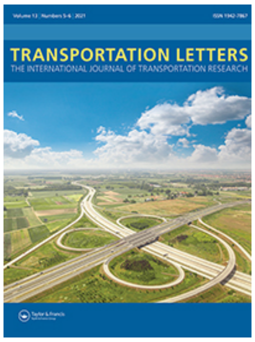

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Measuring travel behavior in Houston, Texas with mobility data during the 2020 COVID-19 outbreak

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ABSTRACT
COVID-19, a respiratory virus violently spread worldwide, has deeply affected people's daily life and travel behaviors. We adopted an autoregressive distributed lag model to analyze changes in travel patterns in Houston, Texas during COVID-19. The results indicated that visit patterns and changes in COVID-19 cases a week prior heavily influence the following week's behaviors. Additionally, unemployment claims, median minimum dwell time, and workplace visit activity played a major role in predicting total foot traffic. Notably, transit systems have seen an overall decrease in usage but were not significant in estimating total foot traffic. This model showcased a unique method of quantifying and analyzing travel behaviors in Houston in response to COVID-19.

KEYWORDS
COVID-19; Economy; mobility; foot traffic; autoregressive models; Houston

Introduction

COVID-19 is a highly contagious respiratory virus that swiftly reached all seven continents within its first two months of inception in December 2019. The virus first hit American shores in late January and by mid-March, all 50 states, the District of Columbia, and four U.S. territories had reported cases of COVID-19. Although most people experience mild to moderate symptoms, older populations, and those with underlying condition are increasingly vulnerable in developing a serious, fatal illness. Because the virus is transmitted through respiratory droplets, saliva, or mucus, the World Health Organization advised limited contact with others to prevent further spread (World Health Organization 2020, June 29).

Thus, the spread of COVID-19 has posed a threat to the economy as a whole and made the aspect of mobility a challenge. From the economic point of view, the shockwaves of the virus pushed businesses into bankruptcy and cost people their jobs and way of life (Poeschl 2020). Moreover, it left many businesses unprepared and some without the resources to adapt to the new challenge of COVID-19. Previous studies (Akhtaruzzaman, Boubaker, and Sensoy 2020; Engelhardt et al. 2020; Parodi 2020) illustrated that many businesses have chosen to shut down and lay off workers which resulted in significant increase in unemployment rates.

Focusing on mobility aspects, there is a direct relationship between traffic levels and the spread of COVID-19 (Lee et al. 2020). This implies that an increase in traffic and frequency of contact between people can increase in the risk of further spreading COVID-19. Hence, various containment measures including cancellation of large events, wearing a mask, and following 'social distancing' procedures were adopted by governments and local authorities to minimize the density, duration, and volume of interpersonal interactions (Gros et al. 2020). Studies (Bholane 2020; Khan et al. 2020; Lee et al. 2020; Gros et al. 2020) have shown that while these changes are beneficial for public health, without the steady or increasing movement of people, the economy is showing signs of a collapse. Areas of business, such as restaurants, airlines, cinemas, financial services, and other recreational locations have seen enormous losses in revenue from decreased foot traffic, which is the number of customers that visit a point of interest (POI).

This article aims to provide guidance for business leaders and policy makers, who are continuing to undertake the challenge of increasing mobility without triggering another violent wave of COVID-19. In order to achieve this, it should be realized what components of our travel behavior and our economy have been affected most by the virus: as those sectors will be vital in understanding where and how to implement COVID-19 policies. Economic factors are important in COVID-19 mobility studies because a healthy economy, with proper resource allocation, facilitates the movement of people. Research by Lin 2020 examined multiple pathways of transportation investment in promoting economic growth in China. Through his structural equation modeling perspective, he gained a better understanding of how economic sectors would be significantly altered under diverse mobility conditions. Further studies by Yabe, Zhang, and Ukkusuri 2020 reinforced this claim through their efforts to quantify business resilience and established the strong link between mobility and the economy.

Obtaining transportation measures of a city were limited and largely built on surveys until the emerging trends in smartphone usage (Bognanni et al. 2020). Dong et al. 2017 and Yabe, Zhang, and Ukkusuri 2020 have found that technology is a more accurate method by employing online mapping applications and social media to track user activity. Thus, mobility data can serve as a method of quantifying travel behavior of specific regions, such as Houston in our case, by utilizing granular mobile data to gauge consumer trends and estimate foot traffic. Allcott et al. 2020 have used cell phone data to see how mobility, business closure policies, and stay-at-home orders affect the spread of COVID-19. They found public policy to be ineffective and is primarily driven by voluntary efforts to decrease mobility and subsequently decrease COVID-19 cases. Further, Bognanni et al. 2020 studied the effects of non-pharmaceutical interventions (NPIs) on the spread of COVID-19 and the economy and found similar results where NPIs were mostly unsuccessful in reducing COVID-19 since they were driven by voluntary efforts. Our paper builds on this idea of balancing between mobility and the growth of the virus, but policy data was not included because the categorical variable cannot be

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attuned to the strength of the policy. For example, a mandatory lockdown order is more effective than a social distancing order, yet the model from Allcott et al. 2020 could not account for this. To improve upon previous work, it will not be included in our model, and policy makers can use the following discussion analysis to determine which orders to admit.

In addition, unemployment and business cycle index variables served as a gage of the economy in analyzing foot traffic behavior. Data on the percent change in unemployment claims from 2019 to 2020 was preferred over conventional unemployment rate data because unemployment claims had a more significant impact on the regression. Moreover, data on the percent change in unemployment claims from 2019 to 2020 illustrated severe increases in unemployment caused by the pandemic and accounts for cyclicality, which unemployment rate data is unable to account for. Previous studies have attempted to analyze the impact of COVID-19 (Liu et al. 2020; Ramelli and Wagner 2020; Zhang, Hu, and Ji 2020) using traditional economic variables, such as stock market indices, but may not have produced accurate predictions of COVID-19's impact. COVID-19 has bred economic uncertainty and using 2020 stock indices data or data from a year prior, in 2019, and performing a comparative analysis will not be fruitful. In order to make accurate COVID-19 predictions applying economic data, it is crucial to employ long-term historical data that includes similar major shockwave patterns seen currently. Moving forward, a business cycle index (BCI) is a composite of leading, lagging, and coincident indexes that aim to forecast the strength of economic expansion or recession in the following months using extensive historical data while accounting for other prominent economic measures. While there are multiple variables that could be used to gage an economy, there are limited time series economic variables available on a county level that do not cause multicollinearity issues in the regression. Previous studies (Liu et al. 2020; Ramelli and Wagner 2020; Zhang, Hu, and Ji 2020) additionally failed to consider the link between mobility and the economy; economies are more efficient when there is developed, utilized transportation. This link is notable because the spread of COVID-19 is associated with mobility levels, meaning mobility variables should be included in COVID-19 related analyses to enhance their claims. Their research was done on a global scale, where mobility measures could not be accurately included.

To illustrate the proposed methodology, the case study of Houston, Texas was conducted. Houston is one of the center points of economic activity, innovation, and, more recently, COVID-19 cases in the US. As a result of the increase in COVID-19 cases, markets and health systems are plummeting; this downfall is linked to mobility (Caduff 2020; Lee et al. 2020; Reddy and Kumaar 2020). Our model aims to predict Houston travel behavior from economic and health indicators as well as to identify which transportation sectors have the most impact on overall mobility behavior. The scope of this paper was narrowed to Houston, Texas in order to incorporate the aforementioned mobility measures, which are gathered on a granular scale and cannot be reliably represented in wide-ranging regressions: such as state or global studies. In contrast, economic measures are normally on a national scale and used for wide-range regressions, but some economic measures, such as unemployment claims and BCI, can be downsized to represent a city without compromising the integrity of the data. Downsizing economic data to a smaller unit of analysis past a city level would not be practical or applicable for policy makers and businesses; they would not benefit from knowing the travel behaviors within a zip code or census block group based on economic and mobility measures.

Research contributions

This paper contributes to the advancement of COVID-19 related literature by incorporating mobility measures as well as economic measures in analyzing COVID-19 travel behaviors. The addition of the BCI, which considers historical data from past recessions and economic shocks, provides a better measure of the Houston economy and the direction it is heading in. More importantly, we developed two autoregressive distributed lag (ADL) models to predict and identify the factors contributing to foot traffic in the short run and long run.

Material and methods

To date, many studies (e.g., Mogaji 2020; Shamshiripour et al. 2020; De Haas, Faber, and Hamersma 2020) investigated the impact of COVID-19 on transportation across the world. They asserted that people's livelihood and travel behaviors drastically altered because of the onset of COVID-19. However, their analysis highly relied on graphical statistical methods and survey data in gauging the impact of COVID-19 on transportation. To contribute to the existing literature, we studied transportation behavior through an ADL model, which was used to analyze granular mobility data in predicting Houston foot traffic. Truong (2020) conducted a similar analysis using an autoregressive integrated moving average (ARIMA) model. He discovered a lag in travel behaviors through the model and speculated a connection between the lagging mobility trends and a lagging reaction to COVID-19, but was limited by the ARIMA model. Our ADL model is able to predict travel behavior whilst taking into account multiple lagging components, rather than lagged travel behavior alone. Lagging the COVID-19 case variable is crucial in assessing delays in people's reactions to the virus. Our epidemiological data was measured through the Texas Department of State, who tracks Houston's daily change in COVID-19 cases, aggregated at a county level. Since the virus and its effects on Houston's mobility are the focal point of our study, its inclusion in the regression is crucial.

ADL model

ADL model is a complex form of a linear regression time series that combines aspects of a distributed lag model and an autoregressive model. The hybrid model is not solely confined to have traditional explanatory variables as predictors (x); it comprises past values of the x and additionally includes one or more past, also known as lagged, dependent variables that operates as another independent variable (Fitri et al. 2017, March). The autoregressive-distributed lag (ADL) has been favored for decades in modeling relationships between economic variables because of the model's flexibility and parsimony (Hassler and Wolters 2006; Kripfganz and Schneider 2018, September). Moreover, an ADL model is useful for estimations and for discerning between the dynamics of a long-run and short-run relationship. The basic form of the model used in our study is shown in Equation 1:

$$\begin{aligned} y_t &= m + \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \beta_0 x_t + \beta_1 x_{t-1} + \ldots + \beta_q x_{t-q} \\ &\quad + \varepsilon_t, E(\varepsilon_t | y_{t-1}, x_t, x_{t-1}) \\ &= 0 \end{aligned} \tag{1}$$

Table 1. Variance inflation factor.

VIF Regression Results		
	ADL Multiple Regression 03/01/2020 – 07/16/2020	ADL Multiple Regression 07/16/2020 – 11/01/2020
Variables	VIF	VIF
L(Percent Change in Total Foot Traffic, 7)	1.48	1.74
Grocery and Pharmacy Visits Percent Change	3.12	3.51
Transit Visits Percent Change	5.37	5.96
Workplace Visits Percent Change	1.77	1.98
Minimum Median Dwell Percent Change	2.04	1.69
Unemployment Claims Percent Change	5.18	5.44
Business Cycle Index	1.99	2.55
L(Change in COVID-19 Cases, 7)	1.47	1.96

Where, $y_t$is a stationary variable representing the total traffic foot at time t. $x_t$is a vector of explanatory variables. β is a vector of unknown parameters, and ε_t is known as the 'error term'. The error term equaling zero ensures that the model has a constant variance, has no correlation with x, and is normally distributed. These assumptions can be further checked by the variance inflation factor. In the case of our ADL model, where a single coefficient can have multiple degrees of freedom, the VIF is the best indicator because it reduces the variance inflation factor to a linear measure and makes it comparable across dimensions. A VIF value at or above 10 would signal serious multicollinearity, in which our model does not violate this condition for either regression (see **Table 1**).

Data

Our regression predicts foot traffic through the following variables: lagged percent change in foot traffic, percent change in median dwell, percent change in grocery and pharmacy visits, percent change in work visits, percent change in transit visits, percent change in unemployment claims form 2019, BCI, and lagged change in COVID-19 cases. Foot traffic and median dwell data was collected through Safegraph while mobility sector data was acquired through Google's Mobility Report. BCI and unemployment data was provided by the Federal Reserve Bank of Dallas and Texas Workforce Commission data respectively. Lastly, COVD-19 case tracking data was provided by the Texas Department of State Health and Human Services. Table 2 represents a summary of descriptive statistics of the variables used in this research. All data variables were acquired and aggregated at a county level. While variables such as the percent change in total foot traffic and minimum median dwell time were available at a census block group or zip code level, variables such as total COVID-19 cases and unemployment claims were not available at that same level. A potential solution was to divide the county data proportionally to zip codes based on their populations. However, this method is invalid because it operates under the assumption that COVID-19 and unemployment essentially affect populations evenly. This massively inflated the residual standard deviation because each zip code is unique and could have varied responses to COVID-19. Thus, transforming variables into a smaller unit of analysis, census block group or zip code level, was not a valid option and the next smallest available unit of analysis was at a county level. Our data used the combined county data to make predictions about the whole of Houston. Moreover, the date March 9th, 2020 and its corresponding values were removed from the regression for being an outlier and a high leverage point, skewing the results. March 9th, 2020 contained an extremely high percent change in grocery and pharmacy visits value. Due to rising uncertainty during initial stages of the pandemic, the Houston population was stocking up on supplies: most likely leading to the variable's increase in percent change in visits. Because this event was only observed once in the data, it was removed. The descriptive statistics of the overall dataset are listed below (Table 2). The final time series data used in the regression was split into two categories: one spans from March 1st, 2020 to July 16th, 2020 and the other spans from July 16th, 2020 to November 1st, 2020. The data was split because there was a notable shift in foot traffic trends in mid-July (see **Figure 1**, **Figure 2a**). Splitting the data based on foot traffic trends, rather than COVID-19 trends, allows for COVID-19 related behavioral observations when transit levels are below normal activity and when they return to its baseline. Shakibaei et al. (2020) employed a similar data splitting method by breaking their COVID-19 and transportation data into three phases: disregard for the virus, its initial outbreak, and public sensitivity toward the virus. In doing so, their survey study was able to reveal a shift from public transport to private vehicle use and highlight a significant drop in public ridership within Istanbul, Turkey. Therefore, dividing the data and analyzing each time period allows comparisons between COVID-19 behavior at its initial onset and its more recent behavior.

Overall, the data was compiled from multiple sources, as previously discussed, that were recorded on a daily basis and at a county level. All variables, except for BCI, were represented as a percent change from normal, pre-COVID-19 activity from February 2020. BCI is an indicator for expansionary or recessionary periods and did not need transforming into a percent change basis. Unemployment claim and transit sector data did not require further

Table 2. Descriptive statistics (N = 245).

	Basic Features: Houston Data Study				
Variables	Min	Max	Mean	Median	SD
Percent Change in Total Foot Traffic	−0.77	1.12	−0.37	−0.41	0.26
Grocery and Pharmacy Visits Percent Change	−35.75	40.11	−0.24	−0.38	8.93
Transit Visits Percent Change	−57.00	24.88	−7.86	−3.28	16.43
Workplace Visits Percent Change	−70.38	4.67	−29.28	−32.22	12.21
Minimum Median Dwell Percent Change	0.00	0.32	0.13	0.12	0.07
Unemployment Claims Percent Change	0.17	19.73	5.93	4.54	5.17
Business Cycle Index	301.02	341.60	312.42	310.74	10.80
Change in COVID-19 Cases	0.00	2962.00	778.19	466.00	729.37

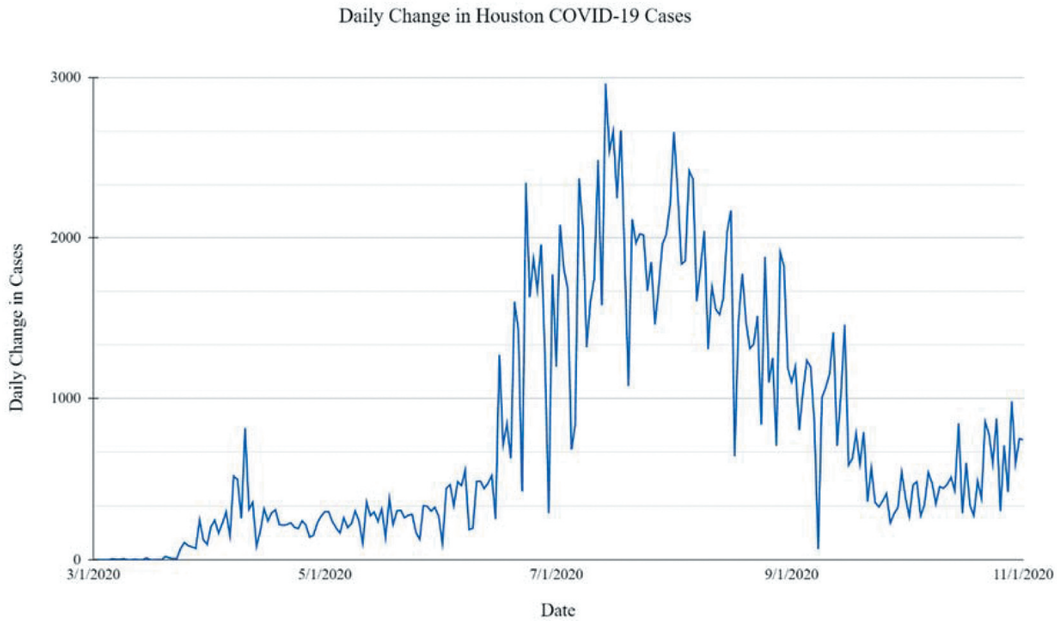

Figure 1. Trendline of growing COVID-19 cases over time in Houston.

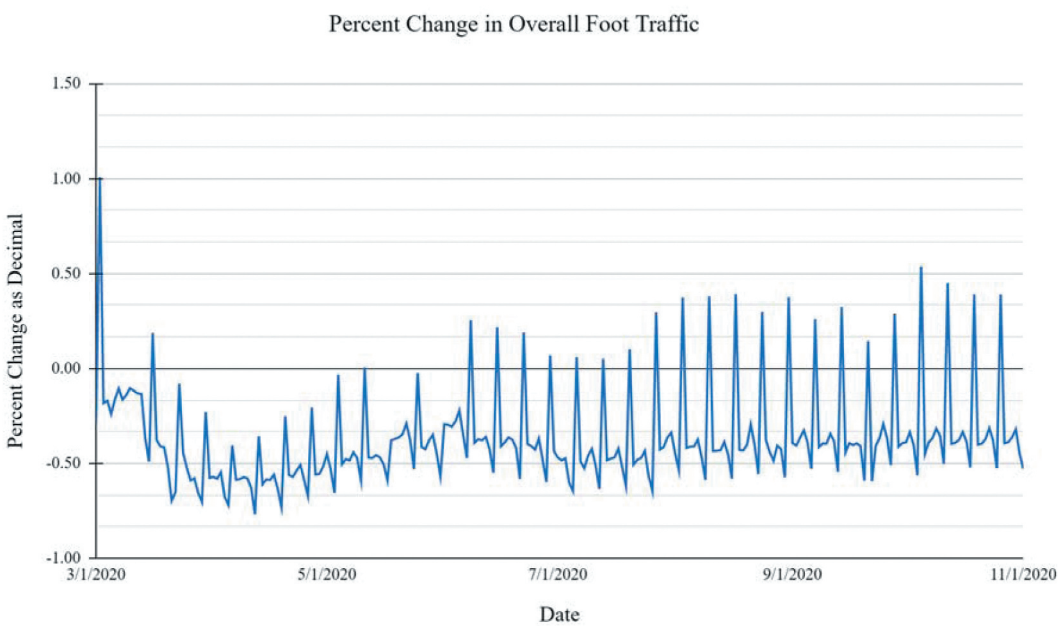

Figure 2a. Trendline for overall Houston foot traffic.

transformation because Google's mobility data and the Texas Workforce Commission's data were presented as a percent change from February 2020. However, minimum medial dwell and overall foot traffic data from Safegraph required further calculation. SafeGraph is a geospatial data company that collects information from mobile applications through APIs and other delivery methods, such as software development kits. The data is limited to individuals above age 16, which could inflate visit counts if included. Within the Safegraph data, there were values for overall foot traffic that were in the twelve-digit range and were considered errors in Safegraph's data processing. Therefore, these misconstrued values were cleaned from the data set and replaced with the average value of overall foot traffic activity. Moving forward, the total daily visit count and daily minimum median dwell time variables were calculated by aggregating all respective values for each POI into a daily sum. Each variable was then calculated into a percent change basis from the average February AOI activity, respectively.

As shown in Figure 1, there is an initial spike around mid-April. Granted, it is a small spike in relation to the whole. However, in retrospect, that was the highest amount of cases and the quickest growth Houston had seen. The panic surrounding the virus was at one of its highest, leading people to be more cautious. As a result, while the daily change in COVID-19 cases rose from mid-April to mid-June, it is at a steady rate. However, around late June and beyond, it seems that the Houston population became desensitized to the virus: as the daily change in COVID-19 cases sharply

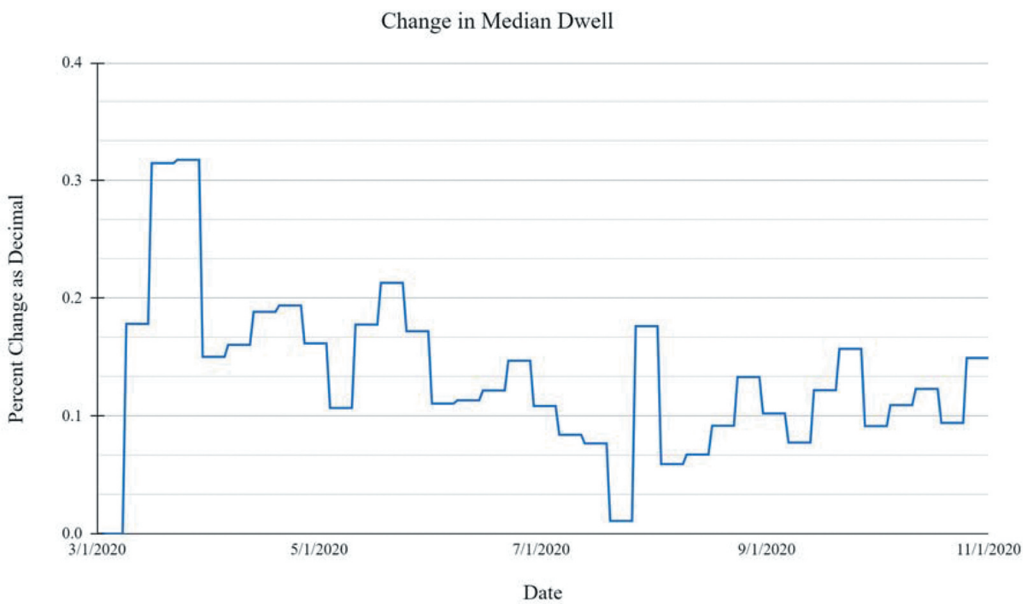

Figure 2b. Trendline for percent change in minimum median dwell time.

increased with mobility factors in Figures 2 through 4 returning to normal levels. In August, the change in COVID-19 cases slowly declines but never tapers off to zero, as the daily change in cases increases again around October.

The method of quantifying travel behavior activity using aggregated mobility data has been used in previous articles. For example, Yabe et al.'s 2020 analysis of the Bayesian time series model estimated the causal impact of hurricanes on businesses through analyzing spatial-temporal big data and point of interest (POI) data. They specifically analyzed the regions of Puerto Rico, Downstate New York, and Upstate New York. They collected their respective data including total daily visits in each area of interest (POI), socio-economic standing, and spatial distribution in the location of the natural disaster. Their inclusion of demographics in an economic analysis provided a deeper understanding of the results. Similarly, Abbasi and Hossein Rashidi 2019 highlighted the importance of socio-demographic variables in measuring human mobility. However, demographics are relatively stationary throughout the year. Therefore, for this paper, with data that was a short-lived time series, demographic variables were omitted. Moreover, other economic measures, such as GDP are calculated annually and nationally. Thus, economic variables were limited to measures that were available at a county level and measured daily, such as unemployment claims. Moreover, Yabe et al.'s 2020 AOI data restricted the analysis to solely business categories offering products or services directly to customers. This omission of data is reasonable for the purposes of their model, analyzing the business impact of COVID-19. However, for the purposes of our regression, all foot traffic data will be included as to observe the impact COVID-19 has on all transit as well as businesses (see **Figure 2a**). In enhancing COVID-19 literature, this paper builds on the POI foot traffic aggregation methods used by Yabe, Zhang, and Ukkusuri (2020) in application to the current pandemic in order to better analyze travel behaviors.

Previous works have used mobility trajectory data to assess built environment in aims of guiding urban planning and enhancing transit services (Sun and Ding 2019; Sun, Zhang, and Shen 2018). According to Safegraph, median minimum dwell time is the median value of the minimum dwell times calculated for each POI visit. This was determined by initially observing the first and last signal from a device during a POI visit. This is a minimum dwell value because the device may have been at the POI longer than the time of the last signal. The grand total values for both Safegraph variables were aggregated from March 1st to November 1st. Furthermore, the average total daily visits during the last week of February 2020 was used as a baseline in calculating the 'Percent Change in Visits' variable. The last week of February 2020 was the earliest data available from Safegraph and was determined as an indicator of normal activity before the onset of COVID-19.

Similar to Figure 1, Figure 2a seems to have a major change in its trendline during mid-April. It can be seen how COVID-19 cases took its first dramatic increase while overall foot traffic took a dramatic decrease. This is an optimal response to the contagion. However, after mid-April, a massive surge in COVID-19 cases has been experienced whilst foot traffic steadily returns to normal levels of activity, measured pre-COVID-19 (see Figures 1 and Figures 2a). While Figure 2)(a is volatile from July through August, the trend centers around zero: the baseline of normal activity. This volatility led to the variable being lagged by one week, which is further explored in the 'Discussion' section. Percent change in median dwell hit its peak in 2020 around the end of March and beginning of April (see Figure 2(b)). Though the trend is decreasing, it remains positive.

Additional mobility data is observed through Google Community Mobility Reports, which details trends over time by county, across different categories (Google LLC 2020). These categories include grocery and pharmacy, retail and recreation, residential, transit station, workplace, and park activities. The data is represented as a percent change from a baseline acting as a normal value for that day of the week. The baseline day was a median value chosen from the five-week period spanning from January 3 to February 6 in 2020. To avoid multicollinearity issues, some variables were eliminated from the model. For example, workplace activity and retail activity were highly correlated and greatly affected the variance inflation factor. Therefore, crucial cataloged mobility sectors most affected by COVID-19 were included in the regression to determine the extent of their contribution to overall travel activity during the pandemic. These included grocery and

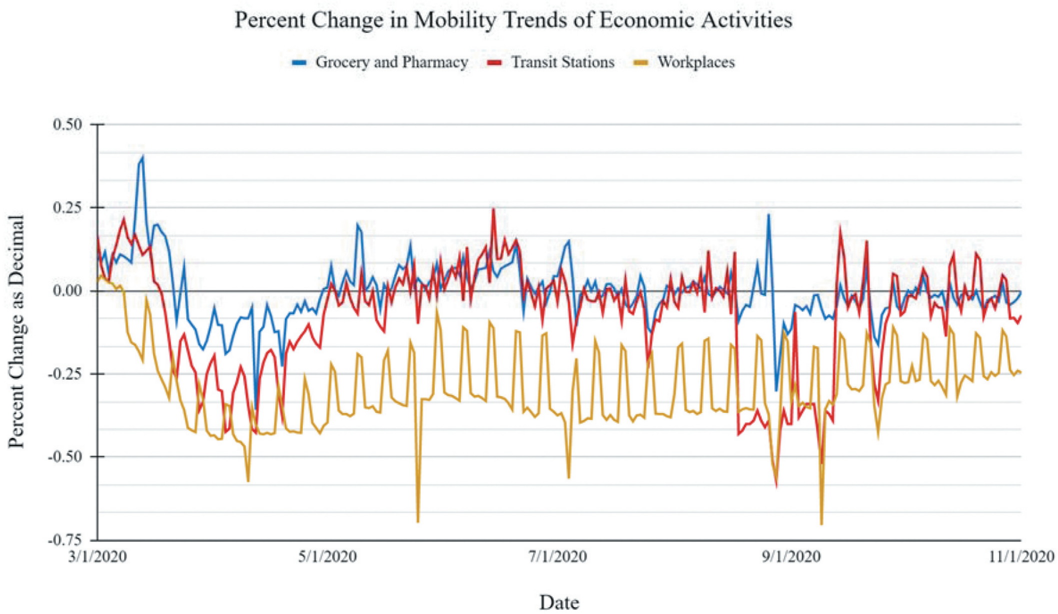

Figure 3. Trendline for percent change in visit activity.

pharmacy, transit stations, and workplace activity with their trend lines shown below (see **Figure 3**).

As shown in Figure 3, all three variables had a drop in mid-April when fears surrounding COVID-19 were at one of its highest. Grocery and pharmacy as well as transit stations seem to have recovered on account of their trendlines roughly returning to the baseline. Despite a positive percent change in unemployment claims seen in Figure 3, grocery and pharmacy stores have been the least affected: with their fall in visit activity being minor in comparison to the others. This could be due to the fact that grocery and pharmacy visits are considered essential and align with the relatively stable trend depicted. In contrast, workplace activity is still operating below the baseline with another major dip near June (see **Figure 3**). The spread of COVID-19 poses a threat to mobility and the economy. As such, businesses aim to limit workplace visits and transition to operating remotely.

An economic variable included was unemployment claims. Unemployed encompasses workers that are currently not working, even though they are able and willing to do so. The unemployment claims variable is measured as a percent change from 2019, comparing it on a matching month to month basis to account for seasonality. The percent change in unemployment claims would allow to more accurately observe how our economy has changed due to the pandemic. Furthermore, it provides insight into the economy's efficiency in capacity and allocation of unused resources. As of now, Houston is experiencing extreme frictional unemployment from COVID-19, which reflects in the consistent positive percent change in unemployment claims compared to 2019

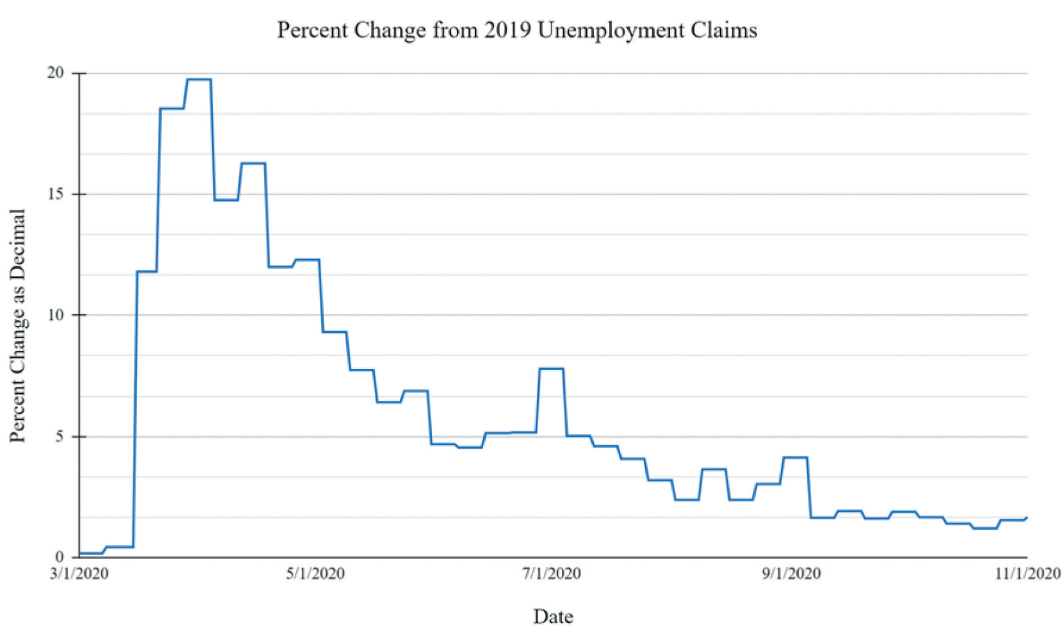

Figure 4. Trendline in the comparative percent change in unemployment claims from 2019.

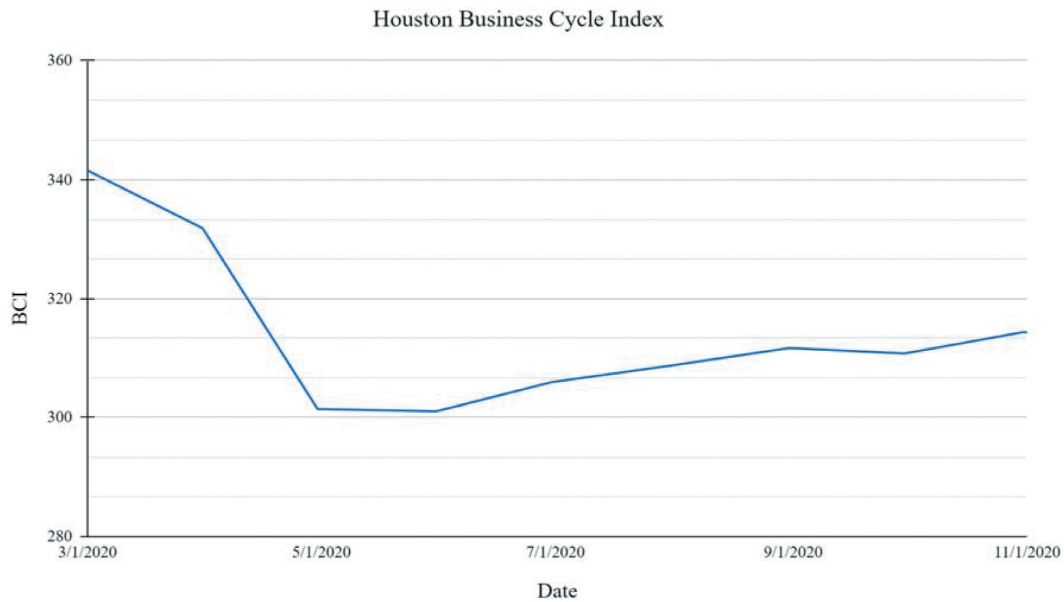

Figure 5. Trendline for Houston's business cycle index.

observed above (see **Figure 4**). This data was issued by the Texas Workforce Commission at a county level.

BCI is another economic variable in the regression that serves to indicate the overall health of the Houston economy as well as its direction of growth (Zarnowitz 1992). Michelsen et al. (2020) revealed that COVID-19 demolished almost all business' potential plans of expanding. Their findings are significant because historically, the BCI has been upward sloping with gradual, slight setbacks from recession periods. However, the onset of COVID-19 resulted in an unprecedented sharp decline in BCI, especially from February to May, that must be considered in COVID-19 mobility studies (see **Figure 5**). The declining BCI indicates low growth prospects and low consumer confidence in markets. This impacts travel behavior because consumption trends have been proven to be strongly correlated with foot traffic (Bholane 2020; Dong et al. 2017).

Results and discussion

As mentioned earlier, in the proposed ADL model, the percent change in weekly foot traffic was the dependent variable and its foot traffic lagged by seven observations was also an independent variable. Including lags within the epidemiological variable allows us to observe a delay in people's behavior based on the severity of COVID-19. This is inherently due to people assessing their current environment and reacting accordingly.

Hein 2020 asserted that the COVID-19 health crisis of 2020 will have severe economic repercussions. His predictions claimed that the US GDP in 2021 will remain far below the expected level derived from estimations pre-COVID-19. Comparisons between the current economic situation and the great recession have been made, holding that 2021 will be defined by financial crisis with merely a partial, weak, and temporary recovery period. Our model results align with that of Hein (2020) as the lagged change in COVID-19 cases were significant only in the first section of data from March 2020 to July 2020 (see **Table 3**). The week-long COVID-19 lag was significant and negative in Table 2. The negative coefficient indicates an indirect relationship with the dependent variable. Meaning, an increase in the change of COVID-19 cases from seven days ago had a significant impact in decreasing current foot traffic. Moreover, the lagged COVID-19 variable reveals a delay in people's responses to the virus. In other words, the foot traffic decreased once the population experienced its severity. However, the lagged COVID-19 variable loses its significance in

Table 3. ADL multiple regression results 03/01/2020 – 07/16/2020.

Dependent Variable: Percent Change in Total Foot Traffic in Houston			
County-level independent variables	Estimate Coefficient	T-value	P-value
(Intercept)	0.414	1.377	0.171
L(Percent Change in Total Foot Traffic, 7)	0.716	13.879	0.000 ***
Grocery and Pharmacy Visits Percent Change	0.00026	0.178	0.859
Transit Visits Percent Change	−0.00015	−0.113	0.910
Workplace Visits Percent Change	−0.0030	−2.900	0.004 **
Minimum Median Dwell	−0.543	−2.816	0.006 **
Unemployment Claims Percent Change	−0.0083	−2.199	0.030 *
Business Cycle Index	−0.0014	−1.499	0.136
L(Change in COVID-19 Cases, 7)	−0.00008	−4.017	0.0001 ***
R-Squared	0.766		
Adjusted R-Squared	0.751		
Number of Observations	128		

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Source: Safegraph, Google Mobility, Texas Department of State Health and Human Services, Federal Reserve Bank of Dallas, and Texas Workforce Commission data

Table 4. ADL multiple regression results 07/16/2020 – 11/01/2020.

Dependent Variable: Percent Change in Total Foot Traffic in Houston			
County-level independent variables	Estimate Coefficient	T-value	P-value
(Intercept)	0.418	1.077	0.285
L(Percent Change in Total Foot Traffic, 7)	0.624	8.920	0.000 ***
Grocery and Pharmacy Visits Percent Change	0.0012	0.677	0.500
Transit Visits Percent Change	0.0004	0.253	0.801
Workplace Visits Percent Change	−0.004	−3.409	0.00097 ***
Minimum Median Dwell	−0.559	−2.605	0.011 *
Unemployment Claims Percent Change	−0.009	−1.987	0.050 *
Business Cycle Index	−0.002	−1.339	0.184
L(Change in COVID-19 Cases, 7)	−0.0002	−1.980	0.051
R-Squared	0.724		
Adjusted R-Squared	0.700		
Number of Observations	99		

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Source: Safegraph, Google Mobility, Texas Department of State Health and Human Services, Federal Reserve Bank of Dallas, and Texas Workforce Commission data

the second section of data from July 2020 to November 2020 (see **Table 4**). Therefore, changes in COVID-19 cases seem to not have a long-term impact on mobility. This means that when COVID-19 cases have been higher, or lower, than normal and remain so for multiple periods, it will have no effect on the percent change in Houston foot traffic. If the threat of the contagion were to have no effect in the future, and we progressively increase our foot traffic, predictions from Hein (2020) could manifest.

Unemployment claims play a major role in assessing economic health. With reference to Houston, the percent change in unemployment claims compared to 2019 had a rising trend but slowly returned to the baseline, as seen in Figure 4. Thus, its significance in the regression indicates that a percent increase in these claims results in decreased percent change in total foot traffic (see **Table 3**). This idea can be seen in the visual maps of Houston's foot traffic from selected dates.

To better understand how foot traffic changes across space and time, we plotted the density of POI visits during different phases of the COVID-19 outbreak. As shown in Figure 6a through Figure 6f, the density of POI visits dramatically decreased after the onset of COVID-19 in March 2020 and remained low until mid-July. The spread of the distribution during this stage appeared to be narrowing as well (see **Figure 6(a-d)**). Afterward, the density of POI visits steadily increased (see **Figure 6(d-f)**). The density of POI visits is steadily increasing while the spread of the distribution appears to be narrowing (see Figure 6(a-f)). This parallels with the course of unemployment claims' percent change from 2019. During April, Houston's percent change in unemployment claims were at its highest so far in 2020 (see **Figure 4**). Consequently, the POI density distribution was at its lowest so far in 2020 (see Figure 6b). When unemployed, individuals lacking stable income become more fiscally conservative. As a result, those individuals will not take as many leisurely visits to POIs and consume goods or services. A similar rationale can be said for workplace visits. Figure 3 illustrates that percent change in workplace visits is negative. Coupled with our regression results, it can be inferred that when more people visit their respective workplace, the lower overall Houston foot traffic will be. When people are physically at work, they usually cannot leave until the end of the day. Thus, they do not contribute to other POI densities and remain relatively stationary in their location. With respect to COVID-19, workplace visits have decreased as businesses are trying to adapt workplace activity to people's homes. From the comfort of one's home and the limitations of working without an office setting, it could lead to an increase in leisurely activity: potentially explaining the

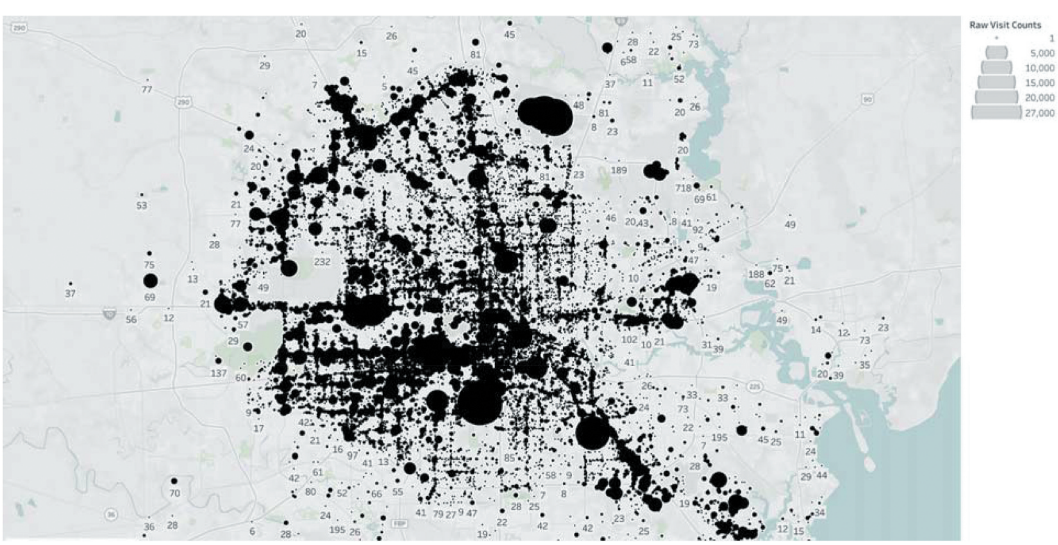

Figure 6a. The POI density distribution from March 1st, 2020 to March 7th, 2020 represents normal foot traffic activity before the disruption of COVID-19. The numeric markers express the minimum median dwell time at each POI.

Figure 6b. The POI density distribution from April 13th, 2020 to April 19th, 2020 significantly decrease compared to Figure 6a. The minimum median dwell experienced an overall increase.

Figure 6c. The POI density distribution from June 1st, 2020 to June 7th, 2020 has slightly increased since the results of Figure 6b but has not fully returned to the standard activity of Figure 6a.

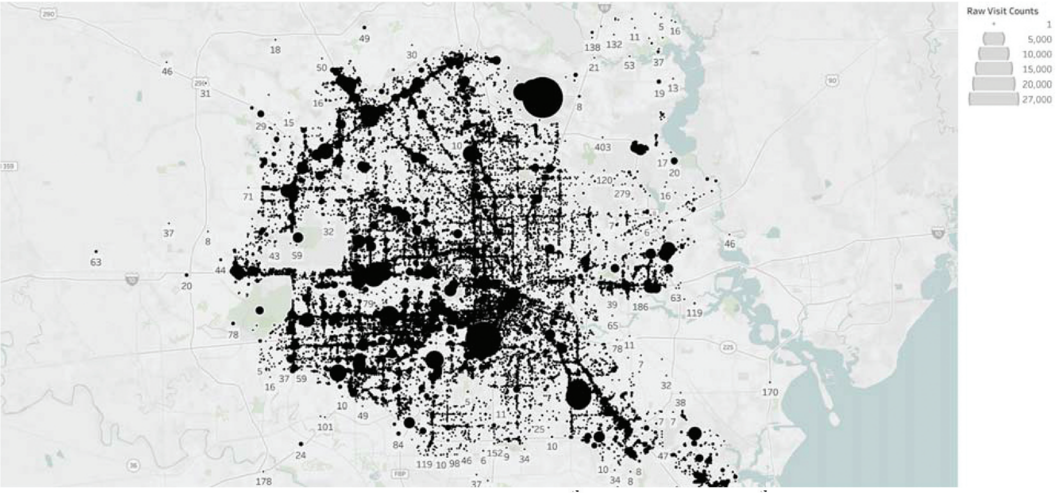

Figure 6d. The POI density distribution from July 10th, 2020 to July 16th, 2020 displays a similar pattern to Figure 6c.

Figure 6e. The POI density distribution from August 26th, 2020 to September 1st, 2020. After July 16th, there was a noticeable change in behaviors, noted by the significant increase in foot traffic during this time frame.

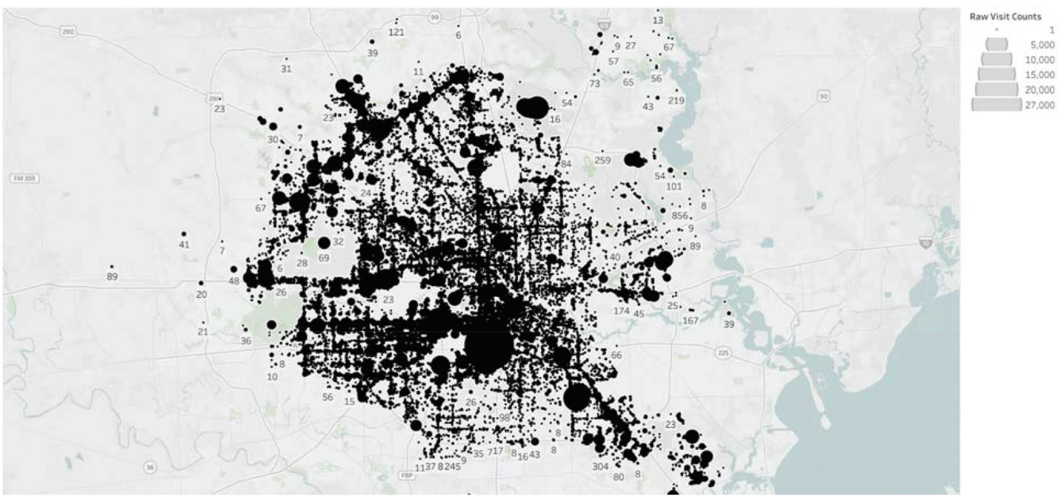

Figure 6f. The POI density distribution from October 27th, 2020 to November 1st, 2020 has practically returned to normal activity represented in Figure 6a.

increase in total visit activity after April. A desensitization to the virus could be another potential explanation for the sudden increase in activity. Additionally, the minimum median dwell time increased as displayed comparatively from Figure 6b to Figure 6f.

Conclusions

Our regression can provide insight into the shifting mobility behavior and future mobility behavior. Notably, the delayed reaction of Houston's population negatively affects overall foot traffic and the economy. Certainly, it is common for a previous week's foot traffic to dramatically affect the current week's decisions and foot traffic behavior. However, when coupled with COVID-19, this becomes a problem. The drawbacks of this regression stem from the limitations of econometrics and the volatile, collective reaction to COVID-19. Factoring in a pandemic to our current environment affected daily life in ways that have not been seen before and were not prepared to face. Previous findings by Truong (2020) proposed a closed loop scenario, where travel behavior altered based on risk perception of COVID-19. Our ADL model was able to provide statistical evidence in support of this hypothesis. Theoretically, as COVID-19 cases increase, it is expected to observe a decrease in foot traffic activity to avoid another wave of COVID-19. Unfortunately, this is not the case. The ADL regression results show that the population's reaction to the spread of COVID-19 cases is not significant in the long run. Increased mobility is linked to an increase in COVID-19 cases. Without fear or concern for the disease, voluntary efforts to limit its growth will diminish. This claim was cemented by previous survey studies (Pawar et al. 2020; Shakibaei et al. 2020; Abdullah et al. 2020) which investigated modal preference of commuters and safety perceptions during the transition and lockdown periods of COVID-19 on a county, city, and global scale, respectively. Interestingly, commuter safety perceptions were not significant in mode choice behavior during the transition phase in all three studies. Meaning, despite public transportation being perceived as the most unsafe, actual commute patterns did not reflect this most likely due to a lack of mobility alternatives or a desensitization to the effects of COVID-19 (Pawar et al. 2020; Shakibaei et al. 2020; Abdullah et al. 2020).

Increasingly disregarding the severity of COVID-19 will have considerable repercussions on the Houston population and its transit systems unless effective, mandatory policies are created to inhibit or enhance mobility. While governments should enforce limiting outdoor activity, they should also focus on making public transit safer for when people make trips out of necessity, grocery and pharmacy visits for example. Employing cleaning staffs to visibly clean public transit stations could help overcome unease in employing shared modes. Additionally, installing hand sanitizer stations or providing disinfecting wipes could also be beneficial. Public transportation operators and policy makers may take advantage of online platforms (Shamshiripour et al. 2020) and smart phone applications in enhancing transit services by providing live updates on when deep cleaning has occurred and how busy transit systems are. Doing so could promote social distancing efforts and provide peace of mind when employing public transit systems. The Houston population would be aware of sanitation efforts and could evaluate the optimal time to use public transit in order to avoid a crowd of people and limit the possibility of contracting the virus.

Essential businesses can also employ online platforms and mobile applications in an effort to mitigate the spread of COVID-19. From the regression results, grocery and pharmacy visits are not significant in predicting foot traffic and have remained at normal levels since they are a necessary AOI visit. Some grocery and pharmacy locations have offered online pickup orders whilst still allowing for in-person shopping, but business policies should emphasize online pickup services. As seen from the ADL regression model, decreasing median dwell time can increase foot traffic. However, this could be the result of more people opting for contactless pick up, increasing foot traffic, but it will be a safer and faster method of completing necessary trips, decreasing median dwell time.

While businesses have made some online transitions, resulting in a decrease in workplace visits, this may result in an increase in overall foot traffic. With the flexibility of online work, people may make more leisurely trips that contribute to the spread of COVID-19. To combat this, stay-at-home or lockdowns policies should be strictly enforced and not on a voluntary basis that has been currently observed. A combination of mandatory policy and safer transit operations will constrict visits to only be conducted on a necessary basis whilst making those necessary trips safer.

Limitations within the regression model stem from variable selection being constrained to time series data available at a county level and within a one-year range. Additionally, while Houston was an optimal case study, only Houston Safegraph data was available to conduct our research.

Future research can be performed in several directions. First, from the model development perspective, additional socio-demographic factors can be utilized in ADL model upon data availability to improve model estimation. Second, the time frame can be selected and split based on the impact coverage of COVID-19 rather than the significant shift in mobility pattern to further investigate the change in results and models parameter estimates.

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Declarations of interest

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