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The effect of eviction moratoria on the transmission of SARS-CoV-2

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Massive unemployment during the COVID-19 pandemic could result in an eviction crisis in US cities. Here we model the effect of evictions on SARS-CoV-2 epidemics, simulating viral transmission within and among households in a theoretical metropolitan area. We recreate a range of urban epidemic trajectories and project the course of the epidemic under two counterfactual scenarios, one in which a strict moratorium on evictions is in place and enforced, and another in which evictions are allowed to resume at baseline or increased rates. We find, across scenarios, that evictions lead to significant increases in infections. Applying our model to Philadelphia using locally-specific parameters shows that the increase is especially profound in models that consider realistically heterogenous cities in which both evictions and contacts occur more frequently in poorer neighborhoods. Our results provide a basis to assess eviction moratoria and show that policies to stem evictions are a warranted and important component of COVID-19 control.

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The COVID-19 epidemic has caused unprecedented public health and economic crisis in the United States. The eviction crisis in the country predated the pandemic, but the record levels of unemployment have newly put millions of Americans at risk of losing their homes[1–7]. Many cities and states enacted temporary legislation banning evictions during the initial months of the pandemic[8,9], some of which have since expired. On September 4th, 2020, the Centers for Disease Control and Prevention, enacting Section 361 of the Public Health Service Act[10], imposed a national moratorium on evictions until December 31st, 2020[11]. This order, like most state and municipal ordinances, argues that eviction moratoria are critical to prevent the spread of SARS-CoV-2. It has been challenged in federal court (Brown vs. Azar 2020), as well as at the state and local level[12,13].

Evictions have many detrimental effects on households that could accelerate the spread of SARS-CoV-2. There are few studies on the housing status of families following eviction[14,15], but the limited data suggest that most evicted households "double-up"—moving in with friends or family—immediately after being evicted (see "Methods" section). Doubling upshifts the distribution of household sizes in a city upward. The role of household transmission of SARS-CoV-2 is not fully understood, but a growing number of empirical studies[16–21], as well as previous modeling work[22,23], suggest households are a major source of SARS-CoV-2 transmission. Contact tracing investigations find at least 20–50% of infections can be traced back to a household contact[24–27]. Household transmission can also limit or delay the effects of measures like lockdowns that aim to decrease the contact rate in the general population[17,22,28].

Here we use an epidemiological model to quantify the effect of evictions, and their expected shifts in household size, on the transmission of SARS-CoV-2, and the prospects of its control, in cities (Fig. 1). We modify an SEIR (susceptible, exposed, infectious, and recovered) model, originally described in Nande et al.[22], to track the transmission of SARS-CoV-2 through a metropolitan area with a population of 1 million individuals. We use a network to represent contacts of the type that can potentially lead to transmission of SARS-CoV-2, between individuals grouped in households. We modulate the number of contacts outside the household over the course of the simulations to capture the varied effects of lockdown measures and their subsequent relaxation. We model evictions that result in 'doubling up' by merging each evicted household with one randomly-selected household in the network. In supplemental analyses, we examine what might happen if some proportion of evicted households enter homeless shelters or encampments.

The model is parameterized using values from the COVID-19 literature and other demographic data (see "Methods" section). The timing of progression between stages in our epidemiological model is taken from many empirical studies and agrees with other modeling work: We assume an ~4-day latent period, ~7.5-day serial interval, and R_0 ~3 in the absence of interventions, and ~1% infection fatality risk. Household sizes are taken from the US Census[29]; households are assumed to be well-mixed, meaning all members of a household are in contact with each other. Individuals are randomly assigned contacts with individuals in other households. The number and strength of these "external" contacts are chosen so that the household secondary attack rate is ~0.3[19], and the probability of transmission per contact is approximately 2.3-fold higher for households, compared to external contacts[18]. Our model naturally admits a degree of overdispersion in individual-level R_0 values. Baseline eviction rates, which we measure as the percent of households evicted each month, vary dramatically between cities at baseline, as do the expected increases due to COVID-19 (refs. [30,31], Supplementary Fig. 2). To capture this range of eviction burdens, we simulate city-wide eviction rates ranging from 0.1–2.0%.

Our initial models assume that mixing between households occurs randomly throughout a city and that evictions and the ability to adopt social distancing measures are uniformly distributed. However, data consistently show that both COVID-19 and evictions disproportionately affected the same poorer, minority communities[32–38]. We, therefore, extend our model to evaluate the effect of evictions in a realistically heterogeneous city. We provide generic results and then parameterize our model to a specific example–the city of Philadelphia, Pennsylvania.

Among large US cities, Philadelphia has one of the highest eviction rates. In 2016 (the last year complete data is available), 3.5% of renters were evicted, and 53% were cost-burdened, meaning they paid more than 30% of their income in rent[30,39]. In July 2020 the Philadelphia city council passed the Emergency Housing Protection Act[40], in an effort to prevent evictions during the COVID-19 pandemic. The city was promptly sued by HAPCO, an association of residential investment and rental property owners (HAPCO vs. City of Philadelphia 2020). Among other claims, the plaintiff questioned whether the legislation was of broad societal interest, rather than protecting only a narrow class (of at-risk renters). An early motivation behind this work was to assess this claim.

Results

Evictions lead to increases in COVID-19 cases across cities. We simulate COVID-19 epidemic trajectories in single metro areas over the course of 2020. To recreate realistic scenarios in the model, we first collected data on COVID-19 cases and deaths aggregated for each US metropolitan statistical area with at least 1 million residents (~50 cities). We then used hierarchical
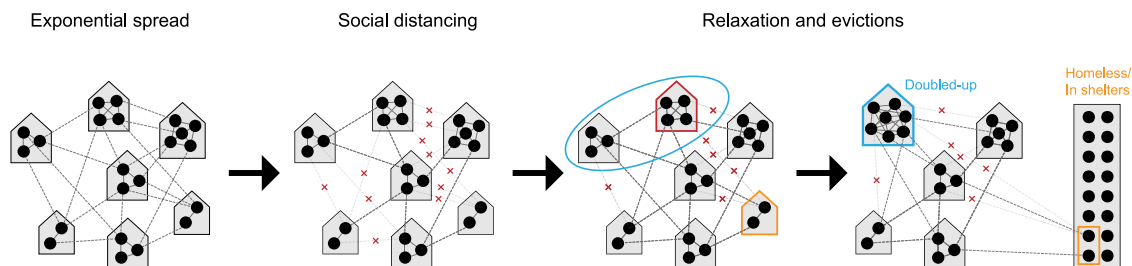
Fig. 1 Modeling the effect of evictions on SARS-CoV-2 transmission. We model the spread of infection over a transmission network where contacts are divided into those occurring within a household (solid gray lines) vs. outside the house ("external contacts", dotted gray lines). Social distancing interventions (such as venue and school closures, work-from-home policies, mask-wearing, lockdowns, etc) are modeled as reductions in external contacts (red x's), while relaxations of these interventions result in increases in external contacts towards their baseline levels. When a household experiences eviction (red outline), we assume the residents of that house "double-up" by merging with another house (blue circle), thus increasing their household contacts. Evictions can also directly lead to homelessness (orange outline), and residence in shelters or encampments with high numbers of contacts.

clustering to group the time series based on similar trajectories through Sept 2020, which resulted in four distinct groups of cities (Supplementary Fig. 3, see "Methods" section). Groups differed in the size of the spring wave, the degree of control in the early summer, and the occurrence and extent of a late summer wave (Supplementary Figs. 4–8). For example, cities like New York, Boston, Philadelphia, and New Orleans (Trajectory 1) had large early epidemic peaks followed by dramatic and sustained reductions in cases; cities including Chicago, Baltimore, Seattle, and San Diego had substantial but smaller spring peaks that were controlled and then followed by a long plateau of cases over the summer (Trajectory 2); metros like St Louis, Raleigh, Salt Lake City, and San Francisco had much smaller spring outbreaks that were only partially controlled and then led to increases in the summer (Trajectory 3); and metros similar to Miami, Houston, Atlanta, and Phoenix experienced large mid-summer outbreaks (Trajectory 4). We calibrated our model (in the absence of evictions) to each of these four trajectory types by modulating the degree of reduction in external contacts over time (see "Methods" section, Supplementary Table 1, and Supplementary Fig. 9).

Many local, county, and state-level eviction moratoria that were created early in the US epidemic were scheduled to expire in late summer 2020, so we modeled the hypothetical effect of evictions taking place starting Sept 1 and continuing for the duration of the simulation. We assume that evictions happen at a constant rate per month, but that the backlog of eviction cases created during the moratoria results in 4 months worth of evictions occurring in the first month. We first considered an epidemic following Trajectory 1 (e.g., large spring epidemic peak followed by a strong lockdown and summer plateau, Fig. 2). During fall 2020, we simulated a resurgence of infection with a doubling time of 2–3 weeks, as has been observed across all large metros. By the end of 2020 in our baseline scenario of no evictions, 16% of individuals in our simulated scenario had caught COVID-19. With a low eviction rate of 0.25%/month about 0.5% more of the population become infected compared to

our baseline scenario of no evictions. This increase corresponds to ~5000 excess cases per million residents. Further increasing the eviction rate to 1%/month, the infection level was ~4% higher than baseline (Table 1). The exact values vary across simulations due to all the stochastic factors in viral spread considered in the model. These results highlight how the increased household spread that results from eviction-driven doubling-up act synergistically with the spread between members of different households during a growing epidemic to amplify infection levels.

Our model predicts that even for lower eviction rates that do not dramatically change the population-level epidemic burden, the individual risk of infection was always substantially higher for those who experienced eviction, or who merged households with evicted individuals, compared to individuals whose households did not change (relative risk of infection by the end of the year, ~1.28 [1.21, 1.37]). However, the increased risk of infection was not only felt by those who doubled-up: even for individuals who were neither evicted nor merged households with those who did, the risk of infection compared to the counterfactual scenario of no evictions was 1.04 for an eviction rate of 0.25%/month and 1.4 for 2.0% evictions per month (Fig. 2d). This increased risk highlights the spillover effects of evictions on the wider epidemic in a city.

We then considered the same scenario but assumed the epidemic resurgence was countered with new control measures imposed on Dec 1. The epidemic was eventually controlled in simulations with or without eviction, but the decline was slower and the intervention less effective at reducing epidemic size when evictions were allowed to continue (Fig. 2e–h). Following the epidemic until March 31 2021 at which point it was nearly eliminated locally, the final size was 0.3% greater with 0.25%/month evictions and 3% larger with 1%/month evictions. Larger households, created through eviction and doubling up, allow the more residual spread to occur under lockdowns. Thus, allowing evictions to resume would compromise the efficacy of future SARS-CoV-2 control efforts.
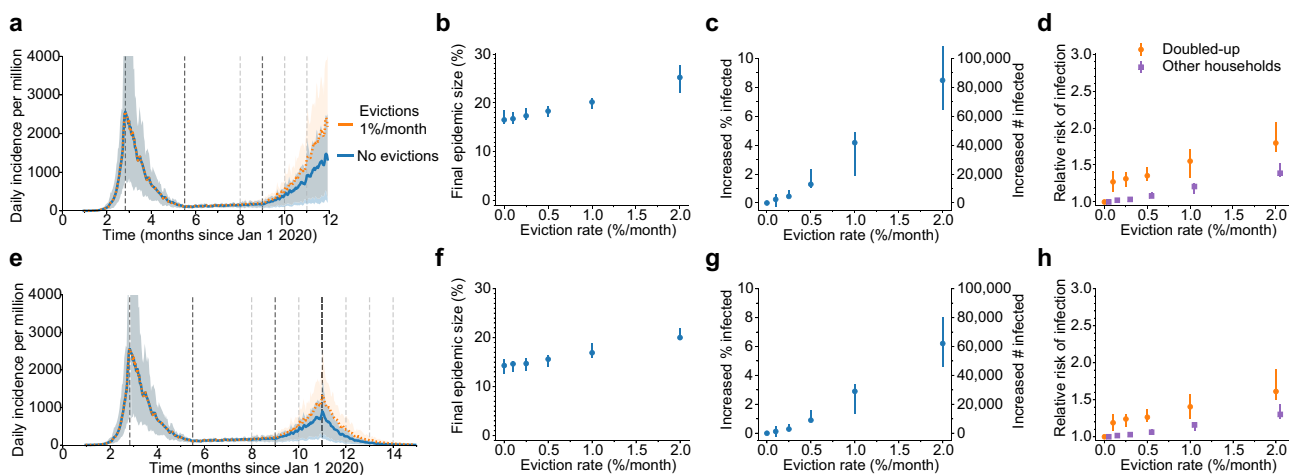
Fig. 2 Impact of evictions on a SARS-CoV-2 comeback during Fall 2020. We model evictions occurring in the context of an epidemic similar to cities following "Trajectory 1", with a large first wave and strong control in the spring, followed by relaxation to a plateau over the summer and an eventual comeback in the fall. Monthly evictions start Sept 1, with a 4-month backlog processed in the first month. **a** The projected daily incidence of new infections (7-day running average) with and without evictions. Shaded regions represent central 90% of all simulations. The first lockdown (dotted vertical line) reduced external contacts by 85%, under relaxation (second dotted line) they were still reduced by 70%, and during the fall comeback, they were reduced by 60% (fourth dotted line). **b** Final epidemic size by Dec 31, 2020, measured as a percent of individuals who had ever been in any stage of infection. **c** The predicted increase in infections due to evictions through Dec 31, 2020, measured as the excess percent of the population infected (left Y-axis) or the number of excess infections (right Y-axis). **d** The relative risk of infection in the presence vs. absence of evictions, for individuals who merged households due to evictions ("Doubled-up") and for individuals who kept their pre-epidemic household ("Other households"). Data in **b–d** shown as median values with interquartile ranges across simulations. **e–h** Same as above but assuming a second lockdown is instituted on Dec 1 and maintained through March 2021.

Table 1 Predicted excess SARS-CoV-2 infections when evictions are continued.

Trajectory	Cumulative prevalence w/o evictions	Eviction rate (%/month)				
		0.1%	0.25%	0.5%	1%	2%
Shown in Fig. 2						
Trajectory 1 and comeback	16.5 [15.7–18.5]	0.25 [−0.24–0.63]	0.46 [0.36–0.87]	1.3 [1.0–2.3]	4.2 [1.9–4.9]	8.5 [6.4–10.8]
Trajectory 1 and lockdown	14.3 [12.6–15.6]	0.12 [−0.25–0.48]	0.29 [0.23–0.64]	0.90 [0.78–1.6]	2.9 [1.4–3.4]	6.2 [4.6–8.0]
Shown in Fig. 3						
Trajectory 2 and comeback	11.7 [10.3–12.5]	0.38 [0.09–0.80]	1.2 [0.67–2.2]	1.4 [0.92–2.6]	4.3 [3.1–5.3]	9.8 [7.2–10.3]
Trajectory 2 and lockdown	9.1 [7.8–10.1]	0.18 [0.05–0.52]	0.80 [0.43–1.4]	0.93 [0.61–1.7]	2.9 [2.3–3.5]	6.9 [5.0–7.3]
Trajectory 3 and comeback	8.9 [7.2–10.0]	0.41 [−0.39–0.80]	0.76 [0.36–1.04]	1.7 [1.0–2.0]	4.1 [3.6–4.4]	9.4 [8.7–10.8]
Trajectory 3 and lockdown	6.6 [5.4–7.5]	0.29 [−0.36–0.60]	0.43 [0.30–0.70]	1.2 [0.63–1.4]	2.7 [2.5–2.9]	6.6 [6.2–7.6]
Trajectory 4 and comeback	9.4 [8.1–10.4]	−0.07 [−0.16–0.34]	0.47 [0.23–0.83]	1.1 [0.94–1.6]	2.6 [2.4–3.1]	7.2 [5.9–7.5]
Trajectory 4 and lockdown	8.4 [6.9–9.2]	0.00 [−0.09–0.24]	0.33 [0.18–0.64]	0.89 [0.76–1.2]	2.0 [1.9–2.3]	5.9 [4.6–6.1]

Excess infections are measured as the increase in the cumulative percent of the population infected by Dec 31, 2020 (or March 31 2021 if a second lockdown implemented) if evictions resume on Sept 1, 2020, compared to if evictions were halted. Values are reported as median [IQR]. All results are from simulations of a metro area of 1 million individuals where evictions all result in "doubling up". Corresponding epidemic trajectories are shown in Figs. 2, 3. The US metropolitan statistical areas that roughly correspond to each scenario are shown in Figs. S3, S5–S8.

Cities across the US experienced diverse epidemic trajectories through August 2020, which we found could be summarized by three additional trajectory patterns (Fig. 3, Supplementary Figs. 6–8). These trajectory patterns, when used to calibrate our model, provide information on the prevalence of susceptible, infected, and previously-recovered (immune) individuals at the time evictions resume, as well as how these cases may be distributed across households. We found that for all trajectories, if we allowed evictions to occur, they led to significant increases in COVID-19 cases, with anywhere from ~1,000 to ~10,000 excess cases per million residents attributable to evictions when eviction rates are lower (e.g., 0.25%/month) and the fall comeback is countered by a strong lockdown in December 2020, to ~ 50–100,000 excess cases for higher eviction rates (e.g 2%) and unmitigated epidemics (Table 1). In most of these scenarios, there was ~1 excess infection in the city attributable to each eviction that took place.

We repeated the above simulations with different values of the household secondary attack rate (SAR) to check the sensitivity of our results to this value (Supplementary Figs. 10, 11). As expected, when the household transmission is more common (higher SAR of 0.5, Supplementary Fig. 10) evictions have a slightly larger effect on the epidemic, and when it is less common (lower SAR of 0.1, Supplementary Fig. 11), the effect of evictions is slightly smaller. If we assumed transmission risk from external contacts was equal to household contacts but reduced the number of external contacts to maintain the same R_0, results were similar to our baseline scenario (Supplementary Fig. 12). We also considered a scenario where evicted households always doubled-up with another household with whom they already had an external contact; this actually led to a small increase in the predicted effect of evictions as doubled-up households now had slightly higher-than-average connectivity (e.g., increase in the final size of 4.2% vs. 5.4% for 1%/month eviction rate, Supplementary Fig. 13). In a previous version of this work, completed before the ubiquity of the fall resurgence became apparent, we examined the impact of evictions under alternate fall scenarios, including a plateau of cases at September levels or more gradual increases[41]. We found that in general, evictions had less impact on infection counts when the epidemic was controlled and maintained at a constant plateau throughout the fall. However, a flat epidemic curve could still be associated with substantial detrimental effects of evictions if the incidence at the plateau is still relatively high.

Evictions interact with urban disparities. Our results so far assume that every household in a city is equally likely to experience an eviction and that the SARS-CoV-2 infection burden and adoption of social distancing measures are homogeneously distributed throughout the population. In reality, evictions are concentrated in poorer neighborhoods with higher proportions of racial/ethnic minorities[38]. Similarly, individuals in these neighborhood types are likely to maintain higher contact rates during the epidemic due to high portions of essential workers among other reasons[42–45]. Many studies have shown higher burdens of infection and severe manifestations of COVID-19 in these demographic groups[32–37]. To examine the impact of city-level disparities on the interaction between evictions and disease spread (Fig. 4), we simulated infection in cities consisting of two neighborhood types: a higher socioeconomic status (SES) neighborhood with no evictions and a high degree of adoption of social distancing measures (low contact rates), and a lower SES neighborhood with evictions, where the reduction in contact rates was less pronounced. We assumed that evicted households doubled-up with other households that are also in the low SES neighborhood (see Supplementary Fig. 15 for the case when doubling-up can happen across neighborhoods). The epidemic time course was simulated using the same population-average transmission rates for each phase as for Trajectory 1 (Fig. 2). In the absence of evictions, infection prevalence differed substantially by neighborhood (Fig. 4b), and despite simulating the same overall reduction in contacts, the epidemic burden was higher when residual contacts were clustered in the poorer neighborhood (Fig. 2b vs. Fig. 4d).

In this heterogeneous context, we found, for equivalent overall eviction rates, a larger impact of evictions on COVID-19 cases than if they had occurred in a homogeneous city. For example, by the end of 2020, for a low eviction rate (0.25%/month) we estimate 1.7% excess cases attributable to evictions in the heterogeneous model, as compared to 0.5% in the homogeneous
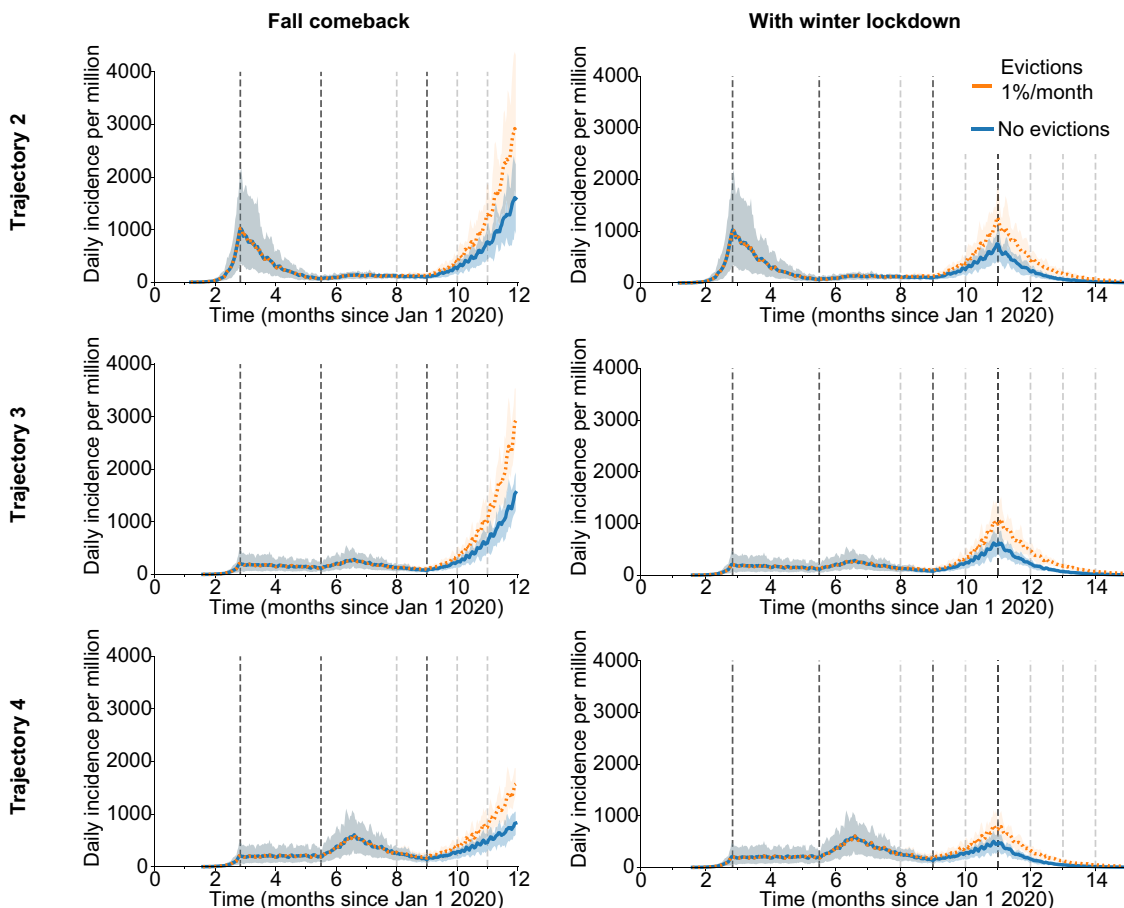
Fig. 3 Alternate epidemic trajectories of SARS-CoV-2 before and after evictions in a large city. Each panel shows the projected daily incidence of new infections (7-day running average) with and without evictions at 1%/month with a 4-month backlog, starting on Sept 1, 2020. Shaded regions represent central 90% of all simulations. In the left column, the spread continues unabated through Dec 31, 2020, whereas in the second column a new lockdown is introduced on Dec 1. Each trajectory scenario is created by calibrating the model to a group of US metropolitan statistical areas with similar patterns of spread (see "Methods" section, Supplementary Figs. 5–8). For all trajectory types, the degree of reduction in external contacts by control measures was modulated on dates March 25, June 15, July 15, and Oct 1, with values, reported in Supplementary Table 1.

version described above. For the higher eviction rate (1%/month) we estimate ~5.4% excess infections due to eviction, as compared to ~4.2% in the homogenous model. Evictions also serve to exacerbate pre-existing disparities in infection prevalence between neighborhoods. For the hypothetical scenario we simulated, evictions increase the relative risk of infection for the low vs. high SES neighborhood from ~1.3 to ~1.5. However, due to spillover effects from low to high SES neighborhoods, individuals residing in the high SES neighborhood also experience an increased infection risk (up to 1.5-fold in the no-evictions scenario) attributable to the evictions occurring in the other demographic group. These results hold even if we assume more extreme segregation between residents of each neighborhood (Supplementary Fig. 14) or if we allow evicted individuals to double up with residents of the high SES neighborhood (Supplementary Fig. 15), though the disparities across neighborhoods are more extreme in the former case and less extreme in the latter. Thus, our results in Table 1 may underestimate the impact of evictions on COVID-19 in realistically-heterogeneous US cities. The concentration of evictions in demographic groups with more residual inter-household transmission serves to amplify their effects on the epidemic across the whole city.

Case study: Impact of evictions in Philadelphia, PA. Finally, we sought to combine these ideas into a data-driven case study

motivated by the court case in Philadelphia, PA, mentioned above. In Philadelphia, like all major US cities, there is significant heterogeneity in housing stability and other socioeconomic factors that are relevant both to the risk of eviction and to COVID-19 infection[46,47]. An early study found clusters of the high incidence of infection were mostly co-located with poverty and a history of racial segregation, such as in West and North Philadelphia[34]. A study of SARS-CoV-2 prevalence and seropositivity in pregnant women presenting to the University of Pennsylvania Hospital System found a more than 4-fold increase in seroprevalence among Black/non-Hispanic and Hispanic/Latino women, compared to white/non-Hispanic women, between April and June 2020[36].

To include these important disparities in our modeling, we first used principal component analysis on a suite of socioeconomic indicators to classify zip codes in the city[48]. We obtained three zip code typologies: a higher income cluster, a moderate-income cluster, and a low-income cluster. The lower-income cluster has both very high eviction rates and higher rates of service industry employment and essential workers. Properties of the sub-populations are summarized in Table 2 and detailed in Supplementary Tables 1, 2.

We then translated these findings into our model by dividing the simulated city into three sub-populations. The fraction of external contacts of individuals residing in each cluster that was
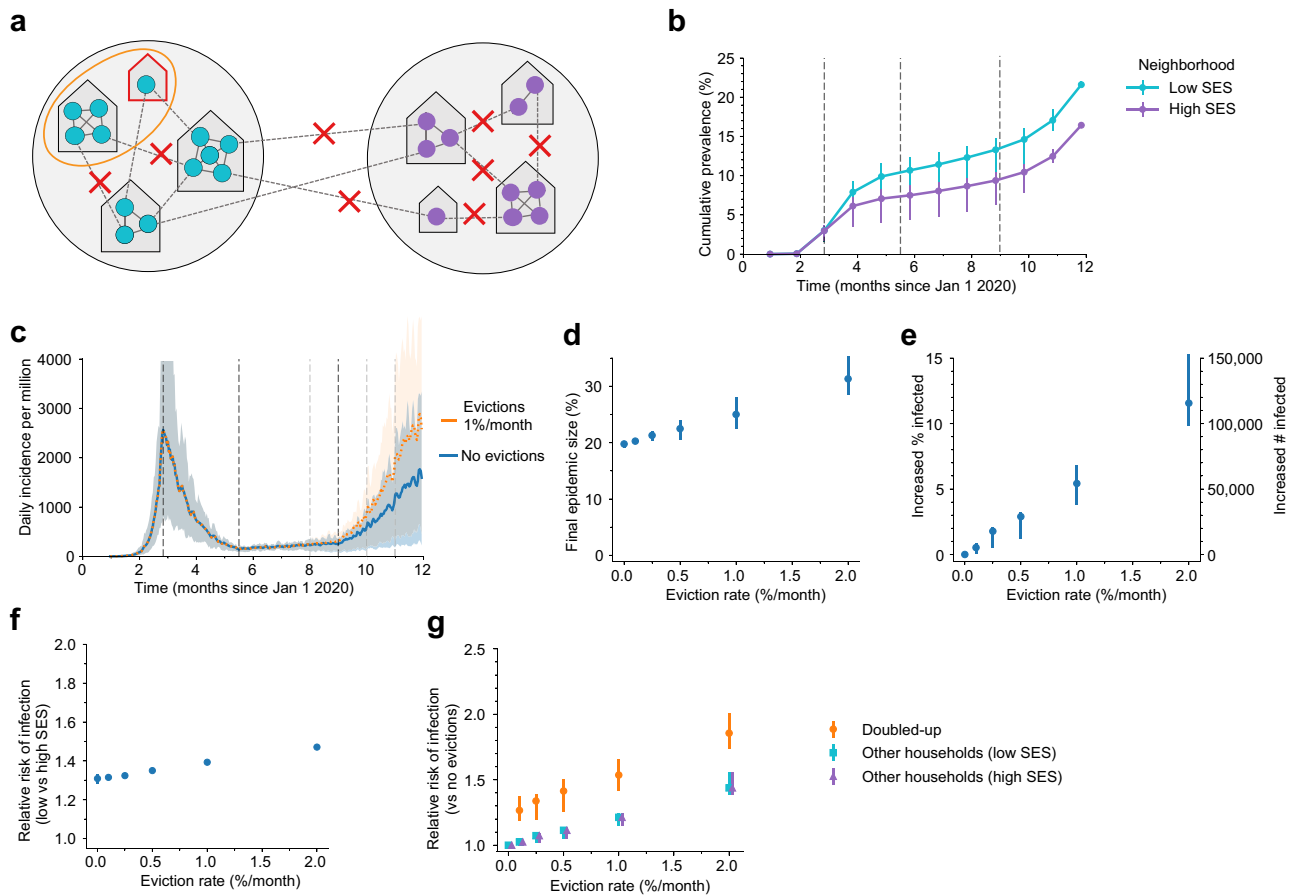
Fig. 4 Impact of evictions on COVID-19 epidemics in heterogeneous cities. a Schematic of our model for inequalities within a city. The city is divided into a "high socioeconomic status (SES)" (purple) and a "low SES" (teal) neighborhood. Evictions only occur in the low SES area, and individuals living in this area are assumed to be less able to adopt social distancing measures, and hence have higher contact rates under interventions (90% vs. 80% reduction in external contacts during lockdown for 85% overall, 75% vs. 65% during a relaxation for 70% overall, and 65% vs. 55% during fall comeback for 60% overall). Before interventions, residents are equally likely to contact someone outside the household who lives within vs. outside their neighborhood. **b** Cumulative percent of the population infected over time, by neighborhood, in the absence of evictions. Error bars show interquartile ranges across simulations. **c** The projected daily incidence of new infections (7-day running average) with 1%/month evictions vs. no evictions. Shaded regions represent central 90% of all simulations. **d** Final epidemic size by Dec 31, 2020, measured as percent individuals who had ever been in any stage of infection, for the heterogeneous city as compared to a homogenous city with the same effective eviction rate and intervention efficacy. **e** The predicted increase in infections due to evictions through Dec 31, 2020, measured as the excess percent of the population infected (left *Y*-axis) or the number of excess infections (right *Y*-axis). **f** Relative risk of infection by Dec 31, 2020, for residents of the low SES vs. high SES neighborhood. **g** The relative risk of infection by Dec 31 2020 in the presence vs. absence of evictions, for individuals who merged households due to evictions ("Doubled-up") and for individuals who kept their pre-epidemic household ("Other households"). Data in **b**, (**d**–**g**) shown as median values with interquartile ranges across simulations.

Table 2 Properties of neighborhood clusters in Philadelphia used in simulations.

	Population in cluster (%)	Eviction rate at baseline (%/month)	Estimated essential workers (%)	Mobility reduction (%, June 2020)	Summary of cluster characteristics
Cluster 1	17	0.07	0.30	89	High income, high % renters, low % cost-burdened, low % <age 18, low % female-headed households, high mobility rate, high % white/Asian
Cluster 2	38	0.12	0.50	72	Intermediate income, high % >65, low % renters, high % cost burdened renters, high % foreign-born, racially/ethnically diverse
Cluster 3	45	0.21	0.54	82	High poverty, low income, high % renters, high vacancy, high % female-headed households, high % service workers, high % Black/Hispanic
Total	(1.58 million)	0.15	0.48	79	

with individuals in each other cluster was estimated using co-location events measured by anonymous mobile phone data, which only includes interactions outside of homes and work-places (see Supplementary Table 5, see "Methods" section, Supplementary Note). Individuals preferentially mix with others residing in the same cluster. The degree of adoption of social distancing measures, which differed for each sub-population and for each contact type, was assumed to be proportional to the reductions observed in the mobility data (Supplementary Table 6). Cluster 1 experienced the largest reductions in mobility, followed by Cluster 3 then Cluster 2. Evicted households were merged with other households in the same sub-population. There are no datasets available tracking the geographic origin and destination of individuals experiencing evictions, but general housing relocations observed using the same mobility data were predominantly within the same cluster (Supplementary Fig. 17).

By tuning only the infection prevalence at the time that strong social distancing policies were implemented in March, we found that our model matched our best available information on the COVID-19 epidemic trajectory in Philadelphia (Fig. 5). The simulated epidemic grew exponentially with a doubling time of 4–5 days until late March. The daily incidence of cases peaked shortly thereafter and deaths peaked with a delay of ~1 month. Post-peak, new cases, and death declined with a half-life of ~3 weeks. In early June, control measures were relaxed, leading to a plateau in cases and deaths that lasted until early October. The seroprevalence over time predicted by the model was in general agreement with results from large serological surveys in different populations in Philadelphia or Pennsylvania as a whole[35,36,49,50], and our model predicted large disparities in seroprevalence among the clusters.

Simulations suggest that allowing evictions to resume would have substantially increased the number of people with COVID-19 in Philadelphia by Dec 31, 2020 and that these increases would be felt among all sub-populations, including those with lower eviction rates (Fig. 5). We predict that with evictions occurring at only their pre-COVID-19 rates, the epidemic would infect an extra 0.3% of the population (~4700 individuals). However, many analyses suggest that eviction rates could be much higher in 2020 if allowed to resume, due to the economic crisis associated with
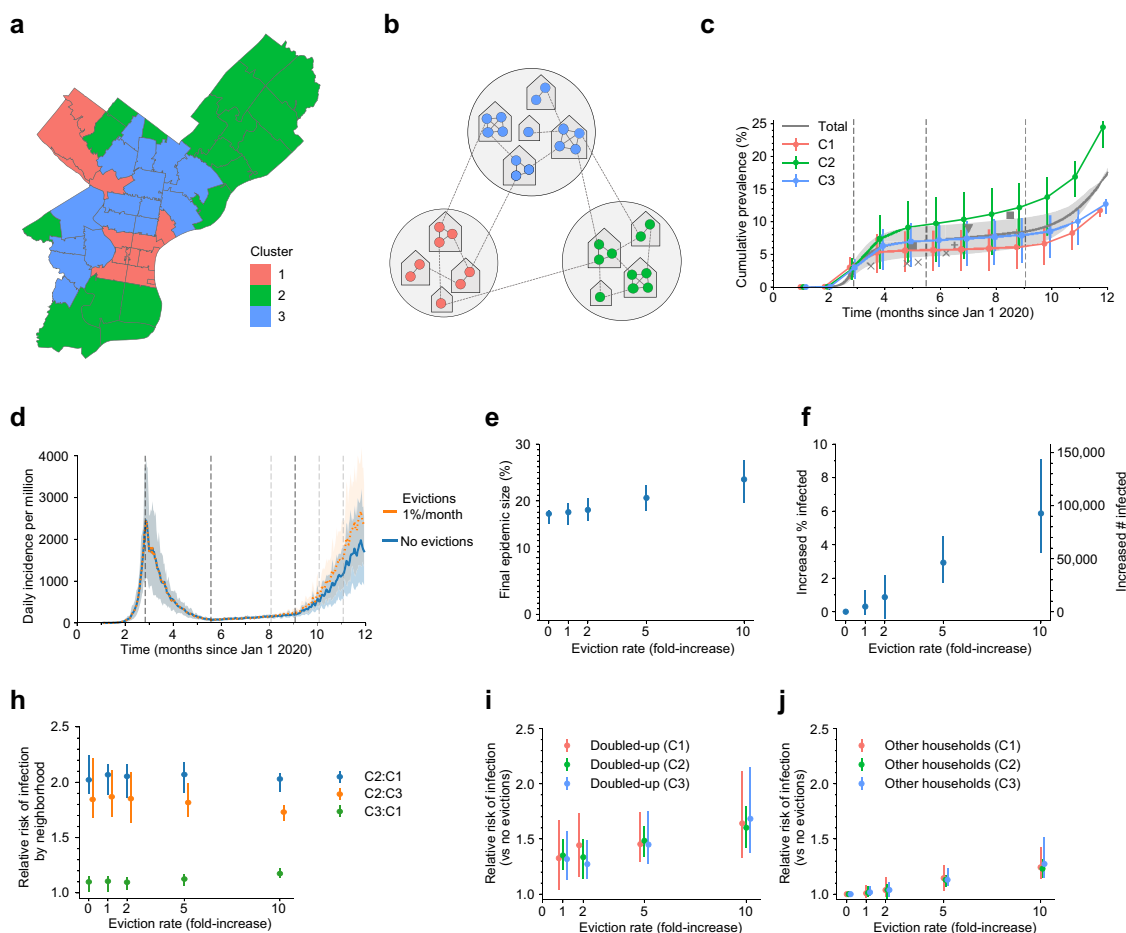
Fig. 5 A detailed example of how evictions might affect SARS-CoV-2 transmission in the city of Philadelphia, Pennsylvania, USA. a Map of Philadelphia, with each zip code colored by the cluster it was assigned to. Properties of clusters are Table 2 and Supplementary Tables 1, 2. **b** Schematic of our model for inequalities within the city. Each cluster is modeled as a group of households, and the eviction rate and ability to adopt social distancing measures vary by cluster. **c** Simulated cumulative percent of the population infected over time, by cluster, in the absence of evictions. Data points from seroprevalence studies in Philadelphia or Pennsylvania: x[50], +[35], triangle[49], square[36]. **d** The projected daily incidence of new infections (7-day running average) with evictions at 5-fold the 2019 rate vs. no evictions. Shaded regions represent central 90% of all simulations. **e** Final epidemic size by Dec 31, 2020, measured as percent individuals who had ever been in any stage of infection. **f** The predicted increase in infections due to evictions through Dec 31, 2020, measured as the excess percent of the population infected (left Y-axis) or the number of excess infections (right Y-axis). **g** Relative risk of infection by Dec 31, 2020, for residents compared by neighborhood. **h–i** Relative risk of infection by Dec 31, 2020, in the presence vs. absence of evictions, for individuals who merged households due to evictions ("Doubled-up", **h**) and for individuals who kept their pre-epidemic household ("Other households", **i**). Data in **c, e–i** showed as median values with interquartile ranges across simulations.

COVID-19 (Supplementary Fig. 2,[31,51]). If eviction rates double, the excess infections due to evictions would increase to 0.9%; with a 5-fold increase in evictions, predicted by some economic analyses, this would increase to 2.6% or ~53,000 extra infections. At this rate, we estimate a 1.5-fold [1.3,1.6] increase in the risk of infection for individuals in households that doubled-up, and a 1.1-fold [1.1,1.2] relative risk in other households, compared to the counterfactual situation in which a complete eviction moratorium was in place and enforced. Despite the differences in both baseline infection rates and eviction rates, all three sub-populations experienced similar proportional increases in infection levels due to eviction (Fig. 5h, i). Overall our results suggest that eviction moratoria in Philadelphia have a substantial impact on COVID-19 cases throughout the city.

Discussion

Our analysis demonstrates that evictions can have a measurable impact on the spread of SARS-CoV-2 in cities and that policies to stem them are a warranted and important component of epidemic control. The effect of evictions on an epidemic is not limited to those who were evicted and those who received evicted families into their homes. Other households experienced an increased risk of infection due to spillover from the transmission processes amplified by evictions in the city.

The most immediate implication of our findings is their relevance to the continued debate taking place in US legislatures and courts over the fate of local and national eviction moratoria. Our results suggest that the CDC-mandated national order prohibiting evictions from Sept 4 - Dec 31 2020 likely prevented thousands of excess COVID-19 infections for every million metropolitan residents. Moreover, simulations show that allowing evictions would increase the relative risk of infection for all households, not just a narrow class of those experiencing eviction. Thus, the legislation is of broad societal interest. A federal judge, citing testimony based on an earlier version of this model, recently issued an opinion in favor of the city of Philadelphia's eviction moratorium (HAPCO v. City of Philadelphia 2020). More generally, our simulations show that in the case of COVID-19, preventing evictions is clearly in line with the mandate of the Public Health Service Act to invoke measures "necessary to prevent the introduction, transmission, or spread of communicable diseases"[10].

Across all scenarios, evictions were predicted to aggravate the COVID-19 epidemic in cities. The effect was greatest in scenarios when the epidemic was growing rapidly during the time evictions took place, but evictions could also significantly increase the number of individuals infected under strong control measures. Even results of models that assume a homogenous population show significant effects of evictions on the city-wide prevalence of SARS-CoV-2 infection. However, when we modeled a heterogeneous city, the effect was more pronounced–presumably because the increase in household size is more concentrated, and those sections of the city affected by evictions, more connected.

The fates of households that experience eviction is difficult to track. Existing data suggest that historically the majority of evictions have led to doubling up (e.g., Fragile Families Study[52]) and we, therefore, chose to focus our modeling on this outcome. However, the current economic crisis is so widespread it is unlikely that other households will be able to absorb all evicted families if moratoria are revoked, and thousands of people could become homeless, entering the already-over-capacity shelter system or encampments[6,7,53–55]. Shelters could only increase the impact of evictions on cases of COVID-19. The risk of contracting COVID-19 in homeless shelters can be high due to close contact within close quarters, and numerous outbreaks in shelters have been documented[7,56]. A recent modeling study suggests that, in the absence of strict infection control measures in shelters, outbreaks among the homeless may recur even if incidence in the general population is low and that these outbreaks can then increase exposure among the general population[57]. When we assigned even a small proportion of evicted households to a catch-all category of shelters and encampments (Supplementary Fig. 18), with an elevated number of contacts, evictions unpredictably gave rise to epidemics within the epidemic, which then, predictably, spread throughout the city. These results are qualitatively in line with the effects of other high-contact subpopulations, such as those created by students in dorms[58,59] or among prisoners[60–62].

Other modeling studies have investigated 'fusing households' as a strategy to keep SARS-CoV-2 transmission low following the relaxation of lockdowns[22,63,64]. The strategy has been taken up by families as a means to alleviate the challenge of childcare among other issues[65,66]. Indeed there are conditions, especially during a declining epidemic, that fusing pairs of households does not have much effect on infection on the population scale[22]. While these findings are not in discord with our work, a voluntarily fused household is a very different entity than an involuntarily doubled-up household. While a fused household can separate in subsequent periods of higher transmission, a doubled-up household would likely not have such an option.

Our model simplifies the complex relationships within households that might affect the risk of ongoing transmission within a home, as well as the complex relationships that might initially bring a pathogen into a home. e.g., ref. [67]. Relatedly, we choose a constant household secondary attack rate. A number of analyses suggest that the average daily risk to a household contact might be lower in larger households[16,18,21]. We hesitate to generalize this finding to households in large US cities that face possible eviction. Empirical studies of secondary attack rate in households of different sizes, in the relevant population, and with adequate testing of asymptomatic individuals, are badly needed. If they show that the infection rate does not scale with household size, then our estimates on the expected effects of eviction would be too large. We also have not considered the effects of household crowding, nor the age structure of households–evicted and otherwise–which can influence outcomes in a network model such as ours[68,69]. We have not considered the effects of foreclosures and other financial impacts of the epidemic which will likely also lead to doubling up and potentially homelessness. There are likely more complicated interactions between COVID-19 and housing instability that we have not modeled, such as the possibility that COVID-19 infection could precipitate housing loss[55], that eviction itself is associated with worsening health[70,71], or that health disparities could make clinical outcomes of COVID-19 infection more severe among individuals facing eviction or experiencing homelessness[57,72,73]. Finally, we note that our model is not meant to be a forecast of the future course of the epidemic, nor the political and individual measures that might be adopted to contain it. We limit ourselves to evaluating the effect of evictions across a set of scenarios, and we limit our projections to the coming months. We also do not consider the possible effects of re-infection or other details that contribute to the uncertainty of SARS-CoV-2 epidemic trajectories.

We caution against using the precise numerical estimates from our model to infer the effects of eviction moratoria in particular locations. While we have attempted to use the best current estimates of epidemiological parameters for COVID-19 transmission and to calibrate our model to epidemic trajectories common across US cities, many uncertainties remain. For example, there is uncertainty in our estimates of the basic reproduction number, the serial interval, the duration of immunity, the infection fatality

risk, the fraction of transmission occurring within vs. outside of households, the distribution of external contacts across individuals and households, and the manner in which they are reduced during different stages of the epidemic. These quantities may vary by setting and over time. The distribution of cases across demographic groups (e.g., age, race/ethnicity) is not considered in detail in our model but may impact the output. Our analyses of different common COVID-19 epidemic trajectories and our sensitivity analyses using different parameter assumptions suggest our qualitative results are robust, but that the precise numbers depend on the details. Ideally, observational studies of households conducted in localities where evictions moratoria (temporarily) expired or were ignored could provide more direct evidence for the impact of evictions on COVID-19 transmission. No such studies exist to date. A recent preprint by Leifheit et al, making a difference in difference approach at the state level, suggests there was some signal of increasing cases when moratoria ended[74]. However, there are likely other contemporaneous policy decisions affecting COVID-19 transmission that occurred in states allowing local eviction moratoria to lapse, making the assignment of causality difficult.

Cities are the environment of an ever-increasing proportion of the world's population[75], and evictions are a force that disrupts and disturbs them. Just as abrupt environmental change can alter the structure of populations and lead to contact patterns that increase the transmissibility of infectious agents[76], evictions change with whom we have the closest of contact—those inside the home—and this change, even when it affects only a small proportion of a population, can significantly increase the transmission of SARS-CoV-2 across an interconnected city.

Methods

Modeling SARS-CoV-2 spread and clinical progression. We describe the progression of COVID-19 infection using a SEIRD model, which divides the population into the following stages of infection: susceptible (S), exposed (infected but not yet infectious) (E), infected (I), recovered, and assumed to be immune (R), and deceased (D). This model is similar to many other published models[28,69,77–79] including our own[22]. All our code is available in a Github repository[80]: https://github.com/alsnhll/COVID19EvictionSimulations. We assume that the average duration of the latent period is 4 days (we assume the transmission is possible on average 1 day before symptom onset), the average duration of the infectious period is 7 days (1-day presymptomatic transmission +6 days of symptomatic/asymptomatic transmission), the average time to death for a deceased individual was 20 days, and the fraction of all infected individuals who will die (infection fatality risk, IFR) was 1%. The distribution of time spent in each state was gamma-distributed with mean and variance taken from the literature (see Supplementary Note). Transmission of the virus occurs, probabilistically, from infectious individuals to susceptible individuals who they are connected to by an edge in the contact network at rate β.

Creating the contact network. We create a two-layer weighted network describing the contacts in the population over which infection can spread. One layer describes contacts within the household. We divide the population into households following the distribution estimated from the 2019 American Community Survey of the US Census[29]. In this data all households of size 7 or greater are grouped into a single "7 +" category, so we imputed sizes 7 through 10 by assuming that the ratio of houses of size n to size $n + 1$ was constant for sizes 6 and above. We assume that all individuals in a household are in contact with one another. The second layer constitutes contacts outside the household (e.g., work, school, social). While the number of these external contacts is often estimated from surveys that ask individuals about the number of unique close face-to-face or physical contacts in a single day, how these recallable interactions of varying frequency and duration related to the true effective number of contacts for any particular infection are not clear. Therefore, we took a different approach to estimating external contact numbers and strength.

We assumed a separate transmission rate across household contacts (β_{HH}) and external contacts (β_{EX}). To estimate the values of these transmission rates, and the effective number of external contacts per person, we matched three values from epidemiological studies of SARS-CoV-2. First, since the transmission probability of household contacts is more easily measured empirically than that for community contacts, we backed out a value of household transmission rate (β_{HH}) that would give the desired value of the secondary attack rate (SAR) in households. We used a

household SAR of 0.3, based on studies within the United States, as well as a pooled meta-analysis of values from studies around the world[16,17,19]. Secondly, we assumed that the secondary attack rate for household contacts was 2.3-fold higher than for external contacts, based on findings from a contact tracing study[81]. We used this to infer a value for the transmission rate over external contacts (β_{EX}). Finally, we chose the average number of external contacts so that the overall basic reproductive ratio, R_0, was ~3, based on a series of studies[82–84]. We did this assuming that the distribution of external contacts is negative binomially distributed with the coefficient of variation of external contacts of 0.5, and using a formula for R_0 that takes this heterogeneity into account[85]. We explore the effects of different assumptions surrounding R_0, the household SAR, and the ratio between the transmission rate within and between households in sensitivity analyses, shown in the Supplementary Information.

Modulating contact rates to recreate epidemiological timelines. We assume that the baseline rate of transmission across external contacts represents the value early in the epidemic, before any form of intervention against the spread (e.g., workplace or school closures, general social distancing, masking wearing). To recreate the trajectories of COVID-19 in U.S. cities throughout 2020, we instituted a series of control measures and subsequent relaxations in the simulations at typical dates they were implemented in reality. In the model, these modulations of transmission were encoded as reductions in the probability of transmission over external contacts. The timing and strength of these modulations in external contacts were chosen in a model calibration procedure that involved first clustering U.S. metro areas into groups based on common epidemic time courses and then tuning the model to recreate a trajectory typical of each group (described below, see Supplementary Figs. 3–8, Supplementary Table 1). For the simulations involving cities divided into multiple neighborhoods, we represented disparities by allowing the strength of these control measures to differ depending on the origin and destination neighborhood of each external contact. For the theoretical two-neighborhood city (Fig. 4), individuals in the higher SES neighborhood were assumed to be better able to adopt social distancing measures and thus were modeled with larger reductions in external contacts. For Philadelphia, the reductions were informed by mobility data which tracked co-locations occurring between residents of different zipcodes (see Details below).

Categorizing city-specific COVID-19 trajectories. To estimate the impact of evictions on COVID-19 transmission, it is necessary to realistically simulate the state of the epidemic at the time evictions are occurring. Theoretically, this would require estimates of infection prevalence over time, the distribution of infections across households, real-time estimates of contact rates of infectious individuals, as well as knowing how the epidemic would unfold in the future. Since in general, we do not have direct estimates of these quantities, our approach was to create realistic scenarios by simulating the entire epidemic course before evictions began, reproducing the trajectories seen in data. Then, for forwarding projections (which in our case is Sept 1 2020 onwards), we considered alternate scenarios of epidemic control and infection resurgence.

Our simulation is at the level of a single U.S. metropolitan area. To avoid the extreme computational costs of fitting a stochastic network model to every U.S. city of interest and including all the observational processes that affect real data (like testing rates, reporting delays, etc), we take a simplified model calibration approach. First, we collected county-specific daily COVID-19 case and death reports from the New York Times database (which is based on reports from state and local health agencies)[86] and aggregated these into metropolitan statistical areas (MSAs). We chose all metropolitan areas with at least 1 million residents (53 cities) and used dynamical time warping and hierarchical clustering (using the `hclust` function with method `ward.D` and the `dtw` package v1.22-3 in R v3.5.1) on case and death time courses (normalized by population) up to Aug 31, 2020, to group cities with similar trajectories. Four groups naturally emerged from this analysis (Supplementary Fig. 3), representing at one extreme metros like New York City and Boston that had large first waves followed by a long period of control over the summer, and at the other extreme cities like Houston and Phoenix that had their epidemic peak over the summer. For all city groups, we observed that the epidemic could roughly be broken down into five phases with the corresponding date ranges (1) early epidemic: pre-March 25, (2) lockdown: March 25–June 15, (3) relaxation: June 15–July 15, (4) continued relaxation or increased control: July 15–Oct 1, (5) fall wave: Oct 1–end of 2020. We then created a trajectory with the model to match each city-group, where during each phase we chose a degree of reduction in external contacts using a simple binary search such that the growth rate of cases or deaths was within the range observed for cities in that group (Supplementary Table 1). The time between the initial epidemic seeding (with 10 individuals) and the first lockdown was chosen to reproduce the size of the first wave. Because of issues with testing limitations and reporting mild or asymptomatic infections, the fraction of cases reported has most likely changed dramatically over the course of 2020, and so we prioritize recreating trajectories of deaths (vs. cases) along with an assumed 1% IFR to infer total cases (Supplementary Fig. 9).

Modeling the impact of evictions. We initially assume all evictions result in "doubling up", which refers to when an evicted household moves into another house along with its existing inhabitants. There are very few studies reporting individual-level longitudinal data on households experiencing evictions[14,87–89], and none of those (to our knowledge) have published reports of the fraction of households that experience each of the possible outcomes of eviction (e.g., new single-family residence, doubling-up, homeless, etc). The best evidence available on doubling-up comes from the Fragile Families and Child Wellbeing Study, one of the only large-scale, longitudinal studies that follow families after eviction[14,15]. The study sampled 4700 randomly selected births from a stratified random sample of US cities >200,000 population[52], and has followed mothers, fathers, and children from 1998 to the present. Among other topics, interviewers asked respondents whether they had been evicted, doubled up, or made homeless in the previous year. In four waves of available interviews among 4700 respondents in 1999–2001, 2001–2003, 2003–2006, and 2007–2010, 402 mothers reported being evicted in the previous year. Of these, an average of ~65% reported having doubled up.

Based on the eviction rate, a random sample of houses is chosen for eviction on the first day of each month, and these houses are then each "merged" with another randomly-chosen household that did not experience eviction. In a merged household, all members of the combined household are connected with edges of equal strength as they were to their original household members. A household can only be merged once.

Homelessness is another possible outcome of eviction. However, a number of studies of the homeless population show that doubling-up often precedes homelessness, with the vast majority of the homeless reporting being doubled-up prior to living in a shelter[90–92]. In the Fragile Families Study data described above, only ~17.4% reported having lived in a shelter, car, or abandoned building. We subsequently model the minority of evictions that result directly in homelessness. These evicted households instead enter a common pool with other homeless households, and, in addition to their existing household and external connections, are randomly connected to a subset of others in this pool, mimicking the high contact rates expected in shelters or encampments. We consider 10% of evicted households directly becoming homeless, and the other 90% doubling up. Individuals are assigned to 'shelters' of size drawn from a Poisson distribution with a mean of 20 and are connected to all other individuals in that shelter only. This number is estimated from considering both sheltered and unsheltered people, which each represent about half of the individuals experiencing homelessness[53]. Data suggesting the average size of shelters is ~25 people, based on assuming ~half of the ~570 K homeless on any given night are distributed over 12 K US shelters, which is similar to a Lewer et al estimate for the UK (mean 34, median 21)[57]. Unsheltered individuals are expected to have less close, indoor contacts, bringing down the average, and the portion of unsheltered homeless may grow as shelters reach capacity[53]. In the model, these connections get rewired each month, since the average duration of time spent in a single shelter is ~1 month[93]. Contacts among homeless individuals are not reduced by social distancing policies. As a result, during the time evictions take place, the individual-level R_0 for the homeless is ~1.5-fold the pre-lockdown R_0 for the general population, similar to Lewer et al[57].

Evictions begin in our simulations on September 1, 2020, and continue at the first of each month at a rate which we vary within ranges informed by historical rates of monthly evictions in metropolitan areas and projected increases (0%, .25%, .5%, 1%, or 2%) (see the justification of this range in Supplementary Note). Note that the denominator in our eviction rate is the total number of households, not the number of rental units. We assume a backlog of 4 months of households are evicted immediately when evictions resume, corresponding to the months during which most local or state eviction moratoria were in place (May through August 2020).

Extension of the model to incorporate heterogeneity in eviction and contact rates. To capture heterogeneities in cities we divide the simulated city (population size 1 million) into two equal-sized interconnected subpopulations—one consisting of high socioeconomic status (SES) households, and the other with low SES households. Connections between households (external contacts) could occur both within the same neighborhood and between the different neighborhoods. We considered two types of mixing for external connections—homogeneous mixing where 50% of external connections are within one's neighborhood and hetero-geneous mixing where 75% of external connections are within one's neighborhood creating a more clustered population. Households in the low SES subpopulation experience all of the evictions in the city, and these evicted households are doubled-up with households from the same subpopulation. To capture the higher burden of infection with COVID-19 consistently observed in poorer sections of cities[32–38], during intervention we down-weighted external contacts among the low SES subpopulation less than in the high SES subpopulation (Supplementary Table 1).

Application to the city of Philadelphia, Pennsylvania, USA. To estimate the impact of evictions in the specific context of Philadelphia, PA, we first developed a method to divide the city up into a minimal but data-driven set of subpopulations, and then encode this into the model (as described above), taking into account the different rate of evictions and of adoption of social distancing measures across these subpopulations.

To create the subpopulations and capture key aspects of heterogeneity in the city, we first extracted 20 socio-economic and demographic indicators for each zip

code of the city from the 2019 US Census and ran an unsupervised principal component analysis[48] to cluster the zip codes based on similarities. The analysis resulted in three typologies: Cluster 1, a higher income rental neighborhood, Cluster 2, a moderate-income and working-class owner neighborhood, and Cluster 3, a low-income rental neighborhood (Supplementary Tables 1, 2). Using zip code-level eviction rates for 2016 sourced from Eviction Lab[30], we estimated 0.7% of households in Cluster 1, 0.12% of those in Cluster 2, and 0.21% of those in Cluster 3 faced eviction each month at baseline. We consider scenarios where these rates are increased 2, 5, and 10-fold during the pandemic.

We used mobility data provided by Cuebiq to estimate the degree of contact between residents of the different clusters and how it varied throughout the epidemic. Cuebiq uses data from mobile phone users who have opted-in to share location information with certain applications, and we defined contacts using co-location events where two individuals were in the same 8-character geohash for 15-mins or more. All data were anonymous and corrected for the degree of population sampling (see Supplementary Note for details). The percent of all within-Philadelphia contacts that occur with residents of a particular cluster is shown in Supplementary Table 5. Between ~50–75% of contacts were with individuals living in the same cluster, whereas ~15–35% occurred in any other specific cluster.

We then calibrated our model to match the best available information regarding the epidemic trajectory for Philadelphia. The goal was to create a trajectory that captured the size of the epidemic peak (measured by daily death counts), the growth rate of decline of cases during each major phase of the epidemic (early phase, post-lockdown, post-relaxation, fall comeback), and the observed seroprevalence at different timepoints[35,36,49,50]. The reduction in mobility over time, measured as the percent reduction in contacts between residents of a pair of clusters averaged over 1 month, was used to determine the reduction in external contacts during each epidemic phase. To do this, in simulations we imposed a strong lockdown (overall 90% reduction in contacts) on March 23, 2020, when the cumulative prevalence of infected individuals was approximately 3% of the total population. This intervention was relaxed on June 15, allowing cases and deaths to plateau over the summer (overall 77% reduction in contacts). We further relaxed measures (overall 66% reduction in contacts) on Oct 1 2020 to create a fall comeback. Since no changes in mobility were observed during this time despite large increases in cases observed during this time period, we hypothesized that other biological or behavioral factors not represented in mobility data must be responsible for this comeback, and implemented it in the model as a 15% increase in β_{EX}. During each phase, each of the three clusters obtained via the typology analysis had different strengths of social distancing measures in their interactions with each other cluster (Supplementary Table 6).

Data on the fate of evicted households is extremely rare, and we do not know how likely evicted individuals would be to double-up with a household within their cluster or in another cluster. To estimate this, we created a cohort of individuals from the Cuebiq data whose inferred home location had changed between Feb 2020 and Oct 2020. Supplementary Fig. 17 reports the frequency of moves to and from each cluster. This data suggests that the vast majority of relocations were to other houses within the same cluster. Assuming that movement patterns following eviction would be similar, in the model we assumed that evicted individuals always double-up with another household in the same cluster.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

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Author contributions

A.N., J.S., D.S., A.G., M.Z.L., and A.L.H. conceived of the study and interpreted all results. A.N., J.S., M.Z.L., and A.L.H. designed the mathematical model. A.N., J.S., and A.L.H. wrote and edited the model code and conducted the simulations. B.A. and A.H.G. contributed to writing and optimizing the code. E.L.W. and A.G. conducted a typographical analysis of Philadelphia zip codes. B.K. and M.C. analyzed mobility data. A.V. and S.V.S. coordinated the acquisition of mobility data and supervised its analysis. J.S. and M.F.T. contributed a literature review on the role of housing policy in infection prevention and the legal aspects of eviction moratoria and writing the Introduction and Discussion sections. A.N., J.S., E.W., B.K., A.H.G., M.Z.L., and A.L.H. created the graphics. M.Z.L. and A.L.H. coordinated and supervised all aspects of the project. All authors contributed to editing the manuscript and approved the final version.

Competing interests

Additional information