Joule

CellPress

How limitations in energy burdens compromise health interventions for COVID outbreaks in urban settings

Nina Fefferman,[1] Chien-fei Chen,[2,3]* Gregory Bonilla,[2] Hannah Nelson,[2], and Cheng-Pin Kuo[4]

[1]Department of Math & Ecology and Evolutionary Biology, University of Tennessee, Knoxville, TN, USA

[2]Center for Ultra-wide-area Resilient Electrical Energy Transmission Networks (CURENT), Department of Electrical Engineering and Computer Science, University of Tennessee, Knoxville, TN, USA

[3]Lead Contact

[4]Department of Civil and Environmental Engineering, University of Tennessee, Knoxville, TN, USA

*Correspondence: cchen26@utk.edu

SUMMARY

Low-income households have experienced increased energy burdens and inaccess to healthcare services during the COVID-19 pandemic, which has limited their ability to practice social distancing and stay-at-home orders. Here, we show that a households' inability to adopt social distancing due to constraints in utility and healthcare expenditure drastically impacts the course of disease outbreak in five U.S. counties. Low-income households shoulder greater burdens of disease and death than other households, while functioning as a consistent source of exposure to higher income households. Health interventions combining social distancing and resource protection strategies (e.g., utility access and healthcare) were the most effective in limiting the spread of COVID-19. Additionally, resource protection strategies tailored to alleviate utilities and financial constraints for low-income households can protect the whole population. Current policies need to address the multidimensionality of energy burdens, housing environment, and public health. The findings also imply methods for future disaster management.

COVID-19, low income, energy burden, energy justice, energy insecurity, stay-at-home orders, social distancing, utility cost

INTRODUCTION

The broader impacts of energy insecurity and burdens on household environments are related to mental and physical health [1–4], which is a serious situation during the COVID-19 pandemic [5–8]; for example, anxiety, stress, and depression are associated with living in poor housing conditions [9–11]. Energy insecurity is defined as households' inability to meet basic energy needs [3,7], while energy burden is generally measured by the inability to pay for utility bills [12]. Certain socioeconomic groups, including low-income, senior, non-white, and renter households, and those without a full-time job, spend significantly higher percentages of their income on energy costs than other groups. Households that experience intense energy burdens often have to make a fundamental trade-off between health-supportive resources like medicine or healthcare to afford utilities, such as water, gas, and electricity [6,12–14]. This situation has adverse effects on individual and family health, especially for households at or below the poverty line, where marginal increases in household expenditure on necessities can compromise the ability to seek basic medical care [15]. Therefore, the narrative of

Context & Scale

This study demonstrates how household economic constraints of utility and health expenditure may affect a county's ability to effectively enact pandemic mitigation policies. The findings suggest that the security of household utilities is necessary to support household health and safety. Additionally, a county's social interaction rates and health infrastructure accessibility significantly impacts the outcomes of health policy interventions, so that low-income households bear most of the burdens of disease and death. Inequities in access to resources (e.g., utilities and healthcare) and health intervention policies (e.g., social distancing) hinder low-income households' ability to protect themselves from infection. The findings provide implications for management of future disasters beyond the COVID-19 pandemic. In particular, there is a critical need for policies to address energy and healthcare affordability and accessibility among vulnerable communities.

adhering to social distancing and quarantine protocols may be fundamentally flawed when considering families under severe financial stress.

While many recent public debates and academic studies have focused on how health information and beliefs factor into the adoption of COVID-19 mitigation efforts, household and economic limitations play a significant role in the ability to adopt behaviors that involve spending more time at home, which sounds deceptively cost-free, but has potential financial and health costs, such as lost wages from voluntary adherence to stay-at-home orders by non-essential employees. More importantly, even if one remains employed, there are increased costs from used supplies and utilities due to increased hours spent at home [16–18].

Current energy burden research is mainly carried out at the individual, small-scale level (e.g., building, person, household), but not at the population level (e.g., national building stock, cities, building typologies). The limited availability of detailed residential energy consumption data during the pandemic makes it challenging to understand the potential impacts of energy burdens and income disparities on health outcomes at the population level. Deeper insights into the presence and persistence of energy burdens and socioeconomic constraints during staying-at-home orders across populations are severely limited, thereby undermining effective health policy and interventions. Further, many policies have provided temporary protection against utility shut-offs or evictions due to non-payment, which has affected households of different income levels, so that counties or cities themselves may have differential success in outbreak control and subsequent population health outcomes.

This study moves beyond extant COVID-19 studies to demonstrate the multidimensional and interconnected factors of energy burdens, socioeconomics, healthcare-related resources, essential workers, health interventions (e.g., social distancing policies), and the spread of COVID-19 cases. This study also presents the epidemiological models to explicitly consider how energy and household economic trade-offs might affect community-level success at mitigating COVID-19. This study is based on Giddens' theory of structuration [19,21], which engages the relationship between social structure and human agency. The theoretical assumption here is that social structural context is something that both constrains and enables; social structure depends on the agency of individuals, but agency is also enabled and constrained by rules and resources [23].

This study highlights how energy burdens can drastically stratify the risks of COVID-19 infection, how contact rates within and across households are likely to be affected by public health intervention policies (i.e., social distancing and resource protecting policies), and how the synergy between those effects increases the burdens faced by the entire population. We estimated energy burdens of low-, middle-, and high-income households (LIHs, MIHs, and HIHs, respectively) in five U.S. counties during the first phase of stay-at-home orders from April to July 2020. This study also considers the age-based demography of the county to estimate the percent likely to be employed and thus affected by shut-downs, as well as the likely proportion of a county's workforce classified as essential workers, who would be exempted from social-distancing policies, and assumed over-representation of essential workers in LIHs, MIHs, and HIHs.

Energy burdens were considered as a proxy for inelastic costs that directly support household health and safety in this study. Income differences in energy burdens lead to differences in COVID-19 exposure risks. They can critically influence the duration of illness and concomitant risks of death, assuming that limited economic resources compromise adequate access to healthcare before and during infection. We further consider households' skewed ability to perform their jobs while safely practicing social distancing. Specifically, we examine four cases of health intervention policies, including 1) "Do Nothing," 2) "Social Distance Only," 3) "Economic Support," and 4) "Try Everything." This study then parameterized the epidemiological model to reflect the conditions of the five counties, chosen for their differences among the relevant socioeconomic metrics. Specially, we used a 3-tiered SEIR model of COVID-19 in a population stratified into three socioeconomic levels: HIHs, in which there was no direct trade-of and families can be assumed to absorb the opportunity costs of social distancing without compromising any other health-supportive resources; MIHs, in which families can absorb the costs of social distancing while maintaining other health-supportive resources for up to a year; and LIHs, in which families do not have a sufficient economic buffer to be able to maintain health-supportive resources while engaging in social distancing.

RESULTS AND DISCUSSION

Socioeconomic status distribution, energy burdens, and COVID-19 outbreak

Our model demonstrated that the socioeconomic status (i.e., number of households unable to adopt social distancing due to the constraints of utility and household expenditure) of a county drastically influenced the expected course of an epidemic outbreak in the population. Under assumed uniform etiology and mixing patterns across cities (i.e., discounting the differences based on access to healthcare, public transportations, and underlying health conditions not correlated directly with income, instead of focusing only on demographic and economic differences), we observed that the model for each county produced drastically different baseline results in the expected outbreak size over the first 120 days after the introduction of a novel COVID-like infection (Fig. 1).

Burdens of COVID-19 over time by socioeconomic status

In understanding the dynamics, our model also showed how, after the introduction of novel infection (for simplicity and consistency, we assumed this to be introduced via MIHs), we observed critically different patterns in which socioeconomic strata of households were likely to shoulder the burdens of disease and death overtime as the COVID outbreak progressed (Fig. 2). For example, in Los Angeles, there was an early transition in both disease and death burdens from MIHs to LIHs (Fig. 2e,f), while Philadelphia experienced a longer delay after introduction, before the burden of cases shifted from the initially infected MIHs to LIHs (shifting from day 20 to day 30; Fig. 2e,i); the lag in the shift of death burdens was even more substantial (shifting from day 37 to day 65; Fig. 2f,j). In other words, LIHs' inability to make overall health-supportive choices due to economic limitations mean they were less able to avoid the infection themselves. LIHs both caught and transmitted the disease more quickly than MIHs or HIHs and acted as a source of ongoing exposure to higher-income households. Therefore, they suffered the most significant burdens and functioned as the greatest barrier to effective, population-wide outbreak control.

Health interventions, energy burdens, and reduction of COVID-like outbreaks

Considering the outcomes of health interventions on these populations, we observed that a county's socioeconomic composition also drastically impacted the intervention's effectiveness (Fig. 3). For the interventions meant to reduce overall transmission as a blanket policy, affecting socioeconomic sub-populations differently (e.g., "Social Distance Only" policy), we see a ~60% to 78% reduction in symptomatic cases from the baseline scenario ("Do Nothing"). In the absence of social distancing, however, health intervention policies aimed solely at supplementing the economic hardships faced by lower-income populations, who would then be less constrained in the individual choices available to them for self-protection (e.g., by accessing appropriate medical care or paying utilities that support household health; the "Economic Support" policy), we were still able to achieve between 6% to 14% reductions in symptomatic COVID cases over the first 120 days of an outbreak. When both resource protective strategies and social distancing policies were imposed together ("Try Everything"), the reduction in total cases ranges from 66% to 81%; however, the improvement of the combined strategies was synergistic rather than additive, ranging between an additional 2% to 5% improvement, depending on the socioeconomic composition of the county.

Health interventions, energy burdens, and reduction of COVID-19 fitted to the 2020 outbreak

We repeated the same comparison of outbreak intervention scenarios, using the models adapted to fit the observed case incidence data from the COVID-19-outbreaks in each county (i.e., baseline parameters for interaction and social distancing were tailored so that the resulting epidemic curve produced similar growth and cumulative symptomatic case counts over 120 days after the first identified case of COVID-19 to the reported outbreak for those counties post-COVID-19 introduction; Fig. 4). In this scenario, our model suggests that each county's social interaction rates and underlying healthcare resource accessibility drastically impacted the expected outcome of health interventions, both in magnitude within each county and relative impact across counties (compare Fig. 3 with Fig. 4). Unsurprisingly, social distancing was more effective in more densely populated counties (now observable due to the tailored interaction rates); for example, the tailored results of Los Angeles showed a reduction in COVID cases of over 90% (Fig. 4), where in the untailored COVID case, Los Angeles achieved 60% reduction. Given these tailored scenarios, however, economic support policies alone were capable of achieving up to 38% reduction in cases. This result means that LIHs acted as drivers of the ongoing outbreak for the entire community due to their economic limitations whether lockdowns were achievable or not, but there is a greater impact when social distancing cannot be imposed. Therefore, resource protection strategies tailored to alleviate financial constraints for LIHs can protect the whole population. While economic support strategies were seen to be more effective overall, their benefits over lockdown policies were reduced, meaning resource protection strategies may be an effective strategy in the absence of social-distancing mandates. Still, they may not be cost-effective to enact once lockdown policies are in place.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Chien-fei Chen (cchen26@utk.edu).

Materials Availability

This study did not generate new unique reagents.

Data and Code Availability

This study used five nationally representative data sources, including the COVID-19 Community Vulnerability Index (CCVI) [20], the U.S. Department of Energy's Low-Income Energy Affordability Data (LEAD) tool [22], John Hopkins' COVID-19 data [24], the American Community Survey (ACS) [25], and the Safegraph data consortium [26].

Methodology

Selection of studied counties

This study selected five counties for epidemiological comparison: Los Angeles, CA; Philadelphia, PA; Oakland, MI; Allegheny, PA; and Hidalgo, TX, based on patterns in vulnerability ranking across selected socioeconomics and health-related variables between each county. The selection of counties was based on population density and per capita income, as well as percentages of people below the national poverty level, people of racial minorities, people without insurance, households with energy burdens by county, and households that spend 30% or more of their income on primary care physicians. Counties were chosen to be maximally distinct from each other in their pattern of vulnerability across these measures (using pairwise Euclidean distance per metric). The following section describes each specific variable source.

Variables

COVID-19 Community Vulnerability Index (CCVI): The CCVI was used to select our countries and measure socioeconomic and health vulnerabilities at the county-level to indicate the communities that may be less resilient to the impacts of the pandemic [27]. The CCVI builds on the U.S. Center for Disease Control and Prevention's (CDC) Social Vulnerability Index (SVI), a validated metric that uses census tract and county-level data [20]. The CCVI's six themes include (1) socioeconomic status, (2) household composition and disability, (3) minority status and language, (4) housing type and transportation, (5) epidemiological factors, and (6) healthcare system factors. Each county is ranked from least vulnerable to most vulnerable in each of these categories.

COVID-19 cases and deaths: For this study, data on COVID-19 cases and deaths was observed from January 21 to July 31, 2020, using data from John Hopkins' University [24] and USA FACTS [28]. The data sources use three main methods to collect this data: first, by drawing aggregate county-level data from the Covid Tracking Project, John Hopkins' utilizes data from 56 U.S. states and territories under CDC guidelines for test positivity [29,30]. Second, USA FACTS indicates where presumed cases are included as positive cases and adjusted per capita to represent the cumulative total. Lastly, USA FACTS estimates the gaps in daily cumulative cases and deaths by direct referencing or scraping from state and local agencies [31]. Both sources were used in validation of cases and deaths to ensure accuracy.

Public intervention policy: Using Safegraph mobility data in 2020 [32], this study analyzed the state-level stay-at-home and social distancing orders that limited movement from areas of residence to places of interest. Safegraph is a data consortium that provides accurate location data for human migration patterns and has been used in various COVID-19 studies [33–36]. The anonymized data in the present study were collected utilizing cellphone pings coupled with the average dwell time per day for each county. The number of devices and the length of time at home were then averaged to create a proxy representing the change in movement for each county population compared to non-pandemic conditions. It is important to note that public intervention policy was only used in the "COVID-19" fitted scenarios and not in the "random disease in the cities using this model shape, but not with COVID parameters" case. Further, county mandate information does not include the factors such as social gatherings, movement restrictions, and curfews; therefore, this paper assumed the counties were following state social distancing guidelines.

Additionally, instead of modeling a city's specific public intervention policies over time, we chose to examine the four following cases of policies: 1) "*Do Nothing*" – there were no social distancing policies and the expected differential economic impacts on household health-supportive spending remain in place, such as LIHs having less access to healthcare or health-supportive utilities due to economic constraints; 2) "*Social Distance Only*" - those who were not essential workers were allowed to social distance, but nothing was done to alleviate disparities in health-supportive spending for LIHs; 3) "*Economic Support*" - there was no social distancing attempted, but there were programs ensuring that pandemic-related loss of income would not compromise household health; and 4) "*Try Everything*" - social distancing was enacted and supplemented by policies that alleviate additional economic burdens on LIHs. In reality, every county had a mixture of these policies, but we tailored the mixed rates of each county to approximate the magnitude of the outbreak in the "do nothing" case by August 2020. Further, while each county has taken different policy actions over time, we discussed these cases separately as "pure strategies" to highlight how emergent household necessities (e.g., the ability to socially distance or afford electricity) can complicate a county or city's ability to control COVID-19 and other illnesses.

Essential workers: An essential worker provides public health and safety, essential products, or other infrastructure support during the COVID-19 pandemic; however, they are more likely to be exempted or prohibited from adopting social distancing policies. Workforce statistics for essential workers were retrieved by analyzing the number of workers per industry and calculating each industries' labor force percentage from the U.S. Bureau of Labor Statistics (BLS) [37] and is based on methodology proposed in a recent study by the United Way [38]. The state-level statistics were used as a proxy for each of the counties because county-level data were not available.

Socioeconomic status: We used a combination of demographic factors and economic levels to estimate population levels of contact throughout different socio-demographic strata. The total population and percent of people over 65 years old and less than 17 years old were retrieved from the CDC COVID-19 index [25]. The estimates of household income level were based on nationally adjusted household sizes and cost of living relative to the area, as well as the percentage of households by county-level that represented low-, medium-, and high-income were estimated using data from the Pew Research Center [39]. We defined LIHs as two-thirds of the national median, medium-income as two-thirds to double the median, and high-income as more than double the median.

Energy consumption burden (ECB): We established the 2020 county-level energy consumption burden (ECB) database for LIHs. Due to the lack of official energy consumption data at zip code or county-level in 2020, the historical energy expenditure (electricity, fuel, and natural gas) and burden estimation among LIHs were collected from the Low-Income Energy Affordability Data (LEAD) Tool by the National Renewable Energy Laboratory (NREL) and the U.S. Department of Energy (DOE) [22] and U.S. Energy Information Administration (EIA) [40]. Technically, the 2020 county-level LIHs' ECB data was estimated from county-level information on LIHs' annual income in 2014-2018 and 2020 state-level energy consumption data by using the following equation:

$$\mathrm{ECB}_{2020\ \mathrm{ij}} = \frac{\sum_1^k \mathrm{Exp}_{2020\ \mathrm{ijk}}}{\mathrm{Income}_{2014-2018\ \mathrm{ij}}}$$
$$= \left(\sum_1^{\mathrm{k}} \mathrm{Exp}_{2014-2018\ \mathrm{ik}} \times \frac{\mathrm{Exp}_{2014-2018\ \mathrm{ijk}}}{\overline{\mathrm{Exp}_{2014-2018\ \mathrm{ik}}}} \times \frac{\mathrm{Con}_{2020\ \mathrm{ijk}}}{\mathrm{Con}_{2014-2018\ \mathrm{ijk}}}\right) \times \frac{\mathrm{ECB}_{2014-2018\ \mathrm{i}}}{\sum_1^{\mathrm{k}} \mathrm{Exp}_{2014-2018\ \mathrm{ik}}}$$

where $\mathrm{ECB}_{2020\ \mathrm{ij}}$ was 2020 ECB for the ith county in the jth month for LIHs, $\mathrm{Exp}_{2020\ \mathrm{ijk}}$ was the sum of energy expenditure for the kth source (electricity, fuel, and natural gas) of the ith county in the jth month in 2020, and $\mathrm{Income}_{2014-2018\ ij}$ was the average income of ith county in the jth month during 2014-2018 for LIHs. $\mathrm{Exp}_{2020\ \mathrm{ijk}}$ was further calculated by using energy expenditure for the kth source of the ith county during 2014-2018 ($\mathrm{Exp}_{2014-2018\ \mathrm{ik}}$), energy expenditure fluctuation ratio in jth month for *k*th source compared with the monthly average ($\mathrm{Exp}_{2014-2018\ \mathrm{ijk}}/\overline{\mathrm{Exp}_{2014-2018\ \mathrm{ik}}}$), and 2020 state-level residential energy consumption ratio for *k*th source of *i*th county in *j*th month compared with 2014-2018 data ($\mathrm{Con}_{2020\ \mathrm{ijk}}/\mathrm{Con}_{2014-2018\ \mathrm{ijk}}$). The applied monthly energy consumption indices for electricity, fuel, and natural gas in each state were sales of electricity to residential sector, prime supplier sales volume (propane), and nature gas consumption by residential sector. $\mathrm{Income}_{2014-2018\ \mathrm{ij}}$ was calculated by using the ECB for *i*th county for LIHs ($\mathrm{ECB}_{2014-2018\ \mathrm{i}}$) and the sum of energy expenditure for the kth source of the ith county during 2014-2018 ($\sum_1^k \mathrm{Exp}_{2014-2018\ \mathrm{ik}}$). The missing values of LIHs' ECB data were replaced with the estimations from the multiple imputation technique [41,42], which includes county-level CCVI data as variables due to its completeness for all counties and socioeconomic relationship with ECB.

Methodological justification

This study did not consider racial and demographic differences in economic stratification (i.e., HIHs, MIHs and LIHs) to highlight how financial resources themselves have the potential to drastically stratify the risks to households, even before further etiological differentiation (thereby also avoiding the potential circular logic that racial differences in health outcomes may be due to poorer socioeconomic conditions). Based on this breakdown, the authors estimated how much of the population's contact rates within and across households were likely to be affected by social distancing policies, including stay-at-home orders. We did consider the age-based demography of the city as part of estimating the percent likely to be employed (and thus affected by shut-downs), but did not include age-based probabilities of infection or death, to highlight again how household economics alone can impact economic-epidemiological dynamics. We further included the likely proportion of a city's workforce classified as essential workers, who would be exempted or prohibited from adopting social distancing policies. We also assumed over-representation of essential workforce in LIHs and MIHs and used COVID-19-inspired rates for etiology of infection (assuming population-level mass averages without differentiating by age, race, or gender).

Based on household income level, we explicitly considered what proportion of household income would be expended on utilities as a proxy for inelastic costs that directly support household health and safety. These differences naturally lead to differences between households in exposure risks, but also critically influence the likely duration of illness (and concomitant risks of death) experienced by individuals who catch COVID-19, assuming that limited economic resources compromise adequate access to critical healthcare before and during active infection. We further consider the skewed ability of these households to perform their jobs while safely practicing social distancing (e.g., working from home, limiting contact with the public, etc.). To be most conservative, we assumed no direct job loss due to either public health policies (such as lockdowns) or from illness-related absenteeism; economic losses due to illness are felt only as temporary losses in income during protective protocols or illness. This means that all the differences in our study come only from the trade-off in exposure and healthcare – relaxing this assumption would meaningfully increase the burden borne by lower income families in negative economic and health outcomes.

Data analysis

1. Epidemiological Model

We employed a Susceptible-Exposed-Asymptomatic-Infectious-Recovered-Dead (SEAIRD) model [43,44] with socioeconomically dependent proportions of the population able to effectively shelter at home and/or afford other health-supportive resources. The former impacts the rates of COVID-19 exposure, where interactions with others decreases as income status increases, and the latter decreases the duration of infection while increasing the probability of recovery relative to death. We first

defined the population of Susceptible individuals in each socioeconomic status class, S_{status}. Similarly, we defined Exposed individuals in each status class, E_{status}, as those who have been infected but were neither symptomatic nor capable of transmitting infection to others. To reflect the possibility that individuals may have never become infectious, we allowed individuals to progress directly from the Exposed class into the Recovered class, R_{status}. Alternatively, individuals may have progressed from Exposed to the first phase of Infectiousness, A_{status}, where individuals could transmit the infection but were not yet symptomatic. Individuals, then, could either recover or progress to the second phase of infectiousness, I_{status}, in which they were both infectious and symptomatic. For simplicity, we assumed that both asymptomatic and symptomatic infectious individuals were equally likely to infect a susceptible individual. Individuals in I_{status} could either recover or progress to disease-related death, D_{status}.
To capture the dynamics of this system, we also defined the composite value, $\beta_{i,j}$, which captured the probability of successful infection transmission due to contact between Infectious individuals of status *i* and Susceptible individuals of status *j*. We separately defined $\rho_{i,j}$, which captured the probability of contact between an individual in status *i* and an individual of status *j* in the absence of social change in response to COVID-19. We defined $\overline{\rho_{\iota,J}}$ to denote the probability of contact when both individuals *i* and *j* were practicing social change in response to COVID-19. Note that status was assumed to affect the possibility of social distancing, such that LIHs were less able to effectively social distance. Further, we assumed that as socioeconomic status increases, the percent impact of social change in response to COVID-19 also increases (i.e., the $\overline{\rho_{\iota,J}}$ decrease), reflecting the proportion of "essential workers" required to report to work despite the desire to socially distance.

This study also defined the rate of becoming infectious, μ, and the rates of progression from A_{status} to I_{status} as δ_1 and from I_{status} to D_{status} as δ_2, each of which is assumed to be status-independent. We defined the rates of recovery from E_{status}, A_{status}, and I_{status} classes as $\gamma_{0,status}$ through $\gamma_{2,status}$, respectively, which were dependent on status as a proxy for both underlying health and access to healthcare, as this access critically depends on economic resources, which may be depleted by expenditure on household access to utilities.

Lastly, we defined η_{status} to capture the decreased rate of recovery from both A_{status} and I_{status}, respectively, due to compromised access to health-related resources (up to and including the luxury of convalescence when ill) in the absence of social change in response to COVID-19. To further incorporate the resource cost burden incurred by social change in response to COVID-19, we defined $\overline{\eta_{status}}$ to reflect alleviation of limitations in resources, such that $\overline{\eta_{status}} > \eta_{status}$, reflecting the intervention of a policy to ensure ongoing access to critical health-supportive resources, such as energy. As socioeconomic status increases, the impact of social change in response to COVID-19 costs decreases (i.e., η_{status} increases) to reflect the increased economic capacity to handle incurred costs (whether due to lost salary from furloughs, hiring help to perform disease-exposure risky tasks, or other burdens associated with distancing). For clarity, we defined $N_{status} = S_{status} + E_{status} + A_{status} + I_{status} + R_{status} + D_{status}$. Finally, we defined the socioeconomic distribution of the population as $\widehat{N} = \sum_{status=1}^{3} N_{status}$. Again, to highlight the processes we wish to consider most clearly, we assumed no births, deaths from any cause other than the disease, or movement into or out of the population.

Based on these definitions, we have defined the baseline dynamics of the model, in the absence of social change in response to COVID-19, in the following way:

$$\frac{dS_{status}}{dt} = -\sum_{\forall j} \rho_{j,status}\beta_{j,status}S_{status}(A_j + I_j)$$
$$\frac{dE_{status}}{dt} = \sum_{\forall j} \rho_{j,status}\beta_{j,status}S_{status}(A_j + I_j) - (\gamma_{0,status} + \mu)E_{status}$$
$$\frac{dA_{status}}{dt} = \mu E_{status} - (\gamma_{1,status}\eta_{status} + \delta_1)A_{status}$$
$$\frac{dI_{status}}{dt} = \delta_1 A_{status} - (\gamma_{2,status}\eta_{status} + \delta_2)I_{status}$$
$$\frac{dR_{status}}{dt} = \gamma_{0,status}E_{status} + \gamma_{1,status}\eta_{status}A_{status} + \gamma_{2,status}\eta_{status}I_{status}$$
$$\frac{dD_{status}}{dt} = \delta_2 I_{2,status}$$

We then modify this baseline model by the use of the appropriate combinations of $\rho_{i,j}$, $\overline{\rho_{i,j}}$, $\eta_{status,}$ and $\overline{\eta_{status}}$ to consider our four scenarios: the baseline scenario of "Do Nothing", where we used $\rho_{i,j}$ and η_{status} unaltered; the "Social Distance Only" scenario, where we used $\overline{\rho_{i,j}}$ and η_{status}; the "Economic Support" scenario, where we used $\rho_{i,j}$ and $\overline{\eta_{status}}$; and the "Try Everything" scenario, in which we use $\overline{\rho_{i,j}}$ and $\overline{\eta_{status}}$.

2. SI Model:

Values for the interaction rate, $\rho_{i,j}$:

$\rho_{i,j}$	Low-income	Medium-income	High-income
Low-income	1	0.3	0.3
Medium-income	0.5	0.5	0.3
High-income	0.5	0.5	0.3

These values indicate assumed percentage-based corrections for cross-socioeconomic interaction rates under unaltered societal function (estimated curve fit to previous, non-COVID outbreaks). To calculate $\overline{\rho_{i,j}}$, we used assumed estimates of the percentage of the households in each socioeconomic category that had at least one worker employed in a job that would have been classified as essential, k_j, such that $k_j = \{0.7, 0.3, 0.1\}$. We then calculated $\overline{\rho_{i,j}} = \rho_{i,j}k_ik_j$. To tailor each of these calculations to each specific county, we used the weighted average of $\rho_{i,j}$ and $\overline{\rho_{i,j}}$, reflecting the overall percentage of that counties' essential labor force reported, scaled by the percentage of the population reported to be between the ages of 18 and 65 (reflecting the assumed demographic description of most of the workforce itself).

Values for the transmission rate, $\beta_{i,j}$:

$\beta_{i,j}$ (from/to)	Low-income	Medium-income	High-income
Low-income	0.6	0.4	0.4
Medium-income	0.6	0.3	0.3
High-income	0.6	0.3	0.3

These values were initially based on estimates of transmission from Weitz et. al [45], and were assumed to increase the probability of transmissible infection as household income decreased, reflecting increased probability of interaction due to decreased access to indoor leisure spaces both within and outside of the home, and the decreased probability of having avoidable public interaction because of employment.

Values for etiological progression:

Further etiological parameters were tailored based on data for each county, including the local case fatality rate (reflecting local differences in healthcare capacity and baseline health of the population), and mixing rates governing all the $\beta_{i,j}$ terms, reflecting differences in average contact rates between individuals in different counties (due to patterns in travel, urban planning, etc.).

Parameter	Value	Source
μ	0.25	Weitz et al. [45]
δ_1	0.25	
δ_2	0.002	The overall estimated case fatality rate for the U.S. as of 10/27/20 times 1/14 (where 14 days was assumed the average duration of fatal illness after the onset of symptoms)

Values for the reduction in average recovery rate, η_i:

η_i	
Low-income	0.6
Medium-income	0.9
High-income	1

From which $\bar{\eta}_i$ was calculated as $\bar{\eta}_i = (\mathbf{1} - \boldsymbol{k_i})\,\eta_i + \boldsymbol{k_i}\,\eta_i(1-c)$, and where c indicated a decreased rate of recovery due to compromised ability to rest and undertake healthcare-related activities while continuing to work (assumed to be 0.2).

Values for duration of infection based on underlying health condition, γ:

$\gamma_{2,i}$	
Low-income	0.06
Medium-income	0.07
High-income	0.09

These values were estimated using medium-income households as the presumed average, representing a fourteen-day duration of infectivity until immune protection. While COVID-19 is now known to be transmissible mostly within a ten-day window, we could assume this for all future potential pandemics, and chose fourteen days since that was the initial window considered for public health response policy estimates. Alterations for duration of infection based on household income were estimated as scaling from medium-income households based on known all-cause health corrections. Values for $\gamma_{1,i}$ were then calculated as $\gamma_{1,i} = \frac{4}{14}\gamma_{2,i}$, reflecting an assumed proportionate risk of death relative to recovery, and $\gamma_{0,i} = \frac{1}{100}\gamma_{1,i}$ as an assumption for what percentage of truly asymptomatic cases may have progressed undetected to full immune protection.

SUPPLEMENTAL INFORMATION

No supplemental information.

ACKNOWLEDGMENTS

C.-F. Chen, G. Bonilla, and H. Nelson are supported by the Engineering Research Center Program of the U.S. National Science Foundation (NSF) and the Department of Energy under NSF award EEC-1041877 and the CURENT Industry Partnership Program.

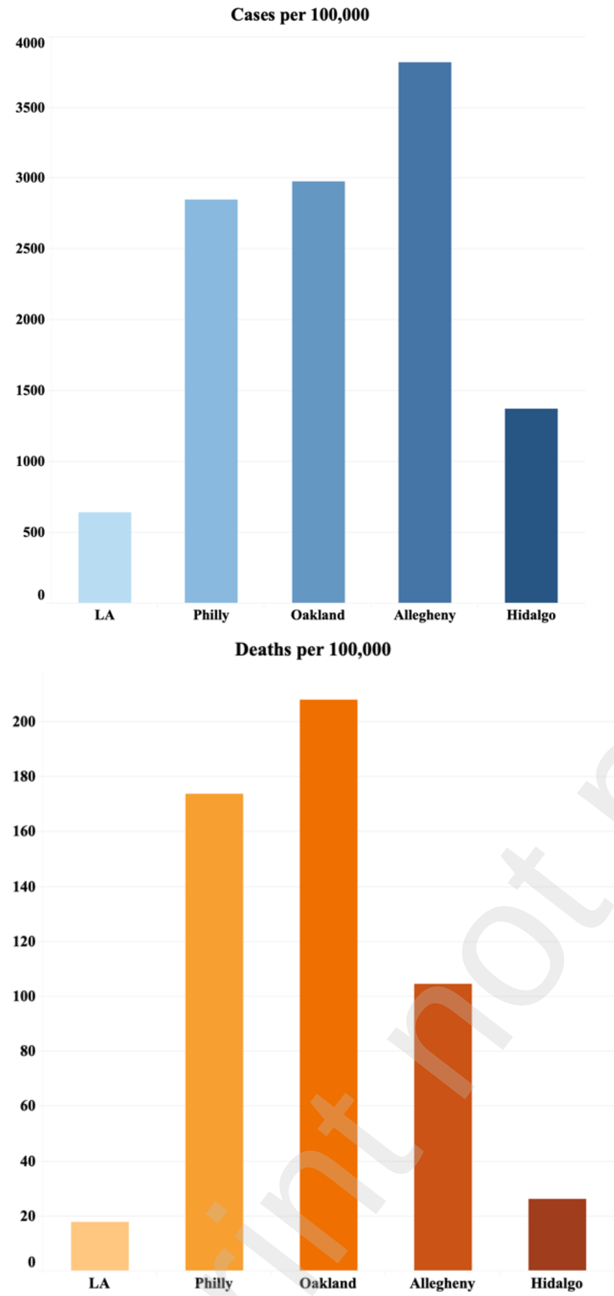
AUTHOR CONTRIBUTIONS

This project was conceived by C.-F. Chen and N. Fefferman. G. Bonilla compiled the majority of data used in the analysis and wrote the data sources; C.-P. Kuo estimated energy consumption burden. N. Fefferman created the math models and analyzed the data. C.-F. Chen, N. Fefferman, and H. Nelson lead the manuscript writing.

DECLARATION OF INTERESTS

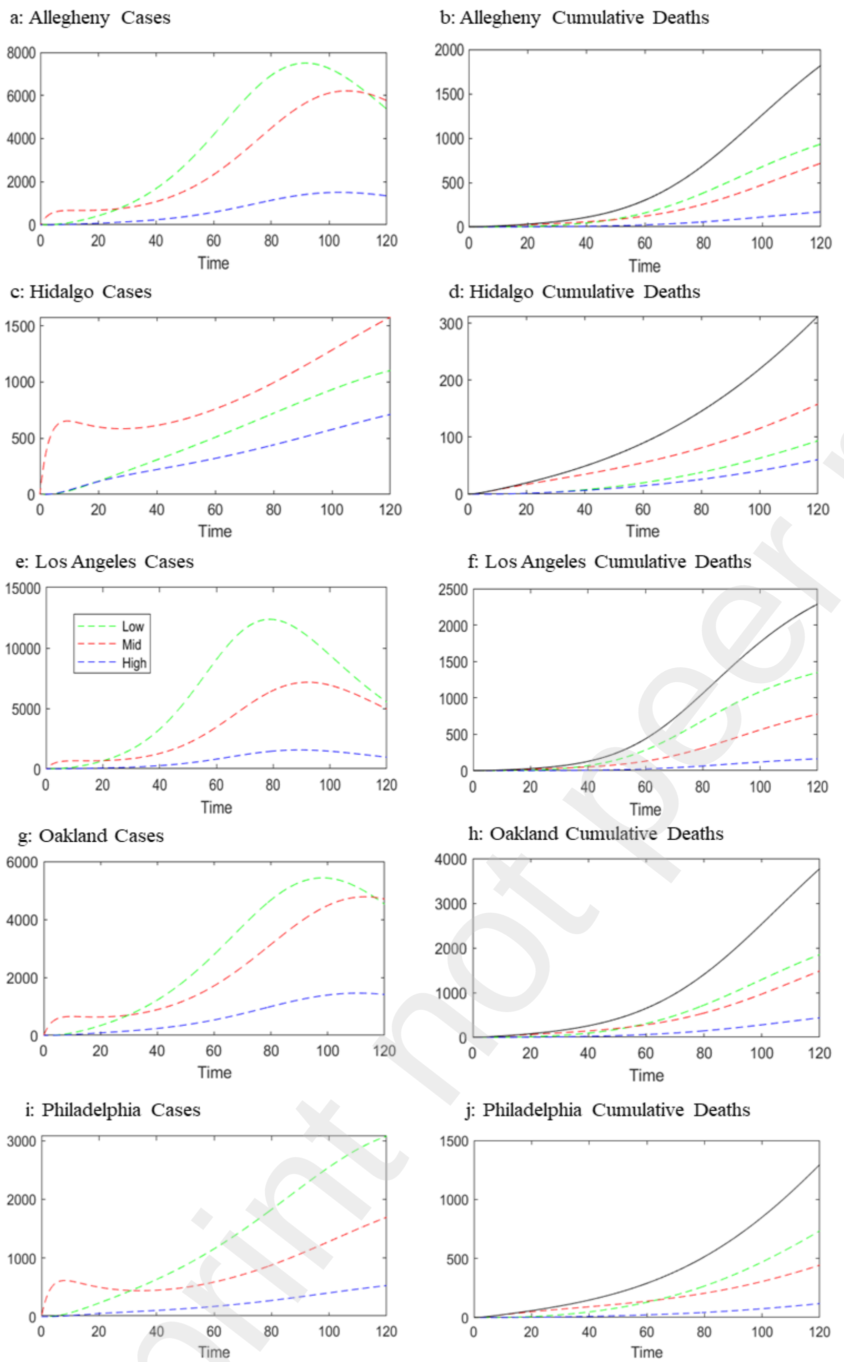
The authors have no financial or non-financial interests associated with the material in this manuscript

Figure 1. County cases and deaths for novel COVID-19 infection



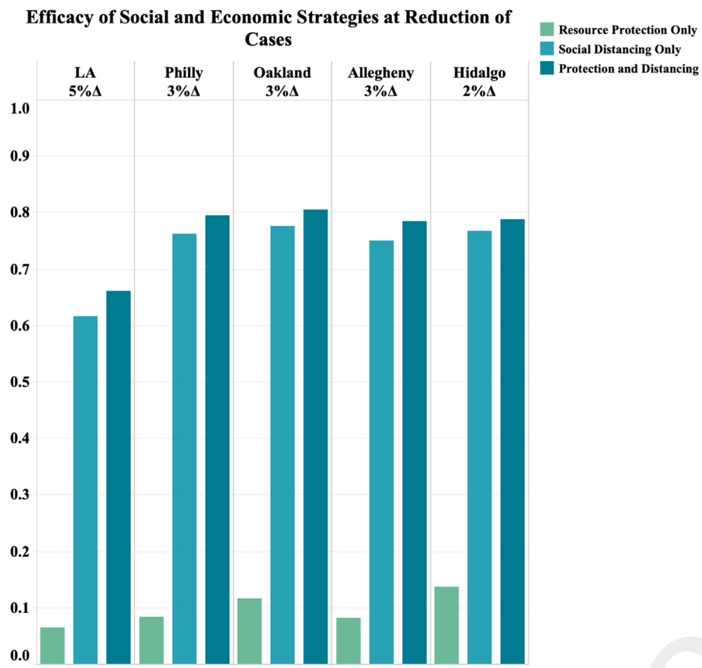
Differences in un-fitted model outcomes across counties due solely to differences in demographic and socioeconomic make-up

Figure 2. Outbreak curves over time in the un-fitted, "do nothing" scenario



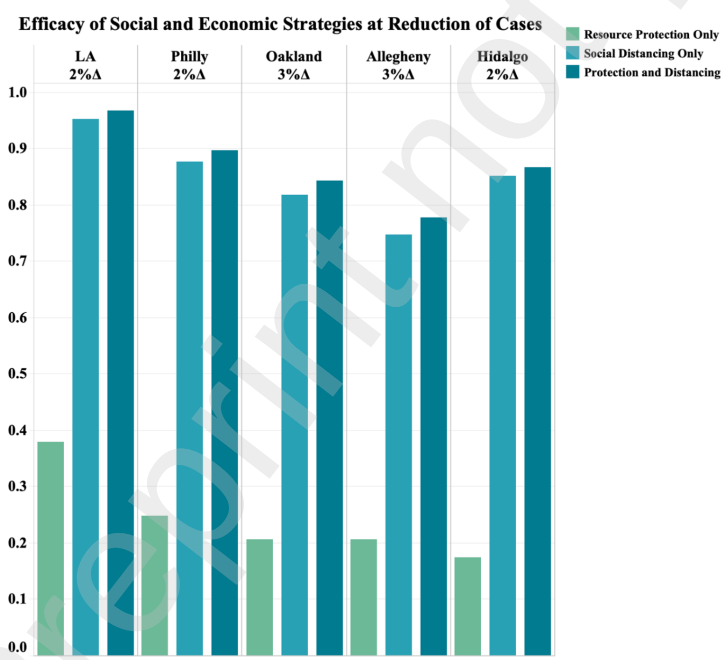
The left column shows symptomatic infectious cases overtime in each socioeconomic category of households in each county. The right column shows cumulative deaths over time in each socioeconomic category of households in each county.

Figure 3. Effect of interventions on symptomatic cases in the different counties for un-fitted outbreak



Delta labels indicate the percentage improvement from the combined strategy above that achieved by social distancing alone.

Figure 4. Effect of interventions on symptomatic cases in the different counties for a COVID-19 fitted outbreak



Delta labels indicate the percentage improvement from the combined strategy above that achieved by social distancing alone.

REFERENCES*

1. Snell, C., Bevan, M., and Thomson, H. (2015). Justice, fuel poverty and disabled people in England. Energy Res. Soc. Sci. *10*, 123–132.
2. Mayer, A., and Smith, E.K. (2019). Exploring the link between energy security and subjective well-being: A study of 22 nations. Energy. Sustain. Soc. *9*, 1–13.
3. Hernández, D. (2016). Understanding 'energy insecurity' and why it matters to health. Soc. Sci. Med. *167*, 1–10.
4. Boateng, G.O., Balogun, M.R., Dada, F.O., and Armah, F.A. (2020). Household energy insecurity: dimensions and consequences for women, infants and children in low- and middle-income countries. Soc. Sci. Med. *258*, 113068.
5. Castán Broto, V., and Kirshner, J. (2020). Energy access is needed to maintain health during pandemics. Nat. Energy *5*, 419–421.
6. Graff, M., and Carley, S. (2020). COVID-19 assistance needs to target energy insecurity. Nat. Energy *5*, 352–354.
7. Memmott, T., Carley, S., Graff, M., and Konisky, D.M. (2021). Sociodemographic disparities in energy insecurity among low-income households before and during the COVID-19 pandemic. Nat. Energy.
8. Chen, C., Zarazua de Rubens, G., Xu, X., and Li, J. (2020). Coronavirus comes home? Energy use, home energy management, and the social-psychological factors of COVID-19. Energy Res. Soc. Sci. *68*, 101688.
9. Liddell, C., and Morris, C. (2010). Fuel poverty and human health: A review of recent evidence. Energy Policy.
10. Hernández, D., Phillips, D., and Siegel, E.L. (2016). Exploring the Housing and Household Energy Pathways to Stress: A Mixed Methods Study. Int. J. Environ. Res. Public Health *13*.
11. Harrington, B.E., Heyman, B., Merleau-Ponty, N., Stockton, H., Ritchie, N., and Heyman, A. (2005). Keeping warm and staying well: findings from the qualitative arm of the Warm Homes Project. Health Soc. Care Community *13*, 259–267.
12. Drehobl, A., Ross, L., and Ayala, R. (2020). Report: Low-Income Households, Communities of Color Face High "Energy Burden" Entering Recession. ACEEE. https://www.aceee.org/press-release/2020/09/report-low-income-households-communities-color-face-high-energy-burden.
13. Xu, X., and Chen, C. (2019). Energy efficiency and energy justice for U.S. low-income households: An analysis of multifaceted challenges and potential. Energy Policy *128*, 763–774.
14. Sovacool, B.K., and Dworkin, M.H. (2015). Energy justice: Conceptual insights and practical applications. Appl. Energy.
15. Jessel, S., Sawyer, S., and Hernández, D. (2019). Energy, Poverty, and Health in Climate Change: A Comprehensive Review of an Emerging Literature. Front. Public Heal. *7*.
16. Meinrenken, C.J., Modi, V., Mckeown, K.R., and Culligan, P.J. (2020). New Data Suggest COVID-19 Is Shifting the Burden of Energy Costs to Households. Columbia Univ. https://blogs.ei.columbia.edu/2020/04/21/covid-19-energy-costs-households/.
17. BBC (2020). Coronavirus: Domestic electricity use up during day as nation works from home.
18. U.S. Energy Information Administration (2020). Stay-at-home orders led to less commerical and industrial electricity use in April. EIA.gov. https://www.eia.gov/todayinenergy/detail.php?id=44276.
19. Giddens, A. (1984). The Constitution of Society: Outline of the Theory of

Structuration (University of California Press).
20. CDC Social Vulnerability Index (2020). Agency Toxic Subst. Dis. Regist. https://www.atsdr.cdc.gov/placeandhealth/svi/index.html.
21. Bryant, C.G.A., and Jary, D. (1991). Coming to terms with Anthony Giddens. In Giddens' theory of structuration: A critical appreciation, C. G. A. Bryant and D. Jary, eds. (Routledge), pp. 1–32.
22. Ma, O., Laymon, K., Day, M., Oliveira, R., Weers, J., and Virmont, A. (2019). Low-Income Energy Affordability Data (LEAD) Tool.
23. Whittington, R. (2015). Giddens, structuration theory and strategy as practice. Cambridge Handb. Strateg. as Pract. Second Ed., 145–164.
24. COVID-19 United States Cases by County (2021). Johns Hopkins Univ. https://coronavirus.jhu.edu/us-map.
25. American Community Survey (ACS) (2020). United States Census Bur.
26. Safegraph: The source of truth for places data (2020). Safegraph. https://www.safegraph.com/.
27. Surgo Ventures (2021). The U.S. COVID Community Vulnerability Index (CCVI). https://precisionforcovid.org/ccvi.
28. US Coronavirus Cases & Deaths by State (2021). USAFACTS. https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/.
29. Project, T.C.T. (2021). About the Data. https://covidtracking.com/about-data.
30. Prevention, C. for D.C. and (2020). Calculating Percent Positivity. https://www.cdc.gov/coronavirus/2019-ncov/lab/resources/calculating-percent-positivity.html.
31. FACTS, U. (2021). Detailed Methodology and Sources: COVID-19 Data.
32. Social Distancing Metrics (2020). Safegraph.
33. Chang, S., Pierson, E., Koh, P.W., Gerardin, J., Redbird, B., Grusky, D., and Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. Nature *589*, 82–87.
34. Charoenwong, B., Kwan, A., and Pursiainen, V. (2020). Social connections with COVID-19-affected areas increase compliance with mobility restrictions. Sci. Adv. *6*.
35. Lamb, M.R., Kandula, S., and Shaman, J. (2020). Differential COVID-19 case positivity in New York City neighborhoods: Socioeconomic factors and mobility. Influenza Other Respi. Viruses, 1–9.
36. Huang, X., Li, Z., Lu, J., Wang, S., Wei, H., and Chen, B. (2020). Time-series clustering for home dwell time during COVID-19: What can we learn from it? medRxiv.
37. U.S. Bureau of Labor Statistics (2021). U.S. Dep. Labor.
38. Area, U.W. of the N.C. (2021). US States with the Most Essential Workers. United W.
39. Bennett, J., Fry, R., and Kochhar, R. (2020). Are you in the American middle class? Find out with our income calculator. Pew Res. Cent.
40. U.S. Energy Information Administration (2020). November 2020 Monthly Energy Review.
41. van Ginkel, J.R., Linting, M., Rippe, R.C.A., and van der Voort, A. (2020). Rebutting Existing Misconceptions About Multiple Imputation as a Method for Handling Missing Data. J. Pers. Assess. *102*, 297–308.
42. Wang, J., and Johnson, D.E. (2018). An Examination of Discrepancies in Multiple Imputation Procedures Between SAS ® and SPSS ® An Examination of Discrepancies in Multiple Imputation Procedures Between SAS and SPSS. Am. Stat. *0*, 1–9.
43. Liu, X.X., Fong, S.J., Dey, N., Crespo, R.G., and Herrera-Viedma, E. (2021). A new SEAIRD pandemic prediction model with clinical and

epidemiological data analysis on COVID-19 outbreak. Appl. Intell.

44. Cohen, J.E. (1992). Infectious Diseases of Humans: Dynamics and Control. JAMA *268*, 3381.

45. Weitz, J.S., Beckett, S.J., Coenen, A.R., Demory, D., Dominguez-Mirazo, M., Dushoff, J., Leung, C.Y., Li, G., Măgălie, A., Park, S.W., et al. (2020). Modeling shield immunity to reduce COVID-19 epidemic spread. Nat. Med. *26*, 849–854.