the direct emission reductions that are achieved when someone telecommutes, there are also "bonus" indirect reductions in emissions that occur network-wide as a result of improved vehicle speeds. For CO_2, this accounts for about 8% of the emission reductions attributable to telecommuting.

A more detailed list of findings is provided below:

- O_3 and NO_2 concentrations at monitoring stations around the region were statistically lower in 2020 than they were in 2017-2019, but concentrations of other pollutants were not statistically different.
    - Peak O_3 concentrations were 0.7 – 5.7 ppb lower at five regional monitors
    - Peak NO_2 concentrations were 6% lower at the region's "near-road" monitor
    - Average annual NO_2 concentrations were 8% lower at the region's "near-road" monitor
- The O_3 and NO_2 reductions appear to have been driven primarily, though not exclusively, by reductions in on-road emissions both within the region and across the country.

- The region's VMT declined by 16% relative to 2017-2019 levels, but all of this reduction was from light-duty vehicles/autos; autos/light-duty VMT declined by 18%, while truck/heavy duty VMT increased by 4%, which was in line with projections.
- Statewide, VMT declined by 7% from 2017-2019 levels, including a 2% decrease in truck VMT and an 8% decrease in auto VMT.
- Some of these ambient air pollution reductions can be related to local telecommuting. Although, the impact of local telecommuting by itself would have been a fraction of a part per billion, and it does not appear likely that it accounts for a majority of these improvements
- The impact of local telecommuting is not large enough to be discernable through analysis of monitoring data alone due to year-to-year variations in air pollution concentrations that occur due to changes in weather conditions year by year.
- The continued emission reduction benefits from federal vehicle and non-road emissions standards nation-wide accounts for a large share of the reductions in O_3 and NO_2 concentrations. Also, reductions in other types of trips within the region and reductions in vehicle usage nation-wide also contributed to the O_3 and NO_2 reductions.
- While there were significant reductions in on-road emissions of CO, PM_{10}, $PM_{2.5}$, and SO_2, these did not correspond to significant reductions in ambient concentrations of these pollutants.
    - In the case of PM_{10}, $PM_{2.5}$, and SO_2, on-road sources do not make up a large share of the direct emissions of these pollutants.
    - "Near-road" concentrations of $PM_{2.5}$ along IH-35 were not significantly higher than concentrations of $PM_{2.5}$ measured in East Austin away from IH-35, which also suggests that on-road sources also are not a significant contributor to secondary $PM_{2.5}$ formation.
    - The lack of improvement in CO concentrations is inconsistent with the significant reductions in CO emissions from on-road sources. On-road sources make up a majority of the CO emissions within the region, so a noticeable reduction in ambient concentrations would have been expected. Overall CO levels within the region remain low, however.
- To the extent that meteorology in 2020 was different than it was in 2017-2019, it would have been expected to result in higher, rather than lower pollution levels, if emissions were unchanged. There are also a few unusual large-scale meteorological events in 2020 that led to PM_{10} concentrations being statistically significantly higher than they were 2017-2019, but these increased levels do not appear to be related to any change in behavior connected to COVID-19.
- Reductions in non-road emissions as a result of federal non-road engine standards also likely contributed to the reductions in ambient O_3 and NO_2.
- Increases in point source NO_X emissions from area power plans and Austin White Lime in 2020 relative to 2017-2019 may have limited the extent of the ambient air pollution reductions that might have otherwise occurred in 2020 as a result of mobile source emission reductions.
- Reductions in VMT across the state and across the country likely also reduced background O_3 and NO_2 concentrations coming into the region.
- There were not significant changes in point source emissions from within the region from 2017-2019 to 2020.
- Up to 1/3 of the reduction in NO_X emissions from mobile sources from 2017-2019 to 2020 can be attributable to reductions in local VMT in 2020 as a result of the pandemic, with the rest attributable to federal mobile source emissions standard.

- While telecommuting played a significant role in reduced VMT within the region, unemployment and reductions in vehicle trips other than commuting also likely played significant roles in the reductions in O_3 and NO_2 from 2017-2019 to 2020.
- About 70-80% of the NO_X emission reduction benefit from telecommuting is a direct result of reduced VMT, while 15-25% is as a result of vehicle starts, and a bit less than 5% is a result of improvements in vehicle speeds network-wide
- The value of telecommuting for reducing regional air pollution will diminish year over year as the average vehicle on the road gets cleaner as a result of federal vehicle emissions standards. Although, telecommuting will continue to have high value for reducing CO_2 emissions and PM emissions from tirewear and brakewear.

APPENDIX A: TEXAS A&M TRANSPORTATION INSTITUTE REPORT

The Appendix A files are attachments in this PDF document. Appendix A1 is the report from the Texas A&M Transportation Institute (TTI). Appendix A2 is the accompanying spreadsheet.

APPENDIX B: AACOG PHOTOCHEMICAL MODELING DOCUMENTATION

The Appendix B file is an attachment in this PDF document.