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COVID-19 impacts on mobility and travel demand

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ABSTRACT

Since the beginning of the COVID-19 pandemic, many travel restriction policies were implemented to reduce further spread of the virus. These measures significantly affected travel demand to levels which could not have been anticipated by most planners in transportation agencies. As the pandemic has proven to have significant short-term impacts, it is anticipated that some of these impacts may translate to longer-term impacts on overall travel behavior and the movement of people and goods. Beyond the pandemic, the observed travel patterns during this period also provides a great opportunity for planners to assess policies such as work from home and remote learning as strategies to manage travel demand. This study provides a scenario analysis framework to re-evaluate travel demand forecasts under uncertain future conditions using the Maryland Statewide Transportation Model (MSTM). Model parameters associated with working from home, household income, changes in discretionary travel, distance learning, increased e-commerce, vehicle occupancy and mode choice were identified. Parameter values were assigned under the various scenarios using employer surveys on workforce teleworking and observed data on e-commerce growth and shopping behavior. The main findings of this study capture the sensitivities of systemwide vehicle miles travel, and vehicle hours travel under different scenarios and implications on future investment decisions. The study found that future investments under the scenarios remain beneficial to systemwide performance and therefore justified. Although this study focuses on the state of Maryland, the scenario framework and parameter definitions can be used in other states or agencies within a travel demand model environment.

1. Introduction

At the onset of COVID-19 in March of 2020 as restrictions where quickly introduced, the need for travel was dramatically reduced. Policies that were introduced that had immediate impact on travel patterns included: Change of schools from in person to online teaching, Work from Home (WFH) for certain industries and those able to do so, near stopping of all business-related travel, reduced recreational opportunities, and reduced social interaction opportunities including closing of restaurants and bars and limited retail activity.

Through the months of March to May of 2020, traffic volumes in the urbanized areas of Maryland were observed to be 30 to 40 % lower than average volumes during this same period in previous years. As the policies introduced at the beginning of the pandemic began to be relaxed through the summer and fall of 2020, traffic volumes began to recover and stabilized to levels around 20 % below averages from previous years.

After summer 2020, as it became clear that social distancing and travel restrictions will continue for an unknown period of time, Maryland Department of Transportation was faced with questions regarding the impact of travel restrictions on mobility and travel demand. Specifically, two main questions were raised: i) What are the immediate

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impacts of the pandemic on travel behavior and what factors contributed to the changes in travel behavior? ii) Which policies and travel behavior changes could be long-term and what are the range of possible impacts on future travel demand? To answer these questions, the Maryland Department of Transportation-State Highway Administration (MDOT-SHA) began the study in two phases: First, identify COVID-19 impacts on different aspects of mobility and travel demand and collect data that was observed in the Fall of 2020 associated with those impacts. Second, identify multiple strategic scenarios and the long-term impacts they would have on the transportation system. For this purpose, using the Maryland Statewide Transportation Model (MSTM), a combination of refinements in parameter values were implemented to capture potential long-term travel impacts of the pandemic. The implication is that decisions about highway and transit projects are tied to forecasts that assume prevailing travel behavior trends will continue. To understand the implications on infrastructure investment decisions across the state a scenario analysis was undertaken to evaluate the uncertainty in the long-term impacts of COVID-19 on the need for infrastructure improvements.

This scenario analysis uses travel data collected during the pandemic as well as current research dealing with the post-pandemic intentions of travelers, consumers, and employers to ground scenario assumptions to realistic ranges of impacts. The resulting ranges of scenario outcomes are thus tied to reasonable limits. While a scenario analysis exercise may resort to asserting limits that are unknown, this is not the case with travel impacts due to COVID-19 as the limits of travel related impacts are known. Furthermore, while the greatest travel impacts were recorded during the strictest period of restrictions, the data also show that a far lesser impact was sustained consistently from the fall of 2020 and into 2021. It is this lesser and more sustained impact that serves as the benchmark limit for what the long-term impacts to travel behavior stemming from the pandemic will look like. This paper presents a scenario-based approach rooted in data driven realistic assumptions for the purposes of assisting transportation planning agencies in assessing the value of their long-range plans in the face of COVID-19 related uncertainty.

The remainder of the paper is organized as follows: The next section discusses a comprehensive literature review of current studies on the impacts of the COVID-19. Although due to the novelty of the pandemic, at the time of this study, there are not many studies related to long-term impacts of COVID-19 on future travel demand. The “Base Year” and “Future Year” sections discuss scenario developments related to the short-term and potential long-term impacts of the pandemic. The model results are discussed in the next section. Finally, the last section summarizes findings of the paper along with avenues of future research.

2. Literature review

At the time of conducting this research, the number of research studies investigating the impacts of the pandemic on travel demand is relatively low. Literature investigating short to long-term changes in travel pattern and demand due to the COVID-19 pandemic can be categorized into three groups based on their objectives. These are i) studies investigating changes in travel mode, ii) studies investigating changes in trips, and iii) studies investigating visits to locations of interest (such as shopping centers, grocery stores, fast food locations, etc.). A brief discussion of findings from existing literature for each category follows.

For the first category, using a survey, Bhaduri et al. (2020) found habitual attachment to modes used before the pandemic. The researchers were interested in change of travel mode choice due to the pandemic. Using multiple discrete choice extreme value models, the authors report larger inertia towards private vehicles compared to other travel modes. The authors attribute this to their ability to provide isolation from other commuters. On similar lines, public transportation such as bus and ridesharing showed lower inertia. Ciuffini et al. (2021) performed a city-level scenario analysis to assess COVID-19 impact on car use and the potential of shifting to active transportation in a post-pandemic world by taking case studies from sample Europe and North American cities. Using taxi data in New York City, Manley et al. (2021) found significant decrease in taxi use during initial COVID-19 outbreak though the drop varied by spatial and temporal dimensions.

To investigate trip changes before and after transition to lockdown by government, Pawar et al. (2021) developed independent models for work and non-work based trips using survey data collected from 1,945 participants. The authors reported lower probability of reduced work-based travels for participants in cities with lower cost of living and population density. Probability of reduced non-work-based trips was significantly higher than work-based trips during the transition. Similarly, Abdullah et al. (2020) surveyed individuals online to study the impact of COVID-19 on mode choice in May 2020. The authors reported, an increase in use of personal cars from 32 % before COVID-19 to 39 % during COVID-19. Their analysis showed significant mode shift from public and paratransit transport to private transport. Aditya and Rahul (2021) analyzed the traveler’s intentions to reduce trip frequency, using various psycho attitudinal survey questionnaire of the variables impacting the travel behavior. Except work trips, the survey respondents showed inclination towards reducing all other trips such as recreational and other trips. Xiong et al. (2020) found that during the initial phase of the pandemic the trip length of individuals across the US reduced to intra-county only, and number of inter-county trips were reduced.

With regard to the third category, a survey was conducted by Shamshiripour et al. (2020) between April–June 2020 in the Chicago metropolitan area to find the difference in activity based travels before and during the pandemic. The researchers found that 15 % of respondents were working full time from home before the pandemic. This rose to 48 % during the pandemic. The authors also report a notable growth in online shopping. Online grocery shoppers increased by 65 %, and 31 % more food was ordered online during the pandemic. About 59 % of respondents preferred to keep shopping for groceries online regardless of the pandemic. Furthermore, the respondents in their survey perceived personal vehicles and bikes as the safest travels modes, while transit and pool ride services were considered to be the riskiest. Mahajan et al. (2021) identified Points of Interest (POI) in Munich, Germany to analyze spatial and non-spatial attributes associates with its visitation rate before and after COVID-19 lockdown. The authors reported a peak in visits during different days of the week and time of day based on the destination. For example, supermarkets showed larger visitation during evening commute hours. During lockdown, supermarkets further away from transit stops were more popular among visitors. On the contrary, before lockdown, supermarkets close to transit stops showed more visitations. Liang et al. (2021) found that in the US, there was decrease in trips to all forms of shopping, food, and restaurants, though the reductions were higher in retail stores than food and grocery stores.

Besides the literature related to the three groups of objectives, researchers have also utilized Travel Demand Models (TDM) for assessing COVID-19 related travel effects. For example, Livshits et al. (2021) demonstrated the application of activity-based TDM developed by Maricopa Association of Governments to plan scenarios for business reopening by projecting activities at locations. Doustmohammedi et al. (2020) used the Huntsville TDM to model trips in Huntsville for different scenarios related to employment categories created due to stay-at-home orders. Their analysis showed measurable reduction in home-based work trips and 12 % of the city population telecommuting through Winter of 2021 under extreme stay-at-home scenario. Their model suggests that a 11 % reduction in Vehicle Miles Traveled (VMT), arising from limited travels by individuals of different employment categories, can be expected to yield a 21 % reduction in miles of congested roadway in Huntsville.

Several investigations are on-going to further explore the impact of COVID-19 on travel behavior. Research is currently ongoing to develop
Table 1 COVID impacts on person and truck travel.

| Factor                       | Assumption                                                                 | Model Parameter               |
|------------------------------|-----------------------------------------------------------------------------|-------------------------------|
| Person Travel                | Increased WFH by higher income workers                                      | HBW Production Rates by income level |
| Work from Home (WFH)         | Increased WFH would be related to job sites associated with higher income types of jobs (service and professional) | HBW Attraction Rates by job type and income level |
| Change in Work Related Travel| Because of increased WFH, lower levels of work-related travel from work sites through the day | Decrease in Non Home-Based Work models as a function of the WFH impacts on HBW rates |
| Remote Learning              | Some level of hybrid education model that would include in person and online teaching | Adjustment of home-based school trips |
| Vehicle Occupancy            | Shift of preference to SOV with reduction of HOV2 and HOV3 trips as well as shift away from transit. | Manual shift of HOV2 and HOV3 trips to SOV as well as reduction of transit trips estimated by model |
| Discretionary Travel (Non-Shopping) | Increased free time for discretionary travel from home. | Increase in home based other trip purposes based on household income |
| E-Commerce                   | Increased rate of adoption of e-commerce including direct delivery of goods and services without need for travel. | Change in home-based shopping trip production rates |
| Discretionary Non Home-Based Trips | With a greater focus on "home", more trips shifting to home-based and fewer trips made while away from home | Reduction in Non Home-Based trips accounting for 2nd and 3rd stops in tours |
| Truck/Commercial Travel      | Increased levels of delivery and distribution movements consistent with the increased adoption of e-commerce | Factoring of the commercial vehicle trip tables that account for delivery and distribution movements |
| E-Commerce deliveries        | Related to e-commerce and increased demand for consumer products, higher levels of long and short distance truck movements | Factoring of the long and short distance single unit and multi truck trip tables |

predictive models to study shifting perspectives and travel needs of commuters in the Northeast Megaregion (Ryerson, 2020). Similarly, Illinois Department of Transportation is currently using its state-wide TDM model as a baseline to compare how travel patterns have been changing since the pandemic began. Their survey shows that about 90% of current teleworkers favor it. Users traveling in public transit and airlines feel safer with vaccines and use of masks (Chen et al., 2020). A number of studies have also focused on the impact of COVID-19 on public transportation. Tirachini and Cats (2020) and Gkiotsalitis and Cats (2021) conducted some of the early studies investigating the research needs and literature review related to the impacts of the pandemic on public transport operations. Coppola and De Fabiis (2020, 2021) also investigated the impacts of COVID-19 and social distancing measures on transit mobility from a viewpoint of public transport.

Next, we present scenario development for the base and future years along with assumptions and modeling steps illustrating the integration of COVID-19 impacts in a travel demand model.

3. Base year scenario (2020)

The purpose of this calibration effort is to align the assumptions about pandemic related impacts to travel behavior with observed reductions in travel so that parameter adjustments for future year scenarios will be reasonably constrained. Though a dramatic decrease in traffic to almost 60% below pre-2020 levels was observed in the March-April timeframe of 2020, this traffic recovered quickly over subsequent weeks coinciding with a general easing of restrictions. This recovery in traffic volumes plateaued at 15% to 20% below pre-2020 levels starting in the fall of 2020. Given the acute and unsustainable nature of the March-April traffic reductions and the longer-term, more sustainable nature of the 15% to 20% traffic reduction, this analysis takes the 15% to 20% traffic reduction as the maximum sustained reduction in traffic that it is reasonable to assume for scenario analysis purposes. It is worth mentioning that these reduced traffic levels are made possible by extremely ambitious government spending programs and workplace restrictions even during the period of the fall of 2020. Post COVID-19 conditions are not expected to maintain such high levels of government support and the actual range of long-term impacts is expected to be less.

Therefore, the goal of the base year scenario calibration is to achieve 15% to 20% VMT reduction as observed in the fall of 2020. For this analysis, a “Pre-pandemic” scenario (calibrated model setting without COVID-19 impacts) and a “Pandemic” (adjusted model parameters based on COVID-19 impacts) are defined. The scenarios are evaluated using the Maryland Statewide Travel Demand Model (MSTM) which is a four-step travel demand model calibrated and validated to 2015 conditions. For brevity, details of the model structure are not presented in this paper but can be found in the literature (Mishra et al., 2013; Mishra et al., 2011; Ye, 2010). The model covers the entirety of the state of Maryland as well as a Halo region that includes the Metropolitan Washington Council of Governments (MWCOG) region in Virginia as well as counties in Pennsylvania, West Virginia and Delaware.
3.1. COVID-19 impacts on travel demand

This section identifies COVID-19 impacts on different aspects of mobility and travel demand and introduces model parameters associated with the impacts. The assumptions are mainly based on data published by Maryland Transportation Institute (2020). Other data sources are also used to adjust the parameters consistent with observed conditions in the Fall of 2020. The following section describes the multiple data sources used to make the assumptions. A summary of person travel and truck/commercial travel assumptions and associated model parameters are provided in Table 1.

3.2. Work from home

With the sudden closure of many workplaces and offices since the beginning of the pandemic, a new era of teleworking has begun that will most probably change how a large share of the work-force will operate in the future. Data from COVID-19 Impact Analysis Platform (2020) indicates that percentage of people working from home (full-time) increased to 40% for most of 2020 (Fig. 1). However, the opportunity of teleworking is not equally distributed among all levels of income. Data from the Bureau of Transportation Statistics (2021), Effects of COVID-19 on Travel Behavior by Income Group show significantly higher telework percentages for higher income level compared to low-income levels. This information was used to reduce work trip productions in MSTM as shown in Fig. 2.

In MSTM, trip attraction rates for work purposes are stratified by employment type. It is assumed that the pandemic shutdowns mostly shifted office space jobs from in-person to teleworking compared to manufacturing or retail employments. Therefore, similar reduction

**Fig. 2.** MSTM work trip production by income group.

**Fig. 3.** MSTM work attractions by county.
factors as in the production model are applied to office employment attractions (Fig. 3).

3.2.1. E-Commerce and shopping behavior

COVID-19 caused a major shift in shopping behavior and pushed millions of consumers to online retail. Data from multiple sources indicate unprecedented growth in e-commerce sales since the beginning of the pandemic. According to data from Digital Commerce (2021), online sales went up 32% in 2020 reaching $791 billion sales. Most notably, Amazon, the largest online retailer in North America, observed a stunning 38% increase in their annual revenue in 2020 (Forbes, 2021). Based on these observations, a 30% reduction is applied to MSTM’s shopping trips.

The rise in e-commerce requires efficient logistics and delivery systems which pushes for more commercial vehicles and delivery trucks on the roads. In the absence of directly observed data on commercial vehicles, the growth in e-commerce sales is used as a proxy to adjust model parameters associated with commercial vehicle and trucks.

3.2.2. Discretionary travel

Data from COVID-19 Impact Analysis Platform shown in Fig. 4 indicates a temporary decline in non-work trips in March and April of 2020, however discretionary trips recovered for the rest of 2020 and continues to increase as people have more flexible work schedules. Accordingly, a 5% increase is considered for discretionary trips which corresponds to “home-based other” trips in MSTM.

3.2.3. Remote learning

Information obtained from Maryland’s public-school websites suggested that in the fall of 2020, classes in most schools operated remotely with a few counties offering hybrid options with one or two days in-person classes. Overall, it was assessed that 75% of students attended classes remotely and therefore a 75% reduction on school trips was applied in the model.

3.2.4. Vehicle occupancy

Data collected on vehicle occupancy along I-270 corridor indicates shifts from High Occupancy Vehicles (HOV) to Single Occupancy
Vehicle (SOV) (Fig. 5). Social distancing and measures to prevent the spread of the virus encouraged many travelers to avoid sharing rides with other people and thus resulted in a rise in single occupied vehicles on the roads. MSTM parameters were adjusted to account for shifts in vehicle occupancy.

3.2.5. Other trips

Other trip purposes in MSTM include trips with non-home and non-work trip ends (other-based-other). Determining reduction factors for other-based-other (i.e., trips not originated or destined at home/work) was challenging as no directly observed data was available for these trips. Therefore, the Household Travel Survey data which was used to calibrate the Baltimore Metropolitan Council InSITE Activity Based Travel Model (Baltimore Metropolitan Council, 2017) was utilized to determine what percentage of other-based-other trips occur during work, discretionary and school trips so that similar assumptions could be applied on those trips. It was discovered that approximately 30 % of other-based-other trips occur during work trips, 45 % during

![Fig. 6. Model VMT output.](image1)

![Fig. 7. VMT reduction by counties in Maryland.](image2)
3.3. Model output

The model parameters were adjusted for the Pandemic scenario in a manner consistent with the assumptions discussed in the previous section. The model was then run for the 2020 Pandemic and 2020 Pre-Pandemic scenarios. Comparing MSTM outputs between the Pandemic and Pre-pandemic scenarios shows a 16% reduction in total VMT consistent with the goal of 15%–20% from observed conditions (Fig. 6).

Fig. 7 demonstrates the geographical distribution of VMT reductions in Maryland counties. It was observed that the majority of VMT reductions during the pandemic occurred around Washington/Baltimore Metropolitan area, southern Maryland, and the southern portion of the Eastern Shore. This was expected as the business closures in high-density areas such as Washington and Baltimore reduced daily commutes and business trips to these areas.

4. Future year scenarios (2045)

4.1. Scenario design

The purpose of the scenario analysis is to evaluate the potential long-term impacts that COVID-19 could have on travel behavior and the related implications on the transportation system as it relates to estimated levels of system utilization, delay and time of day usage.

The study team evaluated the potential factors described above and identified two primary dimensions: Work from Home, Persistence of E-Commerce. Each of the factors defined above can be associated to these two primary dimensions. For example, higher level of work from home have associated changes to non-home-based travel and use of time for discretionary travel. The persistence of E-commerce has implications on home-based shopping, levels of commercial vehicle travel and levels of long-distance truck movements of consumer goods.

Seven scenarios were developed that included:

1) Old Normal: represents the use of the calibrated model and has no long-term impacts of COVID. Historical levels of WFH and e-commerce are captured in the model parameters.
2) Pandemic: Scenario used as a calibration of the model and compared against traffic levels observed in the fall/winter of 2020 and 2021.
3) New Normal: Likely scenario for long term impacts of COVID-19 that represent an expected level of WFH and e-commerce adoption.

The remaining four scenarios considered varying levels of WFH and persistence of E-commerce:

4) High WFH / High E-Commerce
5) High WFH / Trend E-Commerce
6) Low WFH / High E-Commerce
7) Low WFH / Trend E-Commerce

Table 2 Future scenario parameters.

| Impact                  | Level  | Parameter Change  | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 | Scenario 5 | Scenario 6 | Scenario 7 |
|-------------------------|--------|-------------------|------------|------------|------------|------------|------------|------------|------------|
| WFH                     | High   | Increased - all   | X          | X          | X          |            |            |            |            |
|                         |        | possible          |            |            |            |            |            |            |            |
|                         | Med    | Increased - some  | X          |            |            |            |            |            |            |
|                         |        | (Hybrid)          |            |            |            |            |            |            |            |
|                         | Low    | Calibrated        | X          | X          |            |            |            |            |            |
| Remote Learning         | High   | Increased         | X          | X          |            |            |            |            |            |
|                         |        | Near all remote   |            |            |            |            |            |            |            |
|                         |        | Some (Hybrid)     |            |            |            |            |            |            |            |
| Long Distance Truck     | High   | Increase # of     | X          | X          | X          |            |            |            |            |
|                         |        | long-distance     |            |            |            |            |            |            |            |
|                         |        | trucks            |            |            |            |            |            |            |            |
|                         | Med    | Calibrated        | X          |            |            |            |            |            |            |
|                         | Low    | Decrease # of     | X          |            |            |            |            |            |            |
|                         |        | long-distance     |            |            |            |            |            |            |            |
|                         |        | trucks            |            |            |            |            |            |            |            |
| Vehicle Occupancy       | High   | Shift to SOV      | X          |            |            |            |            |            |            |
|                         |        |                   |            |            |            |            |            |            |            |
|                         | Med    | Shift to higher   | X          |            |            |            |            |            |            |
|                         |        | HOV               |            |            |            |            |            |            |            |
| Commercial Vehicle      | High   | Increase #        | X          | X          |            |            |            |            |            |
|                         |        | Moderate          |            |            |            |            |            |            |            |
|                         |        | Increase          |            |            |            |            |            |            |            |
|                         |        | Calibrated        | X          |            |            |            |            |            |            |
|                         | Med    | Decrease #        | X          |            |            |            |            |            |            |
|                         |        | long-distance     |            |            |            |            |            |            |            |
|                         |        | trucks            |            |            |            |            |            |            |            |
|                         | Low    | Increased         | X          |            |            |            |            |            |            |
| Discretionary Travel    | High   |                  | X          |            |            |            |            |            |            |
| (non-shopping)          |        |                   |            |            |            |            |            |            |            |
|                         | Med    | Decrease          | X          |            |            |            |            |            |            |
|                         |        |                   |            |            |            |            |            |            |            |
|                         | Low    | Calibrated        | X          |            |            |            |            |            |            |
| Non Home Based Work     | High   | Decreased         | X          | X          |            |            |            |            |            |
| (Tied to WFH)           |        | all               |            |            |            |            |            |            |            |
|                         | Med    | Decreased         | X          | X          |            |            |            |            |            |
|                         |        | some              |            |            |            |            |            |            |            |
|                         | Low    | Calibrated        | X          |            |            |            |            |            |            |
| Non Home Based Other    | High   | Increased         | X          | X          |            |            |            |            |            |
|                         |        |                   |            |            |            |            |            |            |            |
|                         | Med    | Decreased         | X          | X          |            |            |            |            |            |
|                         |        |                   |            |            |            |            |            |            |            |
| Home Based Shopping     | High   | Higher            | X          | X          |            |            |            |            |            |
|                         |        |                   |            |            |            |            |            |            |            |
|                         | Med    | Lower             | X          | X          | X          |            |            |            |            |
|                         | Low    | Calibrated        | X          | X          | X          |            |            |            |            |

Fig. 8. Total VMT under future scenarios (CLRP).
For each of the identified factors, a spectrum of the parameter values was defined. The calibrated model parameters were included as one of the levels. Levels of WFH are determined using employer surveys on workforce teleworking (Greater Washington Partnership, 2021). To define the levels of each Factor for the 7 scenarios, a Delphi approach was applied among the research team as part of the scenario design. Delphi technique is a general approach in which a consensus view across subject experts is used to answer a research question. In this case, each of the research team members was asked to select the level of the parameter that they felt was intended by the scenario. Selections were scored and shared with the panel. Panelists then met to discuss the outcomes and arrive at a consensus concerning the parameter adjustments. (Table 2). Each of the seven scenarios are combined with two network scenarios namely the Consolidated Transportation Program (CTP) and Constrained Long-Range Plan (CLRP).

By combining the variations in demand with the current assumptions in the committed projects, the study team was able to identify the system utilization and operational characteristics and how the current investment plans hold up under uncertainty with the long-term impacts to travel.

4.2. Model results

4.2.1. Vehicle miles traveled

Fig. 8 compares the VMT outputs across all scenarios. It shows a steady growth starting from 2015 to 2019 with a sudden drop of 16% (as shown previously in the Pandemic scenario) in the year 2020. With the elimination of travel restrictions and re-opening of business and office spaces, a recovery period is assumed between 2021 and 2025. During this period traffic recovers to some extent based on the assumptions of return to work, e-commerce growth and other travel behavior under each scenario. From 2025 to 2045 traffic grows with the
same rate as pre-pandemic conditions. VMT under all scenarios is estimated to be less than VMT under “Old normal” (Pre-pandemic conditions) scenario. It is estimated that 2045 total VMT reduction because of COVID-19 ranges between 3 % and 12 % with an average of 7 % across all scenarios. As expected, the scenario with the highest VMT forecast belongs to the “Low WFH/Trend E-commerce” as more work trips and shopping trips occur under this scenario. Conversely, the lowest future VMT occurs under the “High WFH/High E-commerce” scenario as higher number of people continue to telework and switch from in-store to online shopping.

Fig. 9 presents the geographical distribution of VMT reductions representing the average of all scenarios for counties in Maryland. It is observed that most VMT reductions in 2045 will occur around urban areas such as Washington Metropolitan area (Montgomery and Prince George’s counties) and southern Maryland while less VMT reductions is projected in western Maryland and Eastern Shore.

### 4.2.2. Vehicle hours traveled

Similar to VMT outputs, Fig. 10 compares the Vehicle Hours Traveled (VHT) outputs across all scenarios. A steady growth is shown starting from 2015 to 2019 with a sudden drop in 2020, a recovery period is assumed between 2021 and 2025 and steady growth is considered from 2025 to 2045. VHT under all scenarios is estimated to be less than the “Old normal” (Pre-pandemic conditions) scenario and it is estimated that 2045 total VHT reduction because of COVID-19 ranges between 6 % and 17 % with an average of 11 % across all scenarios. As expected, the scenario with the highest forecasted VHT belongs to the “Low WFH/ Trend E-commerce” and the lowest occurs under the “High WFH/High E-commerce” scenario.

Fig. 11 summarizes the VHT reductions from the average scenario by functional class. It is observed that VHT reductions due to COVID-19 affect arterials more than interstate/freeway functional class. This is due to the fact that truck volumes and long-distance travels mainly use interstate and freeways which are projected to grow higher than pre-pandemic conditions with the rise of e-commerce sales.

### 4.2.3. Time of day

Average hourly traffic data published by Metropolitan Washington Council of Governments (2021) shows that although AM and PM peak travels are recovering to pre-pandemic conditions, the gap at AM peak is...
higher than other periods. MSTM VMT and VHT outputs by time of day also illustrate higher reductions during AM peak period as shown in Fig. 12.

4.2.4. CTP versus CLRP

Future scenarios are applied at the CTP and CLRP program levels to assess whether CLRP investments have positive impacts under COVID conditions. CTP is Maryland’s six-year capital budget for transportation projects while CLRP is the state’s long-range plan. The CTP includes those projects that are fully funded and committed for construction by the state while CLRP includes many long-range projects that are not necessarily approved for funding. In that sense, we treat the CTP as a benchmark to be compared with other investment programs. The comparison of total VHT under CTP and CLRP is demonstrated in Fig. 13. It is seen that under all COVID-19 scenarios, for both CLRP and CTP program levels total VHT is less than the “Old normal” scenario. Although the impacts of COVID scenarios in terms of reducing VHT are greater under CTP as it represents a more congested system, VHT levels under all scenarios in CLRP program are lower than those in the CTP program. This means that the additional investment projects in the long-range program (CLRP) still have a positive impact in terms of reducing VHT and therefore are justified. Although outside the scope of this work, projects in the CLRP program can be further investigated under the “Old normal” and “New normal” scenarios to evaluate the benefits of investments under “New normal” conditions.

5. Conclusion

The first section of this project focused on calibrating and adjusting MSTM parameters based on multiple data sources with a goal of producing VMT reductions consistent with observed conditions in the fall of 2020. Model outputs produced 16% reduction in VMT comparing the pre-pandemic to pandemic scenario consistent with the observed conditions.

The second part focused on designing future scenarios based on multiple levels of work from home, e-commerce sales growth and other future impacts. It is estimated that the total VMT reduction by 2045 because of COVID-19 ranges between 3% and 12% with an average of 7% while 2045 total VHT reduction ranges between 6% and 17% with an average of 11%. VHT reductions due to COVID-19 affect arterials more than interstate/freeway functional class. The highest VHT reduction occurs in the capital region followed by southern, central region, eastern shore and western Maryland. Consistent with observed data, the highest volume and VHT reduction occurs during AM peak period compared to other time of day periods. Under all COVID-19 scenarios, for both CLRP and CTP program levels, total VHT is less than the “Old normal” scenario and the additional investment projects in CLRP program have a positive impact in terms of reducing VHT.

This paper presented a scenario-based approach rooted in realistic assumptions derived from readily available data and research. The analysis should be viewed as more than an analysis of the pandemic impacts. We now see, in the post-pandemic era, almost all business and agencies in the public and private sector maintain some work-from-home policy. Additionally, many companies completely closed down their offices in favor of switching to a virtual workplace for economic benefits. Many retail stores have permanently closed and are operating solely as on-line businesses. Some of the policies such as work from home and remote learning can be viewed as strategies for travel demand management and the pandemic provided an opportunity to evaluate such policies.

The resulting ranges of scenario outcomes in this study showed that while transportation plan benefits were lower in scenarios with greater reductions in travel due to WFH and E-commerce, those plans still improved travel conditions over a no-build scenario. Though the long-term impacts to travel stemming from the COVID-19 pandemic are likely to reduce overall congestion in Maryland, these reductions are not expected to overtake the need for robust transportation investment programs including the Constrained Long-Range Plan (CLRP) and Consolidated Transportation Program (CTP). While this paper deals only with scenario planning analysis in one state, the general approach of using observed COVID-19 related data in setting reasonable constraints for scenario parameters can assist other transportation planning agencies in determining their continuing needs in the face of pandemic-related uncertainty.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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