# Quarantine fatigue thins fat-tailed coronavirus impacts in U.S. cities by making epidemics inevitable

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**Abstract:** We use detailed location data to show that contact rates in most U.S. cities are fat tailed, suggesting that the fat tails previously documented in a small number of case studies are widespread. We integrate these results into a stochastic compartmental model to show that COVID-19 impacts were also fat tailed for many large U.S. cities for several weeks in the spring and summer. Due to thresholds in epidemiological dynamics, fat-tailed impacts would have been more prevalent if not for the gradual increase in contact rates throughout the summer that made an outbreak more certain.

**Keywords:** COVID-19; generalized Pareto distribution; contact rates; infectious disease; stochastic SIR

Public officials have struggled to effectively control the spread of COVID-19. Fat tails in the distribution of global pandemic fatalities over the past 2,500 years (Cirillo and Taleb 2020) offer a possible explanation for these challenges. Fat-tailed damages across disease outbreaks limit the ability to learn and prepare for future outbreaks, as the central limit theorem slows down and fails to hold with infinite moments. We extend recent results showing fat tails in superspreading events (Wong and Collins 2020; Fukui and Furukawa 2020) to demonstrate the emergence and persistence of fat tails in contacts across the U.S. We then demonstrate an interaction between these contact rate distributions and community-specific disease dynamics to create fat-tailed distributions of COVID-19 impacts (proxied by weekly cumulative cases and deaths) during the exact time when attempts at suppression were most intense.

**Results**

We follow the "place-based contact rate" approach developed in (Chang et al. 2020), rather than proxying for contacts with time spent at home (e.g., Goolsbee and Syverson 2020), and utilize the Safegraph weekly patterns dataset of visits to 6 million 'Points-of-Interest' (POIs) to estimate weekly contact rate distributions in 2,293 core-based statistical areas and rural counties (CBSAs) in the U.S. from January 27, 2020 to September 16, 2020 (SI Appendix and Dataset S1). Weekly estimates of the mean, variance, and shape parameter ($\xi$) of the Generalized Pareto distribution (GPD) all have predictive power for COVID-19 cases or deaths (SI Appendix). Virtually all CBSAs (99%) have at least one week of a fat-tailed contact rate distribution with finite variance ($0 < \xi < 0.5$), and 35% of CBSAs have a fat-tailed distribution with infinite variance ($\xi > 0.5$) for at least 1 week.

Average contact rates changed significantly during the epidemic due to defensive behavior and policy (Yan et al. 2020). Generally, contact rates dropped and shape parameters spiked between week 10 (starting March 2) and week 13 (ending March 29)(Fig. 1A-B). For 25% of the CBSAs in our sample, the shape parameter of the contact rate distribution peaked above 0.5 for at least one week while mean contact rates were falling, suggesting that contacts increased at POIs in the tail of the distribution, possibly due to reductions at the lower end of the POI distribution. Our measure of contacts includes both POI and in-home contacts, which have been shown to be an important source of infectious-disease transmission (Bayham and Fenichel 2016); these periods align with dramatic increases in the number of individuals staying completely at home. The histogram of contacts at NYC POIs (Fig. 1C) demonstrates a substantial reduction in low contact POIs between week 10 and week 13. However, the upper tail is thicker in week 13. This result holds across the U.S. and when breaking out different types of POIs, including restaurants, groceries, day care centers, and gyms (Fig. 1D). Restricted business hours and openings may have crowded more people into fewer locations, even as average POI visits fell. Following week 13, quarantine fatigue emerges in most CBSAs, leading to higher contact rates and lower shape parameters.

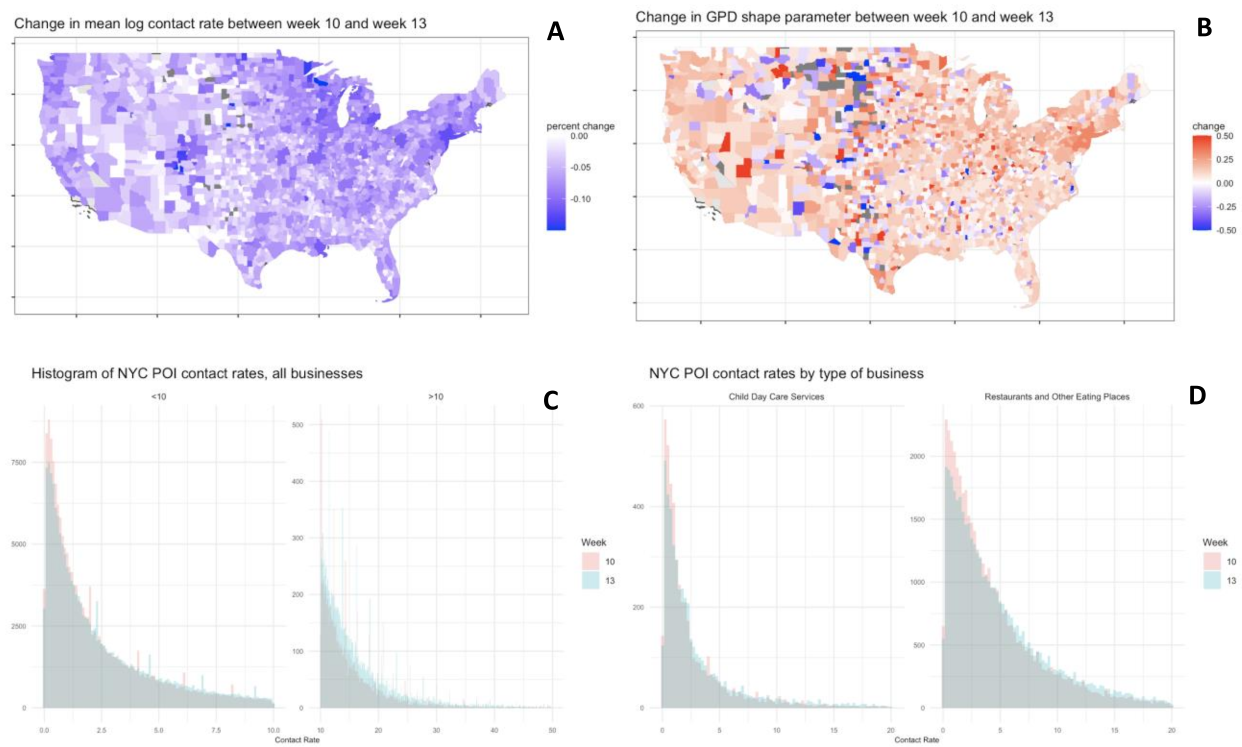


**Fig. 1. Mean and tail thickness of POI contact rate distributions.** Mean contact rates decrease during March (A), while estimated shape parameters increase in many places (B). In New York City, there are large reductions for POIs with low contact rates, but an increase in POIs with high contact rates during this period (C; tail split for ease of visualization). This pattern holds for restaurants and day care centers (D), among other types of businesses not pictured.

To determine whether fat-tailed contact rate distributions lead to fat-tailed estimates of COVID-19 impacts, we applied a two-step process to the four most populous U.S. cities: New York City, Los Angeles, Chicago, and Houston. First, we fit a stochastic SIR model to cases in each city where the contact rate, $C(t)$, follows a stochastic volatility model fit to our place-based contact rate distributions: $dC = \alpha C dt + \sigma(t) C dz_1$ where $d\sigma = \theta(\bar{\sigma} - \sigma)dt + \kappa dz_2$and $dz_1$and $dz_2$ are two independent Wiener processes (Fig. 2A) (SI Appendix). Our stochastic volatility model implies contact rates are fat tailed (Stein and Stein 1991) and displays the quarantine fatigue observed in our POI distributions, $\alpha > 0$. Our stochastic SIR model implies the effective reproductive number also follows a fat-tailed stochastic process (Wong and Collins 2020) and leads to multiple waves of cases with unpredictable timing and magnitude (Fig. 2B) instead of a single noisy wave of cases found in many compartmental models that introduce stochasticity via an additively-separable error term. Second, we perform 100,000 simulations of the parameterized stochastic SIR model and fit a GPD to the 100,000 simulated cumulative cases, yielding weekly estimates of tail thickness of the COVID-19 impact distribution (Fig. 2C). New York City, Los Angeles, and Chicago all had fat-tailed cumulative case distributions in April and May. Houston, which experienced a delayed rise in cases, experienced fat-tailed impacts in late May, June, and July. All cities experienced at least 3 weeks with infinite variance impact distributions. Similar results obtain when fitting the GPD to simulated deaths in each city.

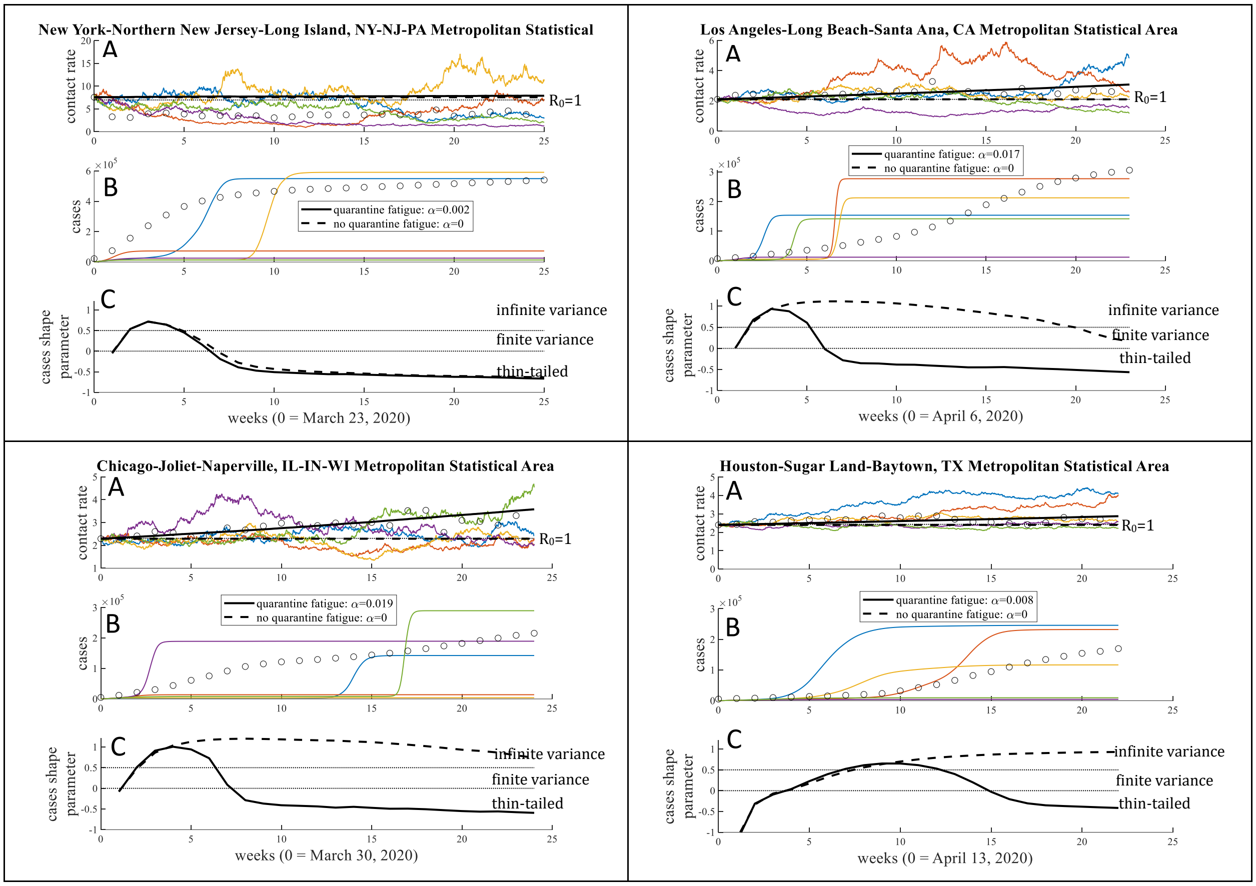


**Fig. 2. Duration of fat-tailed COVID-19 impacts.** (*A*) Contact rates estimated from POI visits (circles) parameterize a stochastic process for contact rates (solid lines show 5 simulations of stochastic process $dC$) with expected increase over time due to quarantine fatigue ($E[dC] > 0$, solid black lines). (*B*) A SIR model fit to weekly cumulative cases is simulated using the stochastic contact rate process (circles), yielding a time-varying distribution of cumulative cases (solid lines show 5 simulations). (*C*) GPD is fit to weekly distribution of cumulative cases with (solid black lines) and without (dashed black lines) quarantine fatigue.

Public health policies developed based on experiences during these months could be viewed as an overreaction if these impacts were mistakenly perceived as thin tailed, possibly contributing to reduced compliance, regulation, and the quarantine fatigue documented in our POI distributions. However, quarantine fatigue reduces the prevalence of fat tails by making an outbreak more certain. The gradual rise in contact rates due to quarantine fatigue causes $R_0$ to rise over time as well. The rise in $R_0$ means that more of the stochastic draws from the SIR model result in outbreaks. Greater certainty about an outbreak causes the shape parameter in cumulative cases to fall even as the mean in cumulative cases rises. Without quarantine fatigue ($\alpha = 0$), $R_0$ hovers near 1 and more stochastic draws from the SIR model result in the epidemic being suppressed. Those stochastic draws resulting in an outbreak, which had previously been viewed as normal under quarantine fatigue, now appear more extreme, leading to a prolonged period of fat-tailed impacts (Fig. 2C). Thus, suppression of the disease can create fat tails due to a well-known threshold in epidemiological dynamics.

## Discussion

While fat-tailed contact rates associated with superspreaders (Lloyd-Smith et al. 2005, Galvani and May 2005) increase transmission (Wong and Collins 2020, Fukui and Furukawa 2020) and case numbers (Anderson and May 1992), they also suggest a potential benefit: targeted policy interventions are more effective than they would be with thin-tailed contacts. If policy makers have access to the necessary information and a mandate to act decisively, they might take advantage of fat-tailed contacts to prevent inaction that normalizes case and death counts that would seem extreme early in the outbreak. Our place-based estimates of contacts aid in these efforts by showing the dynamic nature of movement through communities as the outbreak progresses, which is quite costly to achieve in network models, forcing the assumption of static contact networks in many models (e.g., Bansal et al. 2007).

In extreme value theory, fat tails confound efforts to prepare for future extreme events like natural disasters (e.g., Conte and Kelly 2018) and violent conflicts (Cirillo and Taleb 2016) because experience does not provide reliable information about future tail draws. However, impacts of extreme events play out over time based on policy and behavioral responses to the event, which are themselves dynamically informed by past experiences. A general pattern of fat-tailed contact rate distributions across the U.S. suggests that fat tails in U.S. cases observed early in the outbreak (Beare and Toda 2020) are due to city- and county-specific contact networks and epidemiological dynamics. By unpacking the dynamics that lead to the impacts of extreme events, we show that 1) fat-tailed impacts can also confound efforts to control and manage impacts in the midst of extreme events and 2) thin tails in disease impacts are not necessarily desirable, if they indicate an inevitable catastrophe.

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