Landscape and Urban Planning 205 (2021) 103952

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Compact development and adherence to stay-at-home order during the COVID-19 pandemic: A longitudinal investigation in the United States

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HIGHLIGHTS

- Travel reductions during the shelter-in-place change over time in a nonlinear form.
- Park trips have the least reduction (0.4%, on average) among all three destinations.
- Trip to transit stations has the highest reduction (average 37%) of all destinations.
- Compact development leads to a significantly lower reduction in park trips.
- Compactness leads to a significantly higher reduction in grocery and transit trips.

ARTICLE INFO

Keywords:
Social distancing
Shelter-in-place
Compact development
Urban sprawl
COVID-19 pandemic

ABSTRACT

In the absence of a vaccine and medical treatments, social distancing remains the only option available to governments in order to slow the spread of global pandemics such as COVID-19 and save millions of lives. Despite the scientific evidence on the effectiveness of social distancing measures, they are not being practiced uniformly across the U.S. Accordingly, the role of compact development on the level of adherence to social distancing measures has not been empirically studied. This longitudinal study employs a natural experimental research design to investigative the impacts of compact development on reduction in travel to three types of destinations representing a range of essential and non-essential trips in 771 metropolitan counties in the U.S during the shelter-in-place order amid the COVID-19 pandemic. We employed Multilevel Linear Modeling (MLM) for the three longitudinal analyses in this study to model determinants of reduction in daily trips to grocery stores, parks, and transit stations; using travel data from Google and accounting for the hierarchical (two-level) structure of the data. We found that the challenges of practicing social distancing in compact areas are not related to minimizing essential trips. Quite the opposite, residents of compact areas have significantly higher reduction in trips to essential destinations such as grocery stores/pharmacies, and transit stations. However, residents of compact counties have significantly lower reduction in their trips to parks possibly due to the smaller homes, lack of private yards, and the higher level of anxiety amid the pandemic. This study offers a number of practical implications and directions for future research.

1. Introduction

The novel coronavirus (COVID-19) is recognized as the most serious public health threat in human history since the 1918 Influenza pandemic that infected about a third of world population and caused about 50 million deaths. At the time of this writing, it has been about 2 months since World Health Organization (WHO) declared COVID-19 as a global pandemic on March 11, 2020, and it has led to 3.3 million infections and more than 250,000 deaths while more than a third of total infections and about a quarter of total deaths belong to the United States (Dong, Du, & Gardner, 2020). These public health outcomes coupled with the economic impacts of pandemic are projected to cause about 6.2 percent decline in the U.S gross domestic product (GDP) and more than 25 percent unemployment rate in 2020 and beyond (Thunström, Newbold, Finnoff, Ashworth, & Shogren, 2020).

In the absence of vaccines and/or effective treatments, social

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https://doi.org/10.1016/j.landurbplan.2020.103952
Received 11 May 2020; Received in revised form 6 September 2020; Accepted 9 September 2020
Available online 30 September 2020

distancing measures remain as the only available option to governments to help slow the spread and ideally control the pandemic. A recent study published in March 2020, by researchers from the University of Chicago shows that three months of moderate social distancing measures during the COVID-19 pandemic would save 1.7 million lives in which about 630,000 are saved due to not overwhelming the healthcare facilities (Greenstone & Nigam, 2020). While social distancing could be done in various forms, the most restrictive measure is the shelter-in-place order which requires residents to stay home with the exception of trips to essential destinations such as grocery store and pharmacy.

In theory, compact development could facilitate easier and more effective implementation of shelter-in-place orders in a number of ways. First, density could increase awareness of the virus and make residents more precautious about following social distancing recommendations. In addition, residents in dense areas have more shopping options in close proximity to their place of residence while people in low density, suburban areas often have to rely on a single big-box retailer such as Walmart for all of their shopping needs which potentially increases the concentration of people in the store, the need for travel, and the length of the trips. Third, urban density facilitates online shopping and urban shoppers are more likely to shop groceries online (Farag, Schwanen, Dijst, & Faber, 2007). The same applies to online restaurant home-delivery orders. The service that is less likely to be available in outer low-density suburban areas.

Yes, the impact of compact development on the implementation of shelter-in-place order has not been empirically studied. According to national polls such as Gallup Polls; an American analytics and polling company, survey respondents in denser areas are 24 percent more likely to practice social distancing than people who live in suburban and rural areas. These observations call for further empirical investigations to show whether compact development contributes to the effective implementation of the mandatory shelter-in-place order.

This longitudinal study addresses these gaps in the literature by employing the natural experimental research design to investigate the relationship between compact development and the degree of adherence to shelter-in-place order; measured in terms of reduction in travel to three major destinations in 771 U.S. metropolitan counties during the COVID-19 pandemic. We employed Multilevel Linear Modeling (MLM) for the three longitudinal analyses in this study to model the percentage of reduction in trips to grocery stores/pharmacies (essential trips), parks (non-essential trips) and transit stations (overall transit ridership) while accounting for the hierarchical (two-level) structure of the data. Level-1 includes the repeated observations of percent reduction in trips to each destination; relative to the baseline in January and February, as a function of days since the effective day of shelter-in-place order within each county in our sample and Level-2 includes compactness and other county level variables such as socioeconomic and political characteristics.

1.1. Determinants of effective social distancing implementation

The successful implementation of social distancing interventions requires a substantial engagement from the citizens and communities. Literature points to a number of sociodemographic, political and behavioral characteristics that contribute to the effective implementation of social distancing advisories.

Among sociodemographic factors, literature highlights the role of age, race, ethnicity, educational attainments, income, and working status in peoples' level of engagement in practicing social distancing (Bish & Michie, 2010; Wolf, Serper, Opsasnick, O'Conor, Curtis, Benavente, Wismer, Batio, Eifler, & Zheng, 2020). Previous studies found that older adults and non-White population are more likely to avoid public spaces, large gatherings, and public transit during the epidemic outbreaks such as SARS and Avian Flu (Jones & Salathe, 2009; Lau, Yang, Tsui, & Kim, 2003; Rubin, Amlôt, Page, & Wessely, 2009). Previous studies from Hong Kong during the SARS and Avian Influenza also show that highly educated individuals are more precautious to practice protective behaviors such as social distancing (Lau, Kim, Tsui, & Griffiths, 2007; Leung et al., 2003). Similarly, according to a series of studies, by Quinn, Kumar, and colleagues, low-income and less-educated individuals have more exposure to the H1N1 Swine Flu pandemic due to the lack of access to recourses such as workplace policies, paid sick days and job security that would enable them to practice social distancing (Kumar, Quinn, Kim, Daniel, & Freimuth, 2012; Quinn & Kumar, 2014; Quinn et al., 2011). These findings have been confirmed by recent studies, in March and April 2020, focusing on the COVID-19 pandemic (Block, Berg, Lennon, Miller, & Nunez-Smith, 2020; Weiss & Paasche-Orlow, 2020; Wright, Sonin, Driscoll, & Wilson, 2020).

Perhaps one of the greatest indicators of social distancing measures both in terms of putting the order in place by elected officials and also complying with the order by public is the political affiliation. Research shows that individuals' viewpoints and behaviors are largely shaped by the views of their political party leaders (Cohen, 2003). In other words, political partisanship is an influential force in shaping citizens' attitudes and preferences (Satherley, Yogeeswaran, Osborne, & Sibley, 2018). The behavior towards the COVID-19 pandemic is not an exception. A recent study in the U.S. points to the political partisanship as the strongest predictor of the early adoption of social distancing policies with Democratic "blue" states implementing the Shelter-in-place order far earlier than Republican "red" states (Adolph, Amano, Bang-Jensen, Fullman, & Wilkerson, 2020; Painter & Qiu, 2020). As of April 2020, even after more than 1.2 million confirmed cases and 70,000 deaths in the U.S., still five Republican states including Arkansas, Iowa, Nebraska, North Dakota, and South Dakota have not adopted the shelter-in-place order (Mervosh, Lu, & Swales, 2020). Accordingly, the Republican party leaders and the conservative media have been accused to downplay the severity of COVID-19 pandemic (e.g. Smith, 2020) which has led to substantially lower level of concern by Republican voters; according to multiple national polls, in March and April 2020 (CIVIQS, 2020; Gallup, 2020; Barrios and Hochberg, 2020). In the same line, recent empirical studies in the U.S. counties showed that Republican voters had been less engaged in social distancing from January 27 to July 12, 2020 to reduce the risk of transmission (Allcott, Boxell, Conway, Gentzkow, Thaler, & Yang, 2020). In addition, previous studies show that democrats are more likely to rely on science in decision-making than conservatives who tend to be more skeptical of scientific evidence and recommendations (Blank & Shaw, 2015; Kraft, Lodge, & Taber, 2015).

Finally, civic engagement can also bear a strong relationship to compliance with social distancing (Baum, Jacobson, & Goold, 2009). According to Baum et al. (2009) and Viens, Bensimon, and Upshur (2009) the stronger engagement of public in governmental decision could lead to a stronger trust in the government which effectively contributes to a more effective implementation of governmental decisions (e.g. social distancing orders) in a collaborative manner. In other words, higher levels of social capital and civic engagement could indicate a higher level of social responsibility and particularly compliance with the government decisions that collectively benefit the society such as social distancing, according to two recent studies published in March and June 2020 (Barrios, Benmelech, Hochberg, Sapienza, & Zingales, 2020; Dyevre & Yeung, 2020).

1.2. Pathways linking built environment to the effective social distancing implementation

In addition to the sociodemographic and political factors, urban density could also impact the level of engagement as well as barriers to effective implementation of social distancing interventions. First, density could raise awareness about the severity and seriousness of the pandemic. Studies from the U.S., Australia, UK, Canada, and Europe report that the higher perceived susceptibility to contagious diseases; such as SARS and COVID-19, is associated with more precautionary behaviors such as avoiding public gatherings, non-essential trips and public transit (Allcott et al., 2020; Barr et al., 2008; Blendon, Benson, DesRoches, Raleigh, & Taylor-Clark, 2004; Brug et al., 2004; Carozzi, Provenzano, & Roth, 2020; Cava, Fay, Beanlands, McCay, & Wignall, 2005; Rubin et al., 2009). In Australia, a national survey shows that people who perceived higher risks of pandemic influenza are more willing to adhere to social distancing recommendations (Barr et al., 2008). Similarly, studies in the UK and Canada found a positive and significant relationship between higher compliance with social distancing such as reduction in non-essential travels and the greater perceived risk of Swine Flu and SARS, respectively (Cava et al., 2005; Rubin et al., 2009).

Accordingly, dense areas lead to greater awareness of the risk and severity of the pandemic. Pandemics are more likely to reach earlier to dense areas, particularly if they are highly connected to the outside world (Carozzi et al., 2020; Hamidi, Ewing, & Sabouri, 2020; Hamidi, Sabouri, & Ewing, 2020). Dense areas also are more likely to have a higher number of COVID-19 deaths; although not necessarily on a per capita basis (Dong et al., 2020). Thus, residents of dense areas have a greater exposure to the first-hand information about the susceptibility to the virus. Knowing people who are being infected is a more powerful force in following social distancing advisories than just hearing about the disease from the media outlets.

In addition, residents of suburban and exurban areas face greater barriers in minimizing their non-essential travel in order to comply with the social distancing orders. Urban sprawl has been widely linked to significantly higher reliance on private vehicles for travel to various destinations, higher rates of car ownership, longer trips, and higher number of trips per household (Ewing & Hamidi, 2017; Ewing, Hamidi, Gallivant, Nelson, & Grace, 2014; Hamidi, Ewing, Preuss, & Dodds, 2015). In contrast, dense areas have better access to essential destinations in a walking distance (Ewing & Cervero, 2010; Hamidi, 2019). For instance, people in dense and compact areas are more likely to have multiple options for their essential shopping needs in a walkable distance while people in sprawling areas often rely on a single big-box store such as Walmart for their shopping needs which could increase the risk of transmission in these places.

Finally, people in dense areas have better access to online shopping options which minimizes their needs for travel. Lower population density and longer distance between the grocery stores, distribution centers and residential areas make it fiscally challenging to provide delivery services to sprawling counties. Equally, urban residents are more likely to place online grocery orders than residents of suburban areas. A recent report by Acosta; based on the shopper surveys, google reviews, and social media commentary, concludes that shoppers in dense urban areas are 90 percent more likely than their counterparts in suburban and exurban areas to rank online grocery shopping in their top three shopping experience priorities and about 60 percent of urban shoppers report online grocery shopping as compared to the 29 percent in suburban areas (Acosta, 2019). The same applies to the food delivery from restaurants.

Similarly, Farag et al. (2007) through using Structural Equation Modeling unveil that urban residents shop items online more often as they tend to have a faster Internet connection. In contrary; however, mixed land use feature of compact urban areas could bring a higher shop accessibility causing a more frequent store shopping than less urbanized areas (Farag et al., 2007). With that being said, store accessibility in compact areas could also lead to more cost-effective home delivery services for grocery ecommerce. Reachable distance and delivery time window need to be tight for food materials to deal with the preservation temperature regulation and the increasing number of small orders to be delivered all the way to a customers' homes (Brooksher, 1999; Punakivi & Saranen, 2001). Therefore, greater accessibility in compact areas could benefit e-grocery delivery with a larger pool of customers in a reachable service area.

Nevertheless, the impact of urban density on the effective implementation of social distancing measures has not been empirically studied. This longitudinal study contributes to this gap in the literature by investigating the impact of density on changes in mobility patterns across the U.S. metropolitan counties during the shelter-in-place order. We study changes in travel to three destinations; including grocery stores/pharmacies, parks, and transit stations, controlling for key aforementioned factors as well as confounding variables specific to each destination which is explained the in the next section.

2. Methods

This longitudinal study investigates the changes in movement patterns since the effective day of mandatory shelter-in-place order during the COVID-19 pandemic in 771 urban counties in the U.S metropolitan areas. We excluded rural counties for two reasons. First, the travel pattern data, obtained from Google, are collected based on information from smartphones and according to Google, location accuracy and the quality of trip destinations' data vary significantly between rural and non-rural areas. Second, the dynamics of relationship between built environment and mobility patterns vary significantly between urban and rural areas.

County is used as the unit of geography in this study because people's movement (travel) typically happen beyond their immediate neighborhood. Data from the National Household Travel Survey (2017) shows that about 87 percent of daily trips in the U.S. take place in personal vehicles; and the average driver drives about 29 miles per day (U.S Department of Transportation, 2017). County is the best geography to capture these movements. It has been widely used as the unit of analysis in other studies related to the impacts of urban form on dependent variables of similar nature such as traffic crashes and fatalities (Ewing, Hamidi, & Grace, 2016).

For each county in our sample, we investigate the daily changes in people's movement to three destinations including groceries/pharmacies, parks, and transit stations; representing both essential and non-essential trips. We track these changes on a daily basis for every day since the effective date of mandatory shelter-in-place-order. Due to hierarchical structural for the data (days nested within counties) we employ hierarchical modeling in this analysis which is explained in the next section. Note that social distancing interventions could be implemented in different ways including the school and business closures, isolating infected people from others, wearing masks, adherence to the 6-feet standard distance with other people and the mandatory stay-at-home order which requires all residents to stay at home and leave their residential place only for essential needs. The focus of this study is only on stay-at-home order as one form of social distancing interventions.

2.1. Data and variables

Table 1 presents the list of outcome and independent variables, the data sources, and descriptive statistics. All variables are computed for 771 metropolitan counties in the U.S; although the final sample for each model depends on the availability of travel data to each destination.

The outcome variables representing daily changes in people's travel to three different destinations are based on the data from COVID-19 Community Mobility Reports (CMR); a publicly available resource published by Google to help public health officials better understand the mobility changes as the result of shelter-in-place and other social distancing policies (Aktay, Bavadekar, Cossoul, Davis, Desfontaines, Fabrikant, & Kamath, 2020). According to Google, the mobility metrics are generated based on a set of anonymized information from Google users who opted-in to Location History. Google includes travel data from every Android user who has agreed to turn on location tracking and iPhone users that have Google Maps installed on their smartphones. Google computes the percentage changes of these metrics from a baseline based on historical data. The reference baseline is defined as a five-week period from January 3, 2020 to February 6, 2020 and the baseline

Table 1
Variables, Data Sources and Descriptive Statistics.

Variable Description	Data Sources	Mean (SD)*
Outcome Variables		
Trip reduction to groceries/pharmacies (each day)	Google[1]	Varies by day
Trip reduction to parks (each day)	Google[1]	Varies by day
Trip reduction to transit stations (each day)	Google[1]	Varies by day
Independent Variables Level 1 (Day Level)		
Days since shelter-in-place order issuance	New York Times[2]	15.05 (9.49)
Independent Variables Level 2 (County Level)		
ln of metropolitan population (in 10,000 s)	ACS 2018 (5-year estimates)[3]	13.66 (1.43)
% of population with college degree or higher	ACS 2018 (5-year estimates)[3]	39.36 (10.14)
% of male population	ACS 2018 (5-year estimates)[3]	49.35 (1.30)
% of population aged 65 or over	ACS 2018 (5-year estimates)[3]	15.79 (3.65)
% of active commuters (bike + walk)	ACS 2018 (5-year estimates)[3]	2.62 (2.10)
% of working age population	ACS 2018 (5-year estimates)[3]	65.44(2.76)
% of children	ACS 2018 (5-year estimates)[3]	22.96 (4.02)
% of working population in health occupation	ACS 2016 (5-year estimates)[3]	6.24 (1.35)
% of households below the poverty level	ACS 2016 (5-year estimates)[3]	12.67 (4.42)
% of Trump voters in the 2016 presidential election	MIT Election Lab[4]	54.35 (15.09)
% voted in 2016 presidential election	MIT Election Lab[4]	44.59 (7.41)
# of violent crime offenses (per 100,000 population)	RWJF 2020[5]	334.67 (212.10)
# of open parks (per 10,000 population)	ParkServe® Dataset (2019)[6]	3.98 (2.82)
County Compactness Index	Ewing & Hamidi (2014)[7]	106.27 (18.35)
Avg. VMT (per 10,000 population)	Streetlight (January 2020)[8]	4392.23(1715.53)
# of grocery stores per Sq. Mile.	Esri Retail MarketPlace (2018)[9]	0.24 (0.77)
Unemployment rate changes between Mar. & Feb. 2020	Bureau of Labor Statistics[10]	14.36 (19.54)

1 https://www.google.com/covid19/mobility/ accessed May 7, 2020
2 https://www.nytimes.com/interactive/2020/us/coronavirus-shelter-in-place-order.html accessed May 7, 2020
3 American Community Survey 2018 (5-year estimate). https://data.census.gov/cedsci/deeplinks?url=https://factfinder.census.gov/
4 Retrieved from: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:https://doi.org/10.7910/DVN/42MVDX
5 Robert Wood Johnson Foundation (2020), County Health Rankings & Roadmaps, https://www.countyhealthrankings.org/app/utah/2020
6 The Trust for Public Land. Retrieved from: https://www.tpl.org/parkserve/downloads
7 Ewing and Hamidi (2014). Measuring Urban Sprawl and Validating Sprawl Measures https://gis.cancer.gov/tools/urban-sprawl/
8 https://www.streetlightdata.com/vmt-monitor-by-county/
9 Retrieved https://www.ers.usda.gov/foodatlas/
10 https://www.bls.gov/lau/

value for each day of the week equals to the median value of the same days of the week during the five-week period. For instance, for any Friday the baseline value would be the median value of five Fridays in the 5-week baseline range. The changes in movement (compared to the baseline) for each destination is published as a percentage and if there is not sufficient data to ensure anonymity or reliability of metrics, the value for that specific day and/or destination has not been reported (Aktay et al., 2020). Three trip destinations, representing a range of essential and nonessential trip purposes are included in this study as following:

- *Groceries/pharmacies (essential destination):* grocery stores, food warehouses, farmers' markets, specialty food shops, drug stores and pharmacies.
- *Transit stations:* public transport hubs such as bus stops, trolley, light rail, commuter rail and subway stations.
- *Parks (non-essential destination):* local parks, national parks, public beaches, marinas, dog parks, plazas and public gardens (Aktay et al., 2020).

For each destination, the outcome variable represents the percentage of travel reduction with higher value showing a higher reduction for every day since the effective date of mandatory shelter-in-place order.

Google data has several advantages over other existing GPS-based mobility data sources. First, it has the highest poll of users among all existing mobility apps since Google maps is the most widely used app for travel and direction purposes. Also, in addition to including GPS data from users of Google maps, Google includes GPS data from any smartphone users who turn on the location history feature on their phone. Furthermore, while other GPS-based data are either modeled or are based on a small sample, the Google mobility data is based on 100% actual location-based information of smartphone users and does not have the limitations and errors associated with modeled variables.

The independent variable of interest is the county compactness/sprawl index. This index places urban sprawl at one end of a continuous scale and compact development at the other (Ewing & Hamidi, 2014, 2015, 2017). The index incorporates 21 measures of the built environment and captures four distinct dimensions of sprawl: development density; land use mix; population and employment centering; and street accessibility, which represents the relative accessibility provided by the county. This index is freely available for 994 county and county equivalents from an NIH Website[1] and has been widely used by scholars for analyzing the relations between sprawl/compactness and a range of quality-of-life outcomes such as housing affordability; traffic congestion; traffic safety; open space preservation; physical activity and obesity; social capital; air quality; housing and transportation affordability and upward mobility.

Our models account for confounding factors such as sociodemographic attributes and political partisanship. Political partisanship was measured as the percentage of voting population who voted for President Trump in the 2016 U.S. presidential election as well as the overall voter turnout in that election obtained from the MIT Election Data and Science Lab. Data on other covariates such as race and age distribution and share of adults with college degrees or higher were obtained from the American Community Survey (ACS) 2014–2018 5-year estimate.

Our models also account for confounding factors specific to each destination. The major factors underlying the changes in trips to grocery stores are the availability of grocery stores and shopping behavior variations derived by sociodemographic factors such as gender with men being more inclined to online shopping during the pandemic (Petro, 2020) and age with seniors being more likely to avoid frequent grocery shopping (Carufel, 2020). To account for these factors, we utilized Esri Retail MarketPlace (2018) to measure the number of grocery stores per square mile in each county for the model specified to grocery store trips. Furthermore, we controlled for the gender and age characteristics using the ACS 5-year average (from 2014 to 2018) to compute the percentage of children and male population in each county. Specific to transit station as a trip destination, our model accounts for both neighborhood level service quality in a county and those individuals who potentially need to use transit despite the pandemic. Furthermore, our model

[1] http://gis.cancer.gov/tools/urban-sprawl Accessed May 5, 2020.

accounts for the share of essential workers during the pandemic consists of healthcare workforce, using the ACS 5-year estimate (2014–2018).

Specific to park trips, our model accounts for the availability of parks, the overall safety, and percentage of walking and bilking commuters as a proxy for the share of physically active population in a county. Literature points to the perceived park safety as a strong predictor of park use (Echeverria, Kang, Isasi, Johnson-Dias, & Pacquiao, 2014; Han, Cohen, Derose, Li, & Williamson, 2018; Lapham et al., 2016). Also, research shows that residents with active lifestyle have more visits to parks; while park visits also depend on the number of parks available per capita (Godbey, Caldwell, Floyd, & Payne, 2005). Accordingly, we computed the violent crime rate using the number of violent crime offenses from the County Health Rankings and Roadmaps dataset which is developed by the Robert Wood Johnson Foundation. In addition, using ParkServe® Dataset (2019) released by the Trust for Public Land organization, we computed the number of open parks (at no fee) per capita. We also used the ACS 5-year estimate (2014–2018) to compute the percentage of children and active commuters using biking and walking as their main mode of transportation to work.

2.2. Analytical methods

We employed Multilevel Linear Modeling (MLM) for three longitudinal analyses in this study to model determinants of changes in travel to three destinations during the shelter-in-place order. The MLM in this study accounts for two levels of data structure. Level-1 is the repeated observations (days since the shelter-in-place order was in place) within each county in our sample and Level-2 is the county level variables. The MLM models were estimated using the HLM software.

Multilevel modeling has several advantages that makes it the best fit for these analyses. MLM accounts for the dependency among individual observations which in our work would be the observed days for each county. Furthermore, within a multilevel model, each level in the dataset (e.g. repeated observations within counties) is represented by its own sub-model (see Fig. 1). In other words, MLM can be used to estimate individual growth models for each county and the regression parameters such as intercepts, slopes are used as random effects to explain the variation in level-2 (county level) along with other level-2 (county level) independent variables (Raudenbush & Bryk, 2002). Basically, a separate curve is estimated for each county, with a different intercept and slope. Then, at Level-2, the intercepts and coefficients from Level-1 are modeled in terms of the full range of county-specific variables. County variables were uncentered, as is typically the case in growth curve models. These are random coefficient (random slope) models, as the slopes of the power functions were found to vary significantly from county to county.

The main Level-1 variables are the compliance with the stay-at-home order (or basically reduction in trips to groceries, parks and transit stations) as our three dependent variables, and the number of days since the shelter-in-place order was in place. A power function was chosen because we observed that the relationship between the dependent variables versus days since the effective day of shelter-in-place order is non-linear, as show in Fig. 1. As Fig. 1 shows, the reduction rates in trips to the main three destinations increase at first and then decrease over time. Given the initial explosive growth of reduction in trips, we would expect that the number of days since the shelter-in-place order was in place is raised to a power greater than 1.0 for most counties. These plots also show the day-by-day variation of compliance with the stay-at-home order in each county. Again, MLM allows us to model this daily variation while accounting for the hierarchical structure of the data and the variations in the county-level factors. Days were grand mean centered, meaning that they were measured as deviations from the grand means across all of the counties. At some point, based on the plots generated for counties like Cook County, IL, or New York County, NY, the drop in trips will level off to form an S-shaped or logit curve while in San Francisco County the compliance with the stay-at-home order increase at first and then decrease forming a U-shaped curve. This U-shaped curve is the case across most counties and metropolitan areas of the United States, so the simpler power function seems the right functional form for this modeling exercise.

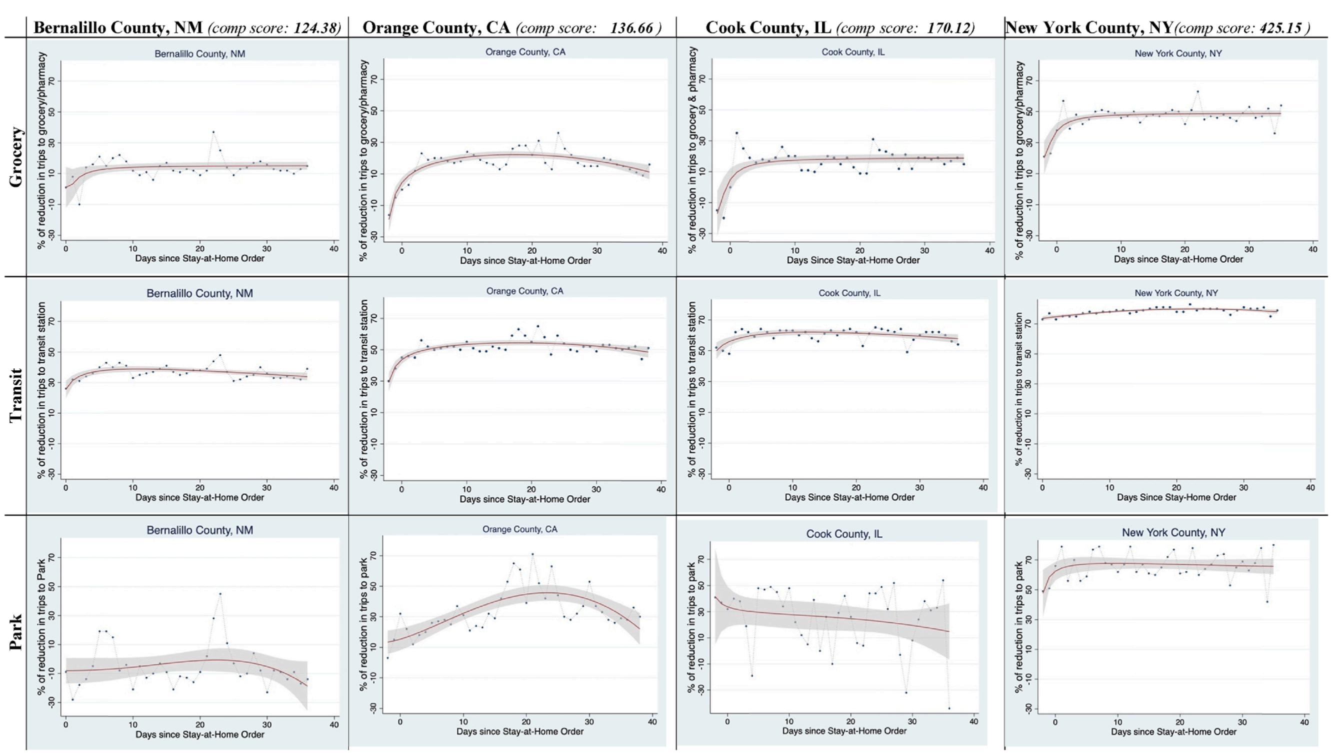

Fig. 1. Changes in Trip Reductions to Three Destinations (Grocery Stores/Pharmacies, Parks and Transit Stations); Relative to January Baseline, During the Stay-At-Home Order Period (Counties are sorted from sprawling to more compact (left to right)).

3. Results and discussion

This study investigates the impact of compact development on changes in travel to three types of destination; representing essential trips, non-essential trips, and the overall transit use, during the shelter-in-place order in the U.S. Table 2 shows descriptive statistics for the three outcome variables at the county level.

As shown in Table 2, park trips have the highest standard deviation and variation and the least average reduction among the three destinations. Even though parks are considered non-essential destinations; on average, trips to parks has only decreased less than 0.4 percent compared to the baseline. This is not surprising considering the well-established literature that shows physical and psychological health benefits of parks and greenspaces (e.g. Sugiyama, Leslie, Giles-Corti, & Owen, 2008). Shelter-in-place order could lead to an increase in the sense of anxiety and isolations in people due to extreme restrictions about social gatherings in workplace, school, and other non-essential places (Jacobson, Lekkas, Price, Heinz, Song, O'Malley, & Barr, 2020). A visit to park serves as a feasible alternative to families for mitigating the anxiety and stress that is generated by the pandemic and its consequences (Jennings & Bamkole, 2019). It is also possible that in some states the stay-at-home order puts more restrictions in place for people's visit to parks. Based on our review of stay-at-home order policies in different states, in most cases the policy allows residents to have a short walk or a visit to parks, following the 6-feet standard distance with others; however, there may be more restrictions in some states and/or counties that is not controlled in this analysis.

In addition, Google data shows an average of 13.3 percent reduction in trips to grocery stores/pharmacies in the U.S. metropolitan counties which are considered essential trips. On the other hand; trip to transit stations, on average, has the highest reduction of all destinations with about 37.4 percent reduction compared to the baseline.

3.1. Determinants of reduction in travel during the COVID-19 pandemic: Evidence from the MLM analyses

While all three destinations have generally experienced reduction in trips compared to the baseline; there exists a substantial geographic variation in the amount of trip reduction to these destinations across the U.S and; surprisingly, many counties have actually experienced an increase in the amount of travel to one or more destinations. For instance, Miami County in Florida has experienced the most reduction (71.9 percent reduction) in park trips while Calumet county in Wisconsin has about 193 percent increase in park trips during the shelter-in-place order. The highest reduction in trips to transit stations belongs to Arlington County in Virginia (about 83 percent) while Shawnee County in Kansas has experienced about 9 percent increase in trips to transit stations. Summit county in Utah has the highest reduction (about 58.5 percent) in grocery trips while Henderson County in Kentucky has experienced 38.6 percent increase in trips to grocery store and pharmacy, compared to the baseline. Our HLM models investigate the role of compact development and other confounding factors in explaining the observed geographic variations in trips to these destinations across the U.S. metropolitan counties. Note that all findings are only applied to the stay-at-home order period and are not applicable to possible reductions in prior days during the pandemic.

Table 2
Descriptive Statistics of Dependent Variables at the County-Level as the Daily Average for Each County.

Variables	Mean	Standard Deviation	Minimum	Maximum
Average daily percent reduction in grocery/pharmacy trips (essential trips)	13.3	9.1	−38.6	58.5
Average daily percent reduction in park trips (non-essential trips)	0.41	32.6	−193	71.9
Average daily percent reduction in transit trips (overall transit use)	37.4	17.2	−9.9	83

Tables 3–5 present the HLM models for trips to grocery store/pharmacy, park, and transit station; respectively. We present the findings related to the variable of greatest interest (compactness score) in this section. Please see Technical Appendix A for model results and discussion of other control variables. Measures of overall model fitness show that the models perform reasonably well. According to Garson (2013), the likelihood ratio (LR) test helps to assess the fitness of Random Coefficients (RC) model using the reduction in deviance of RC models with predictors comparing to the intercept-only (null) model without predictors. The LR test shows whether the reduction was statistically significant which; as the result, the fit of a RC model is significantly better than the null model. We conducted this test and included the results in the Tables 3–5. The results of these tests show that our three RC models' deviances are significantly lower than their null models at the 0.001 probability level across all three models.

One of the most important findings of this study is that travel reductions during the shelter-in-place order change over time in a nonlinear form, as shown in Fig. 1. More days since the shelter-in-place order leads to significantly higher reductions in people's trips to groceries/pharmacies, parks, and transit stations while Republication counties (with the higher percentage of residents who voted for President Trump in 2016) are less likely to experience this reduction. However, the negative sign of days-squared indicates that, at some point in time since the effective date of the shelter-in-place order, the curve turns into a declining trend (see Fig. 1). While we don't have an explanation for this finding, we share one possibility. According to a recent study of shelter-in-place order in Italy, individuals are more likely to jeopardize compliance with the social-distancing measures when they face negative surprises. An example of such surprises is giving a certain date for ending the shelter-in-place while it could be unrealistic due to

Table 3
Results of the Random Slop Model (Outcome Variable = Percent Reduction in Trips to Grocery Store and Pharmacy, During the Shelter-in-Place Order, Per Day).

Variable	Coefficient	Standard Error	t-ratio	p-value
Intercept	−39.070	14.519	−2.691	0.008
% Voted in 2016 presidential election	0.211	0.049	4.293	0.000
% of college & higher educated	0.293	0.035	8.368	0.000
% of Male	0.527	0.268	1.965	0.049
Compactness Index	0.093	0.022	4.156	0.000
% of votes for Trump in 2016	0.010	0.033	0.296	0.767
VMT January 2020 Avg. (per 10,000 population)	0.000	0.000	0.341	0.733
% of Children	−0.493	0.101	−4.895	0.000
% of Hispanics	0.183	0.037	4.892	0.000
Unemployment change (Mar. 2020–Feb. 2020)	0.014	0.015	0.961	0.337
# of Groceries per sq. mi.	−0.730	0.260	−2.805	0.006
ln of metropolitan population	0.485	0.201	2.408	0.016
# of days (stay-home order start till day X)				
Base	0.105	0.047	2.205	0.028
% of voted for Trump in 2016	−0.004	0.001	−7.256	0.000
# of days (stay-home order start till day X) (Squared)	−0.001	0.001	−0.879	0.380
Likelihood Ratio Test				
n	739			
Chi-square statistic	980.972			
Number of degrees of freedom	5			
P-value	0.000			

Table 4
Results of the Random Slop Model (Outcome Variable = Percent Reduction in Trips to Park, during the Shelter-in-Place Order, Per Day).

Variable	Coefficient	Standard Error	t-ratio	p-value
intercept	57.983	27.853	2.082	0.038
Violent Crime Rate	−0.390	0.247	−1.578	0.115
% Voted in 2016 presidential election	0.024	0.007	3.275	0.001
% of college & higher educated	−0.065	0.194	−0.334	0.738
Compactness Index	−0.224	0.090	−2.500	0.013
% of votes for Trump in 2016	0.288	0.128	2.244	0.025
# of Open Park (per 10,000 population)	−1.933	0.604	−3.200	0.002
% of Children	−3.059	0.583	−5.243	0.000
% of Hispanics	0.869	0.105	8.288	0.000
ln of metropolitan population	2.306	0.930	2.481	0.014
% of Active commuters (walk & bike)	0.504	0.722	0.698	0.485
# of days (stay-home order start till day X)				
Base	0.584	0.195	2.997	0.003
% of voted for Trump in 2016	−0.015	0.003	−5.049	0.000
# of days (stay-home order start till day X) (Squared)	−0.007	0.004	−1.985	0.047
Likelihood Ratio Test				
n	561			
Chi-square statistic	461.234			
Number of degrees of freedom	5			
P-value	0.000			

Table 5
Results of the Random Slop Model (Outcome Variable = Percentage of Reduction in Trips to Transit Station, during the Shelter-in-Place Order, Per Day).

Variable	Coefficient	Standard Error	t-ratio	p-value
Intercept	−30.450	28.040	−1.086	0.278
% of college & higher educated	0.339	0.095	3.566	0.001
% of seniors (65 + yrs old)	0.707	0.238	2.973	0.004
Compactness Index	0.171	0.040	4.217	0.000
% of votes for Trump in 2016	−0.297	0.061	−4.851	0.000
% of working age population	0.372	0.350	1.061	0.289
ln of metropolitan population	1.533	0.474	3.234	0.002
% of Households below poverty 2016	0.007	0.186	0.037	0.971
% of pop in health occupation	−0.840	0.453	−1.856	0.064
# of days (stay-home order start till day X)				
Base	0.531	0.064	8.248	0.000
% of voted for Trump in 2016	−0.005	0.001	−5.382	0.000
# of days (stay-home order start till day X) (Squared)	−0.013	0.001	−13.010	0.000
Likelihood Ratio Test				
n	556			
Chi-square statistic	1806.355			
Number of degrees of freedom	5.00			
P-value	0.000			

unexpected outcomes of the pandemic. Sharing a certain end date can falsely generate optimistic expectations while decision-makers will ultimately need to extend the given end date; which would be a negative surprise for the public. This situation causes disappointment leading to individuals jeopardizing their compliance with the stay-at-home order (Briscese, Lacetera, Macis, & Tonin, 2020). Note that the relationship between percent reduction in grocery trips and days-squared is not statistically significant likely due to a large variation between counties.

3.2. Compact development and reduction in trips to three destinations

Turning to the level 2 variables; and the independent variable of greatest interest, our results indicate that the relationship between compact development and trip reductions to all three destinations is significant; although, not with the same sign. Another major takeaway from this study is that compact development results in significantly higher reductions in trips to grocery stores/pharmacies and transit stations.

Compact development is associated with the significantly higher reduction in grocery trips likely due to the fact that residents of compact areas have access to better services of home-delivery grocery shopping and could more easily eliminate their in-store grocery shopping. Even before the COVID-19 pandemic, surveys show that residents of urban areas are more likely to do online grocery shopping than their counterparts in suburban and exurban areas (Acosta, 2019; Farag et al., 2007). This is also evident from our simple *t*-test analysis that shows the per capita e-commerce sale is significantly higher in compact counties than sprawling counties (mean values of 148.2 versus 70.1, respectively). Compact development along with the percentage of college (or higher) educated individuals and percentage of Hispanic population are the strongest predictors of reduction in grocery trips during the shelter-in-place-order.

In the same line, compact development is associated with the significantly higher reduction in transit trips, controlling for the percentage of essential workers and other confounding factors. Previous studies show that compact areas typically have better transit systems and higher ridership than sprawling areas (Ewing & Hamidi, 2017; Hamidi & Ewing, 2014). Compact areas and major cities are also the most vulnerable to the early advent of pandemic outbreaks and could likely experience a higher number of infections and deaths (Hamidi, Ewing, et al., 2020; Hamidi, Sabouri, et al., 2020). Consequently, the residents of compact areas have a greater exposure to the first-hand information about the susceptibility to the virus, and as a result, are more precautious about following the social distancing advisories particularly with regards to public transit which is considered a major disseminator for the pandemic (Barr et al., 2008; Cava et al., 2005; Rubin et al., 2009).

Finally, compact development results in significantly less reduction in park trips. People in compact areas typically live in smaller housing units (mostly apartments and condos) without access to private yard as compared to their counterparts who live in larger single-family detached units with several bedrooms and a private yard. Our simple *t*-test analysis shows that both housing unit density and the number of people per bedroom are significantly higher in compact counties than sprawling. Consequently, staying at home becomes more challenging in compact areas not necessarily because of essential trips to places such as grocery stores, but because the housing units in dense area are not equipped to help residents mitigate the anxiety and stress, resulted from the pandemic (Jacobson et al., 2020). Our model and a follow-up *t*-test show that vising parks and public greenspaces is significantly higher in compact areas than sprawling perhaps as an alternative available to residents to help them mitigate the anxiety and stress, resulted from the pandemic.

4. Conclusions

The widely studied social, economic, health and environmental benefits of compact development (Ewing & Hamidi, 2017; Hamidi & Zandiatashbar, 2019; Zandiatashbar, Hamidi, Foster, & Park, 2019; Hamidi, Ewing, Tatalovich, Grace, & Berrigan, 2018; Zandiatashbar & Hamidi, 2018) have been challenged by the recent COVID-19 pandemic. This longitudinal study is one of the first to investigate the role of compact development on people's adherence to the stay-at-home order; more particularly the shelter-in-place order which requires residents to leave their home only for essential trips. We employed a natural experimental research design and modeled the changes in travel to three destinations: one essential (grocery store/pharmacy), one non-essential (parks) and the last one, transit station, which represents the overall changes in transit ridership to all destinations.

There are three key takeaways from our analyses. First, the relationship between the number of days since the effective day of the shelter-in-place order and reduction in travel is non-linear. At the beginning of the shelter-in-place order, there is a high reduction in people's travel and the reduction in travel has an increasing trend for the first few days. But as we move forward with the order, at some point in time, which varies from county to county, the curve turns into a declining trend, meaning that there is less observed reduction in travel compared to the previous days. This is a common pattern that we observed in trips to all three destinations. It is still an open question why people are more in compliant with the shelter-in-place order at the beginning and what factors change in the middle of this journey that leads to the changes in travel behavior. Considering how costly is the shelter-in-place order to the citizens, communities and the government, these questions are important and call for further investigations in future studies.

Second, we found that the challenges of compliance with the stay-at-home order in compact areas are not related to minimizing essential trips to grocery store and pharmacy. Quite the opposite, residents of compact areas are doing a much better job in reducing their essential trips and have significantly fewer and shorter trips to destinations such as grocery store, pharmacy and transit station. Indeed, compact development could facilitate the implementation of stay-at-home orders due to better services of home-delivery grocery shopping. It is also possible that residents of dense places voluntarily engage in social distancing; being more cognizant of the threat.

Third, we found that residents of compact counties are less likely to reduce their trips to parks during the shelter-in-place order. This is not surprising but could be concerning. It is possible that residents of compact areas experience more stress due to the higher number of COVID-19 deaths in compact areas compared to sprawling and low-density areas. This situation coupled with the smaller homes and the lack of private greenspaces (yard) in compact counties could increase the feelings of anxiety and isolation and visiting a park appears to be one was of mitigating these mental and psychological challenges.

However, visiting parks during the pandemic has its own risks. Similar to transit stations, parks could be a potential hotspot for the transmission of the virus. In addition, the risk of exposure to COVID-19 in parks is potentially even greater among the homeless who use parks frequently and as infection rates among the homeless rise, their use of parks spaces could eventually elevate the risk of COVID-19 exposure to the general population.

We encourage future studies to take a closer look at the extent to which people follow the social distancing recommendations in their visits to parks during the pandemic; particularly in the dense and compact areas. We also recommend decision-makers, planners, and public health officials to design and implement social distancing guidelines specifically for visiting parks and closely monitor people's social distancing behaviors and travel patterns to parks in compact areas with the relatively high per capita COVID-19 mortality rates.

The emergence of COVID-19 pandemic has led decision-makers at different levels of government to make some of the most urgent, significant, and far-reaching decisions about social distancing response measures from school and business closures to public gathering bans and more restrictive polices such as shelter-in-place orders. These policies; while proven to be effective in slowing the spread of pandemic, come with tremendous short-term and long-term economic impacts such as economic recession that will remain for years. It is critical to account for the built environmental and other underlying factors that contribute to more effective implementation of social distancing measures. This study offers new perspectives for more informed decision-making and several pathways for much-needed further investigations of stay-at-home order and its determinants.

CRediT authorship contribution statement

Shima Hamidi: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Ahoura Zandiatashbar:** Data curation, Formal analysis, Software, Visualization, Writing - review & editing.

Acknowledgement

This research was supported by the Bloomberg American Health Initiative at the Johns Hopkins Bloomberg School of Public Health.

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