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Treating two pandemics for the price of one: Chronic and infectious disease impacts of the built and natural environment

Lawrence D. Frank, Behram Wali

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ABSTRACT

Compact walkable environments with greenspace support physical activity and reduce the risk for depression and several obesity-related chronic diseases, including diabetes and heart disease. Recent evidence confirms that these chronic diseases increase the severity of COVID-19 infection and mortality risk. Conversely, denser transit supportive environments may increase risk of exposure to COVID-19 suggesting the potential for contrasting chronic versus infectious disease impacts of community design. A handful of recent studies have examined links between density and COVID-19 mortality rates reporting conflicting results. Population density has been used as a surrogate of urban form to capture the degree of walkability and public transit versus private vehicle travel demand. The current study employs a broader range of built environment features (density, design, and destination accessibility) and assesses how chronic disease mediates the relationship between built and natural environment and COVID-19 mortality. Negative and significant relationships are observed between built and natural environment features and COVID-19 mortality when accounting for the mediating effect of chronic disease. Findings underscore the importance of chronic disease when assessing relationships between COVID-19 natural environment features and COVID-19 mortality. Based on a rigorous simulation-assisted random parameter path analysis framework, we further find that the relationships between COVID-19 mortality, obesity, and key correlates exhibit significant heterogeneity. Ignoring this heterogeneity in highly aggregate spatial data can lead to incorrect conclusions with regards to the relationship between built environment and COVID-19 transmission. Results presented here suggest that creating walkable environments with greenspace is associated with reduced risk of chronic disease and/or COVID-19 infection and mortality.

1. Introduction & background

Facilitating the adoption of active travel toward sustainable and healthy transportation has become an emerging priority in the transportation and planning literatures (Delso, Martín, Ortega, & Van De Weghe, 2019; Frank, Iroz-Elardo, Macleod, & Hong, 2019; Hosseinza-deh, Algomaiah, Kluger, & Li, 2021; Sallis, Bull et al., 2016). A large and growing body of evidence confirms positive relationships between various aspects of walkability and active travel (Cervero & Kockelman, 1997; Frank & Pivo, 1994; Khattak & Rodriguez, 2005; Saelens & Handy, 2008; Saelens, Sallis, & Frank, 2003; Sallis et al., 2006) and physical activity (Ewing, Schmid, Killingsworth, Zlot, & Raudenbush, 2003; Frank, Schmid, Sallis, Chapman, & Saelens, 2005). Additional research shows inverse relationships between these features and time in cars and obesity (Frank, Andresen, & Schmid, 2004). More recently, causal evidence suggests that transit (Hirsch, DeVries, Brauer, Frank, & Winters, 2015) and investments in active transportation infrastructure (Frank, Hong, & Ngo, 2019) can increase physical activity and exposure to more walkable environment over time reduces the risk of obesity and related chronic disease (Frank, Andresen, & Schmid, 2004). More recently, causal evidence suggests that transit (Hirsch, DeVries, Brauer, Frank, & Winters, 2015) and investments in active transportation infrastructure (Frank, Hong, & Ngo, 2019) can increase physical activity and exposure to more walkable environment over time reduces the risk of obesity and related chronic disease (Clark et al., 2017; Frank, Hong et al., 2019). Infectious diseases are far more threatening for those who already have a chronic disease. Obesity and related chronic diseases increase mortality risk in COVID-19 patients (Dietz & Santos-Burgoa, 2020). Active travel between destinations and the engagement in physical activity at destinations such as parks, home, the gym, and other destinations can help to reduce morbidity and risk of mortality from chronic disease (Frank,
Iroz-Elardo et al., 2019; Schmid et al., 2015; Young et al., 2020). From a sustainability and health perspective (Bivina, Gupta, & Parida, 2020; Chan, Schwaben, & Banister, 2021), these links in the literature have served as key foundations for designing lasting population-level interventions to combat inactivity (Sallis, Cerin et al., 2016) and obesity and the onslaught of diabetes (Mokdad et al., 2000) and heart disease; two of the most significant epidemics mankind has ever seen (WHO, 2018).

The COVID-19 pandemic has negatively influenced the world in an unprecedented manner – The 16 Trillion Dollar Virus (Cutler & Summers, 2020), has caused 2.57 million deaths worldwide (as of 03/04/2021) and brought great financial, social, and emotional distress to families. The emergence of COVID-19 has led to concerns that the protective effects of walkability with respect to chronic disease may not be applicable for highly contagious infectious diseases such as COVID-19. These concerns were first expressed through media articles that held “density” and public transit use responsible for infections and deaths from the COVID-19 pandemic. Sprawl itself and the earlier formation of suburbs were a health response to crowded infectious disease that infested dense urban areas in the late 19th and earlier parts of the 20th centuries (Frumkin, Frank, & Jackson, 2004). Compact development typically brings people closer together and supports the potential spread of infectious disease; this reality is quite clear, basic, and intuitive. While larger regions tend to have some of the densest environments; intra-regional variation in density is considerable. Some of the most walkable places are located in medium sized region like Portland (Oregon).

A handful of studies have investigated the links between population density and aggregate COVID infection and mortality rate (Bray, Gibson, & White, 2020; Carozzi, 2020; Hamidi, Ewing, & Sabourii, 2020; Hamidi, Sabourii, & Ewing, 2020; Kodera, Rashed, & Hirata, 2020). Mixed results were reported, i.e., population density not correlated with COVID-19 mortality (Carozzi, 2020), positive correlation between the two (Bray et al., 2020; Kodera et al., 2020), and negative relationship between population density and COVID-19 mortality (Hamidi, Ewing et al., 2020; Hamidi, Sabourii et al., 2020). In particular, Hamidi, Ewing et al. (2020) presented a pathway analysis linking population and employment density with COVID-19 infections and death rate for 913 U.S. metropolitan counties (Hamidi, Sabourii et al., 2020) using data from ~5 months (data as of May 25, 2020). After controlling for age, demographics, population, smoking status at the county level, no relationship was found between density and infection rates; however, a significant negative relationship was found between density and mortality. The authors of this study started analyzing the data in April 2020 and were not able to detect statistically significant relationships between built environment measures (used in this study) and COVID-19 infection and mortality rate up until the end of summer in 2021. This was mainly due to the fluid and rapidly evolving nature of the COVID-19 data (discussed later in detail).

1.1. A sustainable & healthy environment framework

An understanding of the connections between community design, sustainability, and public health requires considering both infectious and chronic disease contemporaneously. Fig. 1 shows a framework to map key linkages.

Several aspects of the physical environment shape our behavior and determine exposures to healthy and unhealthy phenomena. Density is one of several land use or walkability characteristics predictive of sustainable activity patterns and health outcomes (Zlatkovic, Zlatkovic, Sullivan, Bjornstad, & Shahandashti, 2019). Other walkability characteristics include presence of shops, services, and other destinations. Transportation system characteristics, greenspace, and a supportive pedestrian environment with sidewalks, seating, and other features are needed to create complete “live - work - play” communities. Fig. 1 conveys how these factors influence behaviors and exposures which then influence biological responses that impact chronic disease. The majority of people who develop a severe case or die from COVID-19 have a pre-existing chronic condition (CDC Covid-19 Response Team, 2020). One early study from the US Department of Health and Human Services found that 71 percent of COVID Cases had a pre-existing chronic condition. A recent meta-analysis of 109 published studies modeled COVID-19 severity and mortality as a function of chronic disease (Chidambaram et al., 2020). The authors found that the relative risk of having a severe case of COVID-19 was 90 percent greater for those with hypertension and 59 percent greater for those with diabetes (Chidambaram et al., 2020).

Mechanisms through which the built and natural environment impacts infection versus severity of illness and mortality from COVID-19 are quite different. Evidence to date suggests that built and natural environment impacts on disease severity and mortality are mediated by chronic disease whereas exposure effects of the environment may...
directly impact infection. Authors of previous studies have suggested that the scale of urbanization or "Big Cities" are more problematic than degree of densification (Shoichet & Jones, 2020; Tavernise & Mervosh, 2020). Negative relationships between population and employment density and COVID-19 mortality reported by (Hamidi, Sabouri et al., 2020) may be understandable when considering the mechanisms shown in Fig. 1 including chronic disease (Hamidi, Sabouri et al., 2020). However, the inability to detect the correlation between density and infection rates may be a function of type II error resulting from extremely unstable and unreliable estimates of infection rates noting the study relied on data drawn in May of 2020 – very early in the pandemic. At that time, testing regimes varied considerably nationally. Besides the issue of unobserved heterogeneity (described in Section 2.1), the extremely coarse geographic scale upon which population and employment density was measured requires averaging across large areas (entire cities or counties). This averaging across huge areas (entire cities and counties) makes it difficult to detect relationships between physical environments, exposures, behaviors, and health outcomes shown to exist in previous studies (Ewing et al., 2003; Frank et al., 2004, 2019a; Frank, Iroz-Elardo et al., 2019). Distancing has been the key mechanism to avoid spreading COVID-19. Distancing and greater proximity between people (density) are a diametrically opposed spatial concepts. Given the above prevalent gaps, the present study focused on examining the direct and indirect relationships between built environment, chronic disease and COVID-19 mortality within a simulation-assisted heterogeneity-based modeling framework (as discussed next).

1.2. Research objective & contribution

To our knowledge, this is the first study to empirically examine the hypothesized pathway between upstream built environment, chronic disease, and downstream COVID-19 mortality accounting for the profound effect of chronic disease. The study developed a simulation-assisted heterogeneity-based path analysis framework to model the direct links between built environment and COVID-19 mortality (captured as COVID-19 deaths per 100,000 population), and the indirect relationship between the two through prevalence of chronic disease. Such an analysis is fundamental to answer important research questions highlighted elsewhere related to ‘antivirus-built environment’ (Mega hed & Ghoneim, 2020). For example, can COVID-19 be a catalyst for decentralization and walkable cities? (Mega hed & Ghoneim, 2020). Alternatively, can we continue to invest in more compact and walkable infrastructure to seeking combat highly contagious infectious diseases such as COVID-19? The present study is different from the existing studies on COVID-19 mortality and fills in important gaps in the small but growing literature on this topic.

First, we conceptualized prevalence of chronic disease as a key mediator in the behavioral chain linking built environment, chronic disease and COVID-19 mortality within a simulation-assisted heterogeneity-based modeling framework (as discussed next).
testing protocols and their application had been more standardized nationally and a long enough period of time had passed for population level impacts to be documented. Second, we considered a broader set of built and natural environment measures. This is important for capturing a fuller picture of the built and natural aspects of the environment. Third, and most importantly, this study systematically captured unobserved factors that could influence COVID-19 mortality and/or prevalence of chronic disease. In simple words, not all the factors correlated with COVID-19 mortality are available in the existing study as well as the previous studies discussed earlier. Ignoring the “latent” effects of such unobserved factors has two important implications. Foremost, it is impossible to discern that an observed correlation between an observed explanatory factor and outcome variable is a true correlation and not a manifested effect of the unobserved factors (Manning, Shankar, & Bhat, 2016; Manning, Bhat, Shankar, & Abdel-Aty, 2020; Wali & Khattak, 2020; Wali, Greene, Khattak, & Liu, 2018; Wali, Khattak, Bozdogan, & Kamrani, 2018). Second, the presence of such context-specific unobserved factors leads to variations/heterogeneity in the relationships between built and natural environment, chronic disease, and COVID-19 mortality. To this end, compared to frequentist (fixed-parameter) linear regressions or structural equation models, we developed simulation-assisted random parameter models to examine the direct and indirect dependencies. By considering most-recent COVID-19 data as of February 16, 2021, this study offers a relatively more stable picture by considering the fluid nature of the COVID-data especially the resurgence of the virus in the United States during the winters. While not the focus of the present study, we also examine the relationships between density (population density) and COVID-19 infection rate within the heterogeneity-based modeling framework.

The rest of the paper is structured as follows. We present the conceptual framework, data, and simulation-assisted heterogeneity-based path analysis framework in Section 2. Descriptive and modeling results are shown in Section 3 followed by a discussion and synthesis of the results (including direct and indirect effects) in Section 4. We highlight the study limitations and strengths in Section 5 and conclude the study with a discussion about the implications of the findings for the transportation and planning fields and potential avenues for future research.

2. Methods

2.1. Conceptual framework

As discussed earlier, previous studies have examined the associations of density (as a surrogate of built environment) and socio-demographic factors with COVID-19 mortality. Fig. 2 presents the overall modeling framework for the present study. The prevalence of obesity was considered as a chronic disease outcome because it is a common, serious, and costly chronic disease. In addition, obesity predicts the increased risk of heart disease, stroke, and underlying risk factors including high blood pressure, high (low) density lipoprotein (HDL) cholesterol, and type 2 diabetes. Solid scientific evidence exists about the links of chronic disease with the built and natural environment (Booth, Pinkston, & Poston, 2005; Frank, Iroz-Elardo et al., 2019; Sallis, Floyd, Rodríguez, & Saelens, 2012). Primarily through the behavioral pathway, more walkable and greener neighborhoods encourage more active travel and physical activity lowering the prevalence of chronic disease. The chronic disease mediator in turn directly correlates with severe illness and/or mortality from COVID-19. The built environment is hypothesized to be directly correlated with COVID-19 mortality as well. Cities with health-supporting infrastructure likely have greater financial resources, better health infrastructure, education systems, exhibiting innovation clusters and agglomeration (Wu, Wang, Ye, Zhang, & Huang, 2019) – thus more likely to respond to the pandemic leading to lower rates of COVID-19 fatalities over time. Likewise, from a sociodemographic standpoint, factors such as wealth/income, education, and age influences health via diet, physical activity, and lifestyle. Importantly, sociodemographic and built environment factors also interact together in complex ways influencing health outcomes. For example, vulnerable individuals (low education, low income, etc.) typically have lower opportunities to maintain healthier lifestyles but the extent of this negative disposition towards healthy lifestyles could vary across different neighborhoods by the level of walkability. Collectively, built environment and sociodemographic characteristics serve as two key elements (among others) of the socioecological models of health that capture individuals’ transactions with their physical/built and sociocultural environments (Sallis, Owen, & Fisher, 2015).

The conceptual framework also accounts for the important methodological concern of unobserved heterogeneity. In the traditional modeling framework, the correlations between each of the explanatory variable (e.g., density) and outcome are held fixed across all the observations/counts. In other words, a fixed β coefficient is estimated for each of the explanatory variables. This may not be the case, however. Consider the upstream pathway in Fig. 2 linking built environment with prevalence of obesity. Beyond the built and natural environment, and other controls, there could be a broad spectrum of factors known to be correlated with obesity but unobserved in the data at hand, such as other environmental factors, weather elements, individuals’ attitudinal predispositions, preferences, etc. Since such factors are unobserved, its effects could not be explicitly estimated. However, its “latent” effects could manifest through the observed variables (e.g., built environment). This eventually leads to variations in the estimates associated with a specific observed explanatory variable, e.g., a built environment measure. This strong constraint of fixed β’s has severe conceptual implications. First, without accounting for such unobserved factors, it is not possible to certainly attribute an observed adjusted correlation estimate to a specific observed variable, such as built environment or density. Second, the fixed β modeling approach unrealistically assumes that all individuals respond to changes in covariates (e.g., built environment) in a similar fashion. Even individuals living in a same neighborhood will respond (interact) differently to (with) the built environment due to changes in preferences, perceptions, and attitudinal predispositions. Third, in addition to masking the potential heterogeneity in magnitudes of associations, the fixed parameter approach also assumes directional consistency (instead of the highly likely possibility of directional heterogeneity due to individual level differences). By accounting for these unobserved factors, the structural path framework allows for estimation of individual county-level β estimates (as opposed to a fixed β) – allowing a deeper and more granular understanding of the correlates of chronic disease and COVID-19 mortality rate. As our results demonstrate later, incorporating unobserved heterogeneity (especially in an aggregate county-level analysis) is fundamental to obtaining more accurate insights.

2.2. Data

County-level data were used because consistent COVID-19 fatality data are publicly available at this geographic scale. The study considers multiple data streams. We obtained the COVID-19 infection and fatality

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2 Only few papers to date examined spatial heterogeneity in COVID-19 spread and mortality (Sannigrahi, Pillai, Basu, Basu, & Moller, 2020; Li, Ma, & Zhang, 2021; Mansour et al., 2021). Using spatial models, Li et al. 2021 and Mansour et al., 2021 focused on the sociodemographic determinants of COVID-19 spread/infection in China and Oman, respectively. Likewise, Sannigrahi et al. (2020) used spatial analysis methods to analyze socio-demographic composition and COVID-19 fatalities in the European region (Sannigrahi et al., 2020). All of these studies found significant spatial heterogeneity in the underlying associations between socio-demographic factors and COVID-19 infection/mortality. However, none of existing studies (in US or elsewhere) simultaneously considered the complete pathway between built and natural environment, chronic disease, and COVID-19 mortality rates while explicitly accounting for unobserved heterogeneity.
Table 1
Descriptive Statistics of Key Variables at the County Level.

| Variables                      | Mean       | SD         | Min    | Max        | Source                                                                 |
|--------------------------------|------------|------------|--------|------------|------------------------------------------------------------------------|
| **Endogenous Variables**       |            |            |        |            |                                                                        |
| COVID-19 infection rate        | 11808.5    | 4200.83    | 334.73 | 43648.30   | The New York Times (Smith et al., 2020)                                |
| COVID-19 fatality rate         | 221.69     | 141.74     | 0      | 1147.03    | The New York Times (Smith et al., 2020)                                |
| Prevalence of Obesity (%)      | 31.94      | 3.28       | 18.79  | 44.33      | Behavioral Risk Factor Surveillance System (BRFSS, 2017)                |
| **Exogenous Variables**        |            |            |        |            |                                                                        |
| **Built Environment**          |            |            |        |            |                                                                        |
| Residential density (housing  | 0.816      | 1.39       | 7.25E-05 | 24.69      | 2014 Smart Location Database (D1A)                                    |
| units/acre)                    |            |            |        |            |                                                                        |
| Auto Regional Centrality Index | 27.848     | 30.09      | 0      | 91.71      | 2014 Smart Location Database (DSCEI)                                  |
| Pedestrian-oriented links       | 5.495      | 3.75       | 0.02   | 27.20      | 2014 Smart Location Database (D3b)                                    |
| per square mile                |            |            |        |            |                                                                        |
| **Natural Environment**        |            |            |        |            |                                                                        |
| % of tree canopy coverage      | 27.67      | 22.44      | 0      | 89.27      | 2019 National Environmental Database (U_P_FORE_1)                      |
| **Controls**                   |            |            |        |            |                                                                        |
| Nonmetropolitan county         | 0.629      | 0.48       | 0      | 1          |                                                                        |
| % of population aged 65 plus   | 21.985     | 4.72       | 4.89   | 47.81      | American Community Survey                                             |
| % of Black population          | 8.867      | 14.61      | 0      | 86.68      | American Community Survey                                             |
| % of White population          | 75.710     | 19.72      | 0.70   | 100        | American Community Survey                                             |
| % of population with graduate  | 7.397      | 4.28       | 0      | 41.89      | American Community Survey                                             |
| degree                        |            |            |        |            |                                                                        |
| % of low-income individuals    | 48.224     | 10.71      | 12.35  | 81.28      | American Community Survey                                             |
| % of unemployment              | 3.529      | 1.57       | 0      | 16.10      | American Community Survey                                             |
| # of ICU beds per 100         | 0.057      | 0.10       | 0      | 2.48       | Kaiser Health News (2019)                                             |
| individuals aged 60 plus       |            |            |        |            |                                                                        |
| Daily COVID-19 tests per       | 3903.780   | 1919.12    | 1159   | 15183      | State Health Facts, Kaiser Family Foundation (2020)                    |
| million population             |            |            |        |            |                                                                        |

Notes: For information on US EPA’s Smart Location Database (SLD) – see https://www.epa.gov/smartgrowth/smart-location-database-technical-documentation-and-user-guide. The US EPA Smart Location Database is in the process of being updated for 2020. For details about UD4H’s National Environmental Database, see http://ned.ud4htools.com/about/; N = 3,130 counties.

Data (as of February 16, 2021) from The New York Times, based on reports from state and local health agencies (Smith et al., 2020). The detailed built and natural environment data were based on two sources that provide national coverage: the Robert Wood Johnson Foundation’s National Environmental Database (NED) and US Environmental Protection Agency Smart Location Database (SLD). Data on built and natural environment measures were extracted from the US EPA’s SLD and NED, respectively. Developed by Urban Design 4 Health, Inc. (UD4H), the NED contains census block group (CBG) level estimates of natural environment variables known to be correlated with active travel and health outcomes. The NED also contains CBG level measures of demographic and socioeconomic factors such as age distributions, race, education, income, and unemployment using data from the 2017 American Community Survey. These variables were used as key controls in the analysis.

The built and natural environment variables chosen for this study relate to elements of urban form: density, urban design, (auto) accessibility, and natural environments or greenness:

1) The residential density variable has been widely used in the literature to capture neighborhood composition and is shown to be associated with active/sustainable and healthy travel (Frank et al., 2005; Huang, Moudon, Zhou, & Saelens, 2019; Saelens, Sallis, Black, & Chen, 2003).

2) Street network design and layout also influences individuals’ ability to participate in sustainable and healthy travel. To this end, a street connectivity-based measure was considered to capture the urban fabric and degree to which destinations can be reached in a direct pathway. Disconnected street networks mandate circuitous routes and incur vehicle dependence. Street connectivity was found to be the most influential walkability factor in several studies including one that validated one of the earliest and most widely applied walkability indices (Frank et al., 2010). Intersection density is among the most often cited built environment components correlated with active travel (Carlson et al., 2015; Saelens & Handy, 2008). To better capture the support for pedestrian- and bicyclist-oriented mobility, a modified weighted intersection density measure was used that eliminates auto-oriented limited access roadway facilities from the density calculation.

3) A regional auto centrality index was used to capture the level of auto-oriented regional accessibility where a time-decaying travel time in the network is used to capture traffic conditions. Individuals in areas with higher auto-oriented accessibility typically have lower active/sustainable travel participation rates.

4) Tree canopy coverage was chosen since it is shown in the literature to be related with sustainable and active travel (independent from green space access) and has been correlated with obesity and health outcomes (Ulmer et al., 2016). It is also a key predictor of urban heat island effect and is generally easier and cheaper for municipalities to change and alter than expanding acres of park space.3

Data on chronic disease outcomes were obtained from the Behavioral Risk Factor Surveillance System (BRFSS) – which is the nation’s premier system collecting data about U.S. residents concerning health-related risk behaviors and chronic disease outcomes through health-related telephone surveys. Finally, we obtained county-level data on availability of ICU beds from the 2019 Kaiser Health News and state-level COVID-19 testing data (as of 02/16/2021) from the State Health Facts, Kaiser Family Foundation. The description of key variables and source references are provided in Table 1.

3 To capture the combined effects of multiple built and natural environment variables, an earlier version of the analyses used composite indices related to built and natural environment as independent variables. Park index was a composite measure comprised of tree canopy coverage, park access, and forest cover. Likewise, the built environment index was a composite measure comprised of population density, net residential density, intersection density, and employment density. The results were intuitive, but the authors later decided to use key individual built and natural environment measures separately which then enabled clearer and more direct interpretation of results (compared to interpreting composite indices comprised of several variables).
and prevalence of obesity were modeled as a function of built environment and prevalence of obesity. In these models, COVID-19 fatality rate and continuous nature of the two endogenous variables, COVID-19 fatality estimates that capture the systematic variations in unobserved factors across the US counties (Mannering et al., 2016; Wali & Khattak, 2020; Wali, Khattak et al., 2018). Maximum Simulated Likelihood procedures are used to estimate the random parameter models. To perform the hierarchical integrations over densities for latent/unobserved factors, we used 200 scrambled Halton draws in the simulation process (Train, 2009). Compared to the use of traditional Monte Carlo draws in approximating the integrals, variance reduction-based Halton draws were used providing better results by enhancing the coverage and covariance (Train, 2009; Wali, Khattak, & Karnowski, 2020). Finally, regarding the functional form characterizing unobserved heterogeneity parameters, we tested different densities such as normal, lognormal, triangular, uniform, and Weibull distributions (discussed in the next section). Due to space constraints, technical exposition is not provided. For details of random parameter models, see (Mannering et al., 2016; Train, 2009; Wali & Khattak, 2020).

### 2.3. Statistical methods – simulation-assisted heterogeneity-based path models

To operationalize the conceptual framework in Fig. 2, traditional fixed parameter regression models were first estimated given the continuous nature of the two endogenous variables, COVID-19 fatality rate and prevalence of obesity. In these models, COVID-19 fatality rate and prevalence of obesity were modeled as a function of built environment and natural environment variables while controlling for other factors (Table 1). Given the important methodological concern of unobserved heterogeneity (explained in Section 2.1), the traditional regression framework was then extended to include random parameters. The random parameter models allow estimation of county-specific \( \beta \) estimates that capture the systematic variations in unobserved factors across the US counties (Mannering et al., 2016; Wali & Khattak, 2020; Wali, Khattak et al., 2018).
2.3.1. Heterogeneity-based path analysis

Random parameter models provide richer insights about the distributional effects pertaining to each explanatory variable. The county-level $\beta$ estimates (instead of fixed $\beta$s across all counties in a fixed parameter model) were then harnessed to untangle the complex direct and indirect associations conceptualized in Fig. 2. Using vector notation, the heterogeneous direct effect of chronic disease (endogenous variable) and independent variables (including built and natural environment, and controls) on COVID-19 mortality are captured in a parameter model, namely $[\bar{\beta}_1; \bar{\beta}_2; \bar{\beta}_3; \ldots; \bar{\beta}_k]$ – where the i subscript indicates county-level heterogeneous coefficients and the column $\bar{\beta}$ contains heterogeneous effects of chronic disease prevalence on COVID-19 mortality rate. Likewise, the direct effects of built, natural environment, and controls on chronic disease prevalence are captured through coefficients in a $n \times k$ dimensional $\gamma$ matrix, $\{\gamma_{1i}, \gamma_{2i}, \ldots, \gamma_{ki}\}$. To calculate the indirect (heterogeneous) effects of built and natural environment on COVID-19 mortality through chronic disease prevalence, the (heterogeneous) coefficients in matrix $\{\gamma_{1i}, \gamma_{2i}, \gamma_{3i}, \ldots, \gamma_{ki}\}$ were multiplied with the corresponding (heterogeneous) coefficients pertaining to chronic disease prevalence in $[\bar{\beta}_1; \bar{\beta}_2; \bar{\beta}_3; \ldots; \bar{\beta}_k]$, in particular $\bar{\beta}_k$. The heterogeneous indirect effects are thus represented as $[\bar{\beta}_k * \gamma_{1i}, \bar{\beta}_k * \gamma_{2i}, \bar{\beta}_k * \gamma_{3i}, \ldots, \bar{\beta}_k * \gamma_{ki}]$. To arrive at total effects, the direct and indirect effects for each of the exogenous variable can be summed together as $[\bar{\beta}_1 + \bar{\beta}_2 * \gamma_{1i}, \bar{\beta}_2 + \bar{\beta}_3 * \gamma_{2i}, \bar{\beta}_3 + \bar{\beta}_4 * \gamma_{3i}, \ldots, \bar{\beta}_k + \bar{\beta}_k * \gamma_{ki}]$.

3. Results

3.1. Descriptive statistics

Table 1 shows the descriptive statistics of key variables at the county-level. A total of 3,130 counties are considered having complete data on mortality, chronic disease, and built environment features. The average fatality rate (expressed as number of fatalities per 100,000 population) was 221.69 with significant variation across the counties. Built and natural environment variables also showed significant variations across the US counties. The built environment features considered in this study relate to density (residential density), urban design (pedestrian oriented links), and destination accessibility (auto regional centrality index) (Table 1). The average residential density was around 0.81 housing units per acre, whereas around 5.4 pedestrian-oriented links per square mile (design) existed across the sampled counties with reasonable variation. In terms of destination accessibility through sedentary mode of travel (auto), the mean auto centrality index was 27.84 (ranging between 0 and 100). Regarding demographics, around 21% of the population was aged 65 years plus. As expected, around 75% of the population on average was White. Descriptive statistics for other variables are shown in Table 1.

3.2. Modeling results

In this section, we present the results of random parameter models for COVID-19 fatality rate and prevalence of obesity. To highlight the implications of ignoring unobserved heterogeneity, the results of fixed parameter models are presented as well.

First, traditional fixed parameter models were estimated for COVID-19 fatality rate and prevalence of obesity as a function of built and natural environment variables and other controls. In the fatality rate model, prevalence of obesity was included as a chaining variable. The fixed parameter models were derived from a systematic process considering statistical significance, variable importance (e.g., built and natural environment) and specification parsimony. Akaike Information Criterion (AIC) was used for model selection that considers both predictive ability and model complexity. Next, given the important methodological concern of unobserved heterogeneity as it relates to the associations of built and natural environment features with COVID-19 mortality and chronic disease prevalence. Note that the structure of random parameter models allows testing unobserved heterogeneity associated with all exogenous/independent variables. However, not all exogenous variables need to be treated as random parameters. Only those variables are treated as random parameters which exhibit significant unobserved heterogeneity effects (using the criteria discussed above). Besides capturing the heterogeneity patterns (providing

4 While not the focus of the present study, we estimated fixed and random parameter models for COVID-19 infection rate. In a basic fixed parameter model with only population density, regional auto centrality index, tree canopy and nonmetropolitan county indicator as key explanatory variables, density variable and nonmetropolitan county indicator were statistically significantly and negatively correlated with COVID-19 infection rate. The negative association between (population) density and infection rate in the fixed parameter model is consistent with other studies (Khalfi-Garmir, Sharifi, & Moradpour, 2021; Li, Peng, He, Wang, & Feng, 2021) – while acknowledging that there could be differences in the construction of density measures in these studies. Whereas regional auto centrality index was positively correlated with infection rate. However, when county demographics and other unobserved factors are accounted for (through random parameters), the relationship between density and infection rate became positive (statistically significant at 95% confidence level). Likewise, the normally distributed random parameters for nonmetropolitan counties exhibited substantially larger (relative to mean coefficient) and statistically significant standard deviation – implying substantial directional heterogeneity in the magnitudes of coefficients for nonmetropolitan county indicator. This highlights the importance of controlling for unobserved factors and demographics for avoiding misleading insights. Intuitively, tree canopy was negatively correlated with infection rate. Regarding demographics, counties with greater black and low-income population had higher infection rates. The reverse was true for counties with greater percentage of graduate degree holders. The results for fixed and random parameter infection rate models are provided in Appendix A.
stress (Björk, 2020). Physical activity has been shown to improve mental health and immune function, which can lower COVID-19 fatality rates after controlling for other factors (Ali, Khattak, & Atkinson, 2021). Finally, using the heterogeneity-based path analysis framework explained earlier - we collectively synthesize the direct effects of built and natural environment on COVID-19 fatality rate and the indirect effects on COVID-19 fatality rate through prevalence of obesity. Unless otherwise stated, the below discussion is based on the best-fit random parameter models for COVID-19 fatality rate and prevalence of obesity.

4. Discussion and synthesis

We base our discussion of the key findings on the results of random parameter models given its relative best fit. We first discuss the results of random parameter COVID-19 fatality rate model followed by discussing the random parameter modeling results for prevalence of obesity as a mediator. Finally, using the heterogeneity-based path analysis framework explained earlier - we collectively synthesize the direct effects of built and natural environment on COVID-19 fatality rate and the indirect effects on COVID-19 fatality rate through prevalence of obesity. Unless otherwise stated, the below discussion is based on the best-fit random parameter models for COVID-19 fatality rate and prevalence of obesity.

4.1. Associations of obesity, built and natural environment with COVID-19 fatality rate

Prevalence of obesity is strongly and statistically significantly related with COVID-19 mortality rate. A one percent increase in obesity is correlated with a 9.4 unit increase in COVID-19 fatality per 100,000 population. As a normally distributed random parameter, the associations between COVID-19 fatality rate and obesity vary across the counties (with a mean of 9.43 and standard deviation of 0.5) (Table 2). These variations capture the context-specific characteristics of counties – systematic variations in which lead to heterogeneity in the coefficients associated with prevalence of obesity. After controlling for demographics, chronic disease prevalence, and more importantly unobserved factors, our results indicate that residential density (housing units/acre) is negatively correlated with COVID-19 fatality rate. A one-unit increase in residential density is associated on-average with a 4.5 unit decrease in fatalities per 100,000 population (Table 2). Regarding natural environment, a one percent increase in tree canopy is correlated with a 0.88-unit reduction in COVID-19 mortality rate. These findings suggest that counties with walkable and greener built environment on-average have lower COVID-19 fatality rates after controlling for chronic disease, demographics, and other unobserved factors. In addition, the finding related to greener environment is unique to the present study on COVID-19 in United States. Tree canopy is important since a lot of studies have confirmed the significant relationships between natural environment and COVID-19 mortality (Viezzer & Biondi, 2021). Among other reasons, the highly aggregate nature of the data (as discussed earlier) could be a cause of the inability to detect statistically significant relationship between greenspace and obesity. Regarding demographics, a one percent increase in Black population is correlated with a higher prevalence of obesity in a non-linear fashion (see the statistically significant polynomial terms in Table 2). As expected, counties with greater a concentration of low-income individuals have on-average higher prevalence of obesity, whereas the reverse is true for counties with greater graduate degree holders. The associations of low-income and high education with prevalence of obesity exhibit substantial heterogeneity. For example, the associations vary significantly across the counties (Table 2). Overall, the positive correlation between nonmetropolitan counties and COVID-19 mortality is intuitive since metropolitan areas typically have (besides other factors) healthier and active transportation supportive infrastructure which has significant health benefits. Finally, testing rate is positively correlated with COVID-19 mortality rate but exhibits substantial heterogeneity in magnitude and direction of association. With a mean of 0.004 and standard deviation of 0.005, the associations are positive for around 78 % of the population and negative for the rest. Such insights cannot be obtained from traditional fixed parameter model which implies a fixed association of 0.003 for all the counties despite the differences in physical and social characteristics across counties.

4.2. Associations of built and natural environment with prevalence of obesity

Referring to the results for prevalence of obesity outcome (Table 2), relationships of both built environment and natural environment variables with prevalence of obesity were examined. Regarding density, a one-unit increase in residential density (housing units/acre) is associated with 0.26 % decrease in obesity. Built environment design is also significantly correlated with prevalence of obesity. A unit increase in pedestrian-oriented links per square mile correlates with a 0.06 % decrease in prevalence of obesity. On the contrary, a unit increase in regional auto centrality index (as a measure of destination accessibility through sedentary travel mode) is positively correlated with a 0.016 % increase in the prevalence of obesity. Overall, these findings are intuitive and in line with the literature suggesting that more walkable environments (in terms of density, design, and accessibility) shape our behaviors and determine exposures to unhealthy phenomenon (chronic disease) (Frank, Iroz-Elardo et al., 2019). The relationship between natural environment (tree canopy) and prevalence of obesity was not statistically significant. Note that this finding may not be generalized since a lot of studies have confirmed the significant relationships between natural environment and prevalence of obesity (Ghimire et al., 2017; Lovasi et al., 2013). Among other reasons, the highly aggregate nature of the data (as discussed earlier) could be a cause of the inability to detect statistically significant relationship between greenspace and obesity. Regarding demographics, a one percent increase in Black population is correlated with a higher prevalence of obesity in a non-linear fashion (see the statistically significant polynomial terms in Table 2). As expected, counties with greater a concentration of low-income individuals have on-average higher prevalence of obesity, whereas the reverse is true for counties with greater graduate degree holders. The associations of low-income and high education with prevalence of obesity exhibit substantial heterogeneity. For example, the associations between proportion of graduate degree holders and obesity are negative for around 97 % of the population and negative for the rest. Note that this does not imply causation. Instead, it means that in ~3% of the population, the unobserved factors when combined with observed factors lead to a seemingly positive correlation between graduate degree holders and obesity prevalence. A fixed parameter approach discards
such heterogeneity present in the data and implies a fixed/constant association despite differences in individual contexts. Finally, compared to metropolitan counties, nonmetropolitan counties have significantly higher prevalence of obesity (Table 2). This is intuitive since nonmetropolitan counties typically have less compact and less walkable infrastructure compared to metropolitan counties.

4.3. Direct and indirect effects – built and natural environment, prevalence of obesity, and COVID-19 fatality rate

Table 3 provides the direct effects of built and natural environment variables, and other controls on COVID-19 fatality rates and prevalence of obesity, and the indirect effects of the independent variables on COVID-19 fatality rates through prevalence of obesity. Since we have individual county-specific $\beta$’s for random parameters in both models, we provide, where applicable, a range of the direct and indirect effects in Table 3. Density, design, and destination accessibility are indirectly associated with COVID-19 fatality rate through its associations with

Table 3
Heterogeneous Direct and Indirect Associations of Built and Natural Environment with Prevalence of Obesity and COVID-19 Mortality Rate.

| Variables                        | Direct Effect on COVID-19 Mortality Rate | Direct Effect on Prevalence of Obesity (%) | Indirect Effects on COVID-19 Mortality Rate Through Obesity Prevalence |
|----------------------------------|------------------------------------------|-------------------------------------------|------------------------------------------------------------------------|
|                                  | $\mu$ | $\sigma$ | Min | Max     | $\mu$ | $\sigma$ | Min | Max     | $\mu$ | $\sigma$ | Min | Max     |
| Endogenous Variable              |       |          |     |         |       |          |     |         |       |          |     |         |
| Prevalence of obesity* (%)       | 9.432 | 0.07 | 9.12 | 10.25 |        |          |     |         |       |          |     |         |
| Built Environment (Density & Design) |       |          |     |         |       |          |     |         |       |          |     |         |
| Residential Density (housing units/acre) | -4.578 |        |      |        | -0.270 |        |      |        | -2.542 | 0.01 | -2.76 | -2.45 |
| Auto Regional Centrality Index (0–100) |      |        |      |        | 0.016 |        |      |        | 0.151 | 0.001 | 0.14 | 0.16 |
| Pedestrian-oriented links per square mile |       |        |      |         | -0.064 |        |      |        | -0.608 | 0.004 | -0.66 | 0.58 |
| Natural Environment              |       |          |     |         |       |          |     |         |       |          |     |         |
| Percent of tree canopy coverage  | -0.889 |        |      |        |        |          |     |         |       |          |     |         |
| Demographics (% of county population) |       |          |     |         |       |          |     |         |       |          |     |         |
| Older individuals (65 years plus) | 3.558 |        |      |        |        |          |     |         |       |          |     |         |
| Black                            | 0.974 |        |      |        | 0.044 |        |      |        | 0.417 | 0.003 | 0.40 | 0.45 |
| White                            | -1.338 |        |      |        |        |          |     |         |       |          |     |         |
| Low income* (< USD 50 K)         |        |          |     |         | 0.062 | 0.004 | 0.04 | 0.08 | 0.587 | 0.04 | 0.42 | 0.76 |
| Graduate degree holders*         |        |          |     |         | -0.189 | 0.02 | -0.31 | -0.04 | -1.783 | 0.25 | -2.95 | -0.36 |
| Other Correlates                 |       |          |     |         |       |          |     |         |       |          |     |         |
| Nonmetropolitan county* [1/0]    | 29.474 | 66.9 | -166.4 | 379.9 | 0.443 |         |     |         | 4.182 | 0.03 | 4.04 | 4.54 |
| Testing rate*                   | 0.004 | 0.001 | 0.001 | 0.021 |        |          |     |         |       |          |     |         |

Notes: (*) indicates random parameters for which summary statistics are provided of the individual county-specific conditional estimates; (—) indicates not applicable.

Fig. 3. Indirect Effects of Residential Density on COVID-19 Mortality Rate (Fatalities per 100,000 population) Through Prevalence of Obesity. (Note: county boundaries omitted for visual convenience; Please zoom-in for better visibility).

5 Note that the direct and indirect effects for random parameters are based on individual county-specific estimates. In particular, we estimate the conditional distribution of $\beta_i$. That is, we estimate $E[\beta_i|\text{data}, \theta]$ – where data denotes all the information at hand about county $i$ and $\theta$ are the estimates of population parameters underlying each random parameter (as shown in Table 2). Therefore, the means and standard deviations of the conditional distribution of $\beta_i$ (shown in Table 3) can be different than the means and standard deviations shown in Table 2 (which are estimated structural parameters). For more details, interested readers are referred to Chapter 11 of Train (2009) (Train, 2009).
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obesity (mediator). A unit increase in residential density is directly correlated with a 4.57 unit decrease in COVID fatality rate. Regarding indirect effects, a unit increase in residential density correlates with a 0.27 % decrease in obesity - which in turn is associated with an on-average 9.43 unit increase in COVID fatality rate. This sums up to a total indirect effect of 2.54 units (-0.27 × 9.43) reduction in COVID-19 mortality rate due to residential density. Likewise, regional auto centrality index was indirectly correlated with a 0.15 unit increase in COVID-19 mortality through influencing obesity. In terms of design, a unit increase in pedestrian links per square mile (i.e., greater street connectivity) was indirectly associated with a 0.61 unit decrease in COVID mortality rate. The demographic related direct and indirect effects can be interpreted in a similar fashion (Table 3).

Figs. 3 through 5 illustrate the heterogeneity in built-environment related indirect effects on COVID mortality (using the heterogeneity-based path analysis procedure described in Section 2.3.1). For instance, while the indirect effects of residential density on COVID-19 mortality through prevalence of obesity are consistently negative nationwide, heterogeneity also exists in the magnitude of the negative indirect effects. The indirect effects of residential density are relatively less pronounced in the southern- and mid-western US states (Fig. 3). In some cases, spatial agglomeration patterns can be observed (e.g., the indirect effect of residential density is relatively lower in Oklahoma and this pattern is consistent for almost all the counties in Oklahoma). In other cases, relatively lower indirect effects are observed for specific counties, e.g., see the purple-shaded counties in Tennessee (Fig. 3). As discussed earlier, this heterogeneity could be an outgrowth of other unobserved factors (factors unavailable in the data such as attitudinal predispositions and other individual-specific variations) – latent effects of which are manifested through the built environment related observed exogeneous variables. For instance, the attitudinal predispositions of individuals in certain counties may be more sustainable-travel oriented (relative to those in surrounding counties) and which can lead to a relatively more pronounced negative indirect effect of residential density on COVID-19 mortality.
density on COVID-19 mortality. In addition, these spatial patterns could also be reflecting high-level similarities in observed exogenous variables itself across space (proximate states/counties). Heterogeneous patterns were also observed in the indirect effects of auto-oriented accessibility (Fig. 4) and street connectivity (Fig. 5). As evident, such richer insights cannot be obtained from the traditional fixed parameter structural models.

5. Limitations and strengths

This study has several limitations and thus caution must be exercised in interpreting the findings. The study analyzed the relationships between COVID-19 fatality rates and built/natural environment features at the county-level rather than in smaller areas immediately around where people live and are exposed. This was a requirement due to the fact that COVID cases are not reported for smaller units of geography nationally. This is problematic because these factors vary hugely within counties. The pathway connecting built environment with chronic disease and COVID-19 mortality rate likely operates at a more microscopic level (e.g., neighborhood). The above limitations also apply to all relevant existing studies. The study focused on sociodemographic, built and natural environment, and chronic disease related variables. As a limitation of the study, other potentially important variables (such as air pollution and wind speed) were not considered in the analysis. Wind speed could be an important predictor of COVID-19 spread. Studies have also shown a positive association between air pollution and COVID mortality rates (Travaglio et al., 2021; Wu, Nethery, Sabath, Braun, & Dominici, 2020). We note that increased tree canopy (considered in this study) is inversely correlated with air pollution levels. While the present study did not explicitly quantify the associations of these factors, our heterogeneity-based methodological framework accounts for the latent effects of such unobserved factors and are tracked as unobserved heterogeneity in our analysis. Finally, this is a correlational study and despite the heterogeneity-based modeling methods, causal inferences cannot be made.

Strengths of the study include the joint consideration of chronic and infectious disease and the ability to directly capture how obesity related chronic diseases pre-dispose individuals to a much greater risk of dying from COVID-19 once exposed. It further documents how chronic disease and COVID-19 are related with the built and natural environment where we live. The simulation-assisted random parameter approach is a novel application to COVID mortality and documents the critical importance of unobserved heterogeneity and the ability to arrive at potentially inaccurate conclusions when employing highly aggregate spatial data to topics of this nature. Given the seriousness the COVID-19 pandemic presents; it is critical to take extreme caution when arriving at conclusions based on fixed parameter methods employing highly aggregate spatial data. Compared to previous studies, the heterogeneity-based path analysis framework enabled an understanding of the heterogeneous associations of built environment. By rigorously tracking the local variations, the findings exhibit greater generalizability compared to previous studies. In addition, previous nationwide US-level studies on COVID-19 mortality focused on specific geographies (such as considering only metropolitan counties). When coupled with the more rigorous analytical framework, the use of nationwide data while controlling for metropolitan vs. non-metro county status is expected to enhance the generalizability potential of the findings presented. The current study provides a tractable pathway from the environment where we live to explain systematic differences and disparities across population subgroups in the spatial distribution of risk of chronic disease and COVID-19 mortality. Despite the rigorous methodology, the authors were not comfortable using a fluid and greatly evolving COVID-19 data at the county level early on the pandemic. The current study was delayed 3 times until more reliable estimates were available at the county level across the nation. The authors dismissed models run using data up until the end of Summer 2020. When the authors revisited the analyses in November 2020, the data were more representative, and the findings were more stable. The models presented are based on data from February of 2021 employing 26813148 cases and 453679 deaths and predict both COVID-19 incidence and mortality while also employing a more complete set of built environment measures and further include tree canopy as a natural environment predictor. Finally, besides our main focus on COVID-19 mortality, our study is the first to report that density is associated with an increased risk of getting COVID-19 (i.e., greater infection risk); a hugely unpopular finding for an urban planner to report.

6. Concluding remarks & future research

This study presents unique and novel information and contributes by presenting and empirically testing a conceptual model linking built environment and natural environment with both chronic and infectious disease (COVID-19) pandemics. By harnessing integrated county-level data on COVID-19 fatality rates, prevalence of obesity, built and natural environment, the rigorous simulation assisted heterogeneity-based path analysis sheds new lights on the direct and indirect links between built/natural environment, chronic disease, and COVID-19 fatality rate. The key empirical results are:

- Obesity is significantly and inversely related with residential density and walkable urban design.
- Obesity mediates the relationship between the built and natural environment and COVID-19 mortality.
- Built environment relationships with obesity and COVID-19 are systematically different across income and ethnicity. The most vulnerable populations have much higher rates of obesity and COVID-19 mortality and these differences are partially explained by the environments in which they live.
- Strong and statistically significant negative correlations between built/natural environment and COVID-19 fatality rate were found after controlling for unobserved factors and demographics.
- Tree canopy and green space is associated with lower COVID-19 mortality rates.
- Population density was positively associated with COVID-19 incidence rates.

The findings of this study have important implications for transportation, land use, and public health policy makers. The findings suggest that healthier (active) and greener transportation infrastructure is not just effective in fighting obesity related chronic diseases including diabetes and heart disease; but also provides a protective effect in reducing the mortality risk of highly contagious infectious diseases such as COVID-19. Compact development and densification are essential to reduce vehicle dependence and reliance on private vehicles and support transit and active transportation. Compact transit-oriented development is also shown to reduce the risk of obesity related chronic disease which in turn is associated with lower COVID-19 mortality rates. However, compact development also brings people together and the positive relationship between density and COVID incidence rates shown here is realistic and intuitive. Cities play an essential function to enable 7.6 billion people to call earth home.

Designing health promoting and environmentally sustainable
communities requires densification. Therefore, more effective strategies focused on behavior modification are needed during pandemics in cities. The days of spreading out growth to mitigate against spread of infectious disease as done in the latter 1800s and early 1900s are long gone. By continuing to advocate and design active-transportation supportive infrastructure, the health and well-being of individuals can be improved at a population level. The findings emphasize the importance of creating a less obesogenic built environment to reduce COVID-19 severity and mortality. The findings that obesity and old age are correlated with greater COVID-19 mortality risk reveals equity and social justice issues with significant global health implications. Individuals with obesity are more likely to die from COVID-19. In addition, older age and comorbidities (including obesity) have also been reported as key risk factors for more severe clinical manifestations of COVID-19 in China, Italy, and globally (Busetto et al., 2020; Popkin et al., 2020; Yang et al., 2020). At the same time, obesity rates have increased significantly over the last two decades in United States and globally (CDC, 2021; WHO, 2020). To this end, designing active travel supportive infrastructure can help reduce the equity and social justice related impacts of chronic and infectious diseases. We note that the strategies to create active transportation friendly places may differ globally since sociodemographic, cultural, and built environment factors interact in complex ways influencing health outcomes. Our findings also highlight the importance of considering broader built environment design factors to have a more accurate and comprehensive understanding of the connections between community design and COVID-19 mortality. From a methodological standpoint, the findings underscore the importance of accounting for unobserved heterogeneity and ignoring which can lead to inaccurate results and inferences.

This study highlights promising avenues for future research in this field of research that could help other experiences. Despite the treatment of unobserved heterogeneity, we re-emphasize that the connections between built environment with chronic disease and COVID-19 mortality rate are likely more localized in nature (such as neighborhood-level or census block group level). This warrants the use of higher resolution COVID-19 mortality and built environment data (such as census-tract/neighborhood level) to explore the key pathways presented in this study. Thus, future studies could potentially benefit from analyzing higher resolution data to develop more place-based insights. In this regard, the conceptual model presented in this study can be better operationalized and tested by considering individual-level data on COVID-mortality, chronic disease prevalence, and fine-grained environmental attributes. Related to the use of higher resolution data, a reasonable trade-off will need to be achieved with respect to the generalizability potential of the findings based on high resolution spatially referenced data. The study demonstrated the detrimental effect of obesity on COVID-19 mortality rates in the United States and this detrimental effect of obesity could be different for other countries. Likewise, while being effective, the magnitude of the effectiveness of compact and walkable built environments could also vary across countries. This necessitates the need to examine the key pathway presented herein in other countries (especially developing or undeveloped countries). Physical activity and active transportation serve as a key behavioral element in the pathway connecting built environment with chronic and infectious diseases. Thus, there is a need to empirically examine physical activity/active travel outcomes in the pathway presented. Finally, besides the eventual mortality outcomes, there is a need to consider hospitalization rates to more fully capture the actual harm imposed by COVID-19.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A

Table A1

Table A1
Fixed and Random Parameter Models for COVID-19 Infection Rate (Number of cases per 100,000 adult population).

| Variables                                      | Fixed Parameter Model (Reduced) | Random Parameter Model |
|------------------------------------------------|---------------------------------|------------------------|
| Intercept                                      | 12615.5                         | 13586.8                |
| Density                                        | z-score                         | 31.79                  |
| Population Density (people/acre)               | –86.12                          | 44.43                  |
| Auto Regional Centrality Index [1 if > 14 % (median), 0 otherwise] | 2.01                           | 3.32                   |
| Natural Environment                            |                                 |                        |
| Percent of tree canopy coverage                | –44.18                          | –54.31                 |
| Demographics (% of county population)          |                                 |                        |
| Black                                          |                                 | 39.61                  |
| Low income* (< USD 50 K)                      |                                 | 20.66                  |
| standard deviation of random parameter         |                                 | 2.03                   |
| Graduate degree holders                        |                                 | –271.25                |
| Nonmetropolitan county* [1/0]                  | 635.83                          | 96.31                  |
| standard deviation of random parameter         |                                 | 2302.2                 |
| Summary Statistics                             |                                 |                        |
| N                                              | 3130                            | 3130                   |
| Log-likelihood at constant                     | –30554.48                       | –30554.48              |
| Log-likelihood at convergence                  | –30455.45                       | –30247.43              |
| AIC                                            | 60919.19                        | 60516.9                |

Notes: (*) indicates random parameters; N is sample size; AIC is Akaike Information Criterion; scale parameters/standard deviations provided for random-held variables.
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