Retail store customer flow and COVID-19 transmission

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We examine how operational changes in customer flows in retail stores affect the rate of COVID-19 transmission. We combine a model of customer movement with two models of disease transmission: direct exposure when two customers are in close proximity and wake exposure when one customer is in the airflow behind another customer. We find that the effectiveness of some operational interventions is sensitive to the primary mode of transmission. Restricting customer flow to one-way movement is highly effective if direct exposure is the dominant mode of transmission. In particular, the rate of direct transmission under full compliance with one-way movement is less than one-third the rate under two-way movement. Directing customers to follow one-way flow, however, is not effective if wake exposure dominates. We find that two other interventions—reducing the speed variance of customers and throughput control—can be effective whether direct or wake transmission is dominant. We also examine the trade-off between customer throughput and the risk of infection to customers, and we show how the optimal throughput rate drops rapidly as the population prevalence rises.

COVID-19 | disease transmission | industry: retail | customer flow models

To limit the spread of COVID-19 the US Centers for Disease Control and Prevention recommend that individuals practice social distancing by limiting face-to-face contact and maintaining at least a 6-foot distance from other people (1). While vaccines are now available, they will take some time to distribute and administer, and during the next few months COVID-19 will continue to spread in many communities. Therefore, public health measures such as social distancing and wearing masks will remain important (2, 3).

Retail establishments have been linked to COVID-19 outbreaks among both employees and customers (4), and a large-scale study based on mobility networks found that the risk is higher in relatively crowded stores visited by lower-income customers (5, 6). Some retailers are attempting to help their customers follow social distancing guidelines by implementing one-way aisles and limiting the number of customers in stores (7). Some stores are also dedicating specific shopping times for high-risk customers. In Massachusetts, for example, grocery stores must schedule daily shopping periods that are exclusively for customers who are 60 y old or older (8). Trying to avoid chaotic traffic in corridors, some schools are also limiting hallway traffic and implementing one-way corridors (9, 10).

Implementation of these practices, however, varies widely among retail stores and across geographic areas. This indicates that their relative effectiveness is not well understood, nor is it clear which factors in the environment and which characteristics of virus transmission have an impact on their ability to reduce infection. To address this problem, we calculate the rate of disease transmission in a retail store by combining simple models of customer traffic flow and disease transmission.

We focus on the two most important modes of transmission, respiratory droplet and aerosol (11, 12). Fomite transmission due to touching contaminated surfaces may occur but does not seem to play a significant role in driving spread (13–15). The first model captures direct transmission through the air when two customers are close to each other, for example when passing each other in a narrow supermarket aisle. The second model captures wake transmission that occurs when a customer inhabits the more distant airflow or "wake" of another customer. Direct and wake transmissions correspond to the two primary methods of spread, heavy droplets and aerosol, that have been identified for previous viruses such as influenza and severe acute respiratory syndrome coronavirus 1 (SARS-CoV-1). These are likely to be factors in the spread of COVID-19 (16–18). An infected person expels both types of particles when breathing, talking, coughing, and sneezing. Heavy droplets fall out of the air relatively quickly and therefore pose a higher risk when customers are close (19) while aerosols hang in the air and may be inhaled at a distance (20, 21).

To reduce direct transmission, it would seem reasonable to implement one-way traffic to limit the number of face-to-face interactions. Indeed, in the analysis below we find that one-way movement can dramatically reduce direct transmission. Intuition about the impact of one-way traffic on wake transmission is less clear: On the one hand, customers are less likely to move close to each other, but on the other hand they spend more time walking behind each other. We show that these effects balance each other: The direction of traffic does not impact the degree of wake transmission at all in our model. Additional analysis shows that reducing variation in speed reduces both direct and wake transmission. When considering a retailer's trade-off between throughput (or revenue) and the risk of exposure to customers, we find that disease transmission exhibits diseconomies of scale in customer throughput and that the optimal throughput rate drops rapidly as the fraction of people who are contagious in the population rises. In general, these models provide a link between the biology of COVID-19 and operational choices to limit infection. The results highlight the need for a better understanding of how the virus spreads in

Significance

To reduce the transmission of COVID-19, many retail stores use one-way aisles, while local governments enforce occupancy limits or require "safe shopping" times for vulnerable groups. To assess the value of these interventions, we formulate and analyze a mathematical model of customer flow and COVID-19 transmission. We find that the value of specific operational changes depends on how the virus is transmitted, through close contact or suspended aerosols. If transmission is primarily due to close contact, then restricting customers to one-way movement can dramatically reduce transmission. Other interventions, such as reductions in customer density, are effective at a distance but confront store operators with trade-offs between infection rates and customer flow.

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real-world conditions, so that we may choose the most effective interventions.

Customer Flow and Transmission Models

To model customer flow in a retail area, we assume that customers move along a path of length L through a retail area (Fig. 1). An example would be a supermarket department in which all customers flow through the same set of aisles.

We assume that customers enter a facility according to a Poisson process with rate λ. To allow different traffic patterns to emerge in the aisles, customers enter one side of the area with probability α for the "right" side and $(1-\alpha)$ for the "left" side. Therefore there are two flows in opposite directions with Poisson arrival rates $\alpha\lambda$ and $(1-\alpha)\lambda$. A store that strictly enforces one-way movement in the retail area would have $\alpha = 0$ or $\alpha = 1$. Each customer walks at a constant speed p, where the speed p of an individual customer is a random variable with distribution $f(p)$, cumulative distribution function $F(p)$, $\bar{F}(p) = 1 - F(p)$, minimum value $\underline{p}$, and maximum value $\bar{p}$.

Following recent literature (22, 23), a fraction π_i of customers are infectious and they spread the virus through direct and wake exposure. Direct exposure to heavy droplets, for example from a sneeze or cough, may occur in front, to the sides, or behind the infectious person, that is, anywhere within a small radius. Furthermore, a fraction π_n of the population are not susceptible because they have been exposed to the virus and developed immunity (24), and therefore a fraction $1-\pi_n$ of the population are susceptible. In our model, susceptible customers have a direct exposure risk c, where c is defined as the probability of COVID-19 transmission whenever a susceptible customer passes, or is passed by, an infectious customer (25). Note that the two customers may be traveling in the same direction (one-way direct exposure) or in opposite directions (two-way direct exposure) when they pass each other. Given transmission probability c, our model calculates the overall rate of new infections in the store due to direct transmission.

In addition to direct exposure, customer movement creates airflow behind and away from the direction of movement (26), and recent research on SARS-CoV-2 in hospitals found that "virus-laden aerosols were mainly concentrated near and downstream from the patients" (ref. 27, p. 1589). To model this wake exposure, we assume that as a customer travels the customer leaves behind aerosols that diffuse as the customer moves away. Given that a susceptible customer is d distance behind an infectious customer, we assume that the susceptible customer has an infection risk $h(d)$ per unit time, where $h(d)$ is decreasing in d (for our baseline model we assume that $h(d)$ has negative exponential decay in d). Therefore, to find the total transmission risk for a particular susceptible customer due to wake exposure, we will calculate the cumulative time that customer spends behind infectious customers, taking into account the varying distances between customers as they move through the area.

Our model is characterized by the disease transmission parameters ($\pi_i, \pi_n, c, h(d)$ for $d \geq 0$), the facility size (L), and the customer flow characteristics ($\lambda, \alpha, F(p)$ for $\underline{p} \leq p \leq \bar{p}$). This relatively simple model is in the spirit of the "scratch models" for COVID-19 described in ref. 28. We believe that our model captures the main drivers of transmission. In *Conclusions* we discuss additional real-life phenomena that may be added to the model.

Disease Transmission Analysis

In this section, we calculate the average total rate of transmission per unit of time. That is, for a particular area of a store, the model calculates the rate at which infectious customers transmit COVID-19 to susceptible customers. First, we analyze direct transmission, next wake transmission, and in the final subsection we discuss the total transmission rate from the retailer's and individual customer's perspectives.

Analysis of Direct Transmission. To find the rate of direct transmission, we calculate the rate at which susceptible and infectious customers pass each other. This rate of direct exposure is then multiplied by the parameter c to find the rate of infections transmitted in the store.

First consider only those customers who are moving in the same direction. We focus on a susceptible customer moving from right to left who is traveling at speed q, and we will sometimes refer to this focal customer as "customer q." Assume that customer q has reached time τ in the journey, $0 \leq \tau \leq L/q$. At that moment τ, any infectious customer arriving on the right and traveling at speed p such that $p(L/q - \tau) \geq L$ will overtake and pass customer q. Therefore, during an infinitesimal interval $[\tau, \tau + d\tau]$, the probability that an infectious customer arrives who will eventually pass customer q is $\pi_i \alpha\lambda \bar{F}(L/(L/q - \tau))\, d\tau$. After customer q reaches $\tau = L/q - L/\bar{p}$, however, no other customers will be able to pass customer q. As a consequence, the expected number of infectious customers who pass customer q while moving in the same direction during customer q's entire journey is

$$\pi_i \alpha\lambda \int_0^{L/q - L/\bar{p}} \bar{F}\left(\frac{L}{L/q - \tau}\right) d\tau. \quad [1]$$

Now consider the expected number of infectious customers that customer q overtakes. Logic similar to that above shows that customer q would expect to pass the following number of infectious customers:

$$\pi_i \alpha\lambda \int_0^{L/\underline{p} - L/q} F\left(\frac{L}{L/q + \tau}\right) d\tau. \quad [2]$$

Next, we find the overall rate of direct exposure due to customers who pass each other in the same direction. Note first that a susceptible customer q who arrives to the left, rather than the right, will also expect to be passed by, or pass, infectious customers according to the rates calculated in expressions **1** and **2**, but with α replaced by $1 - \alpha$. To uncondition on q and find the overall rate of exposure, note that susceptible customers who travel at speed q arrive on the right at rate $(1-\pi_n)\alpha\lambda f(q)$ and arrive on the left at rate $(1-\pi_n)(1-\alpha)\lambda f(q)$. Therefore, the rate of exposure due to customers passing

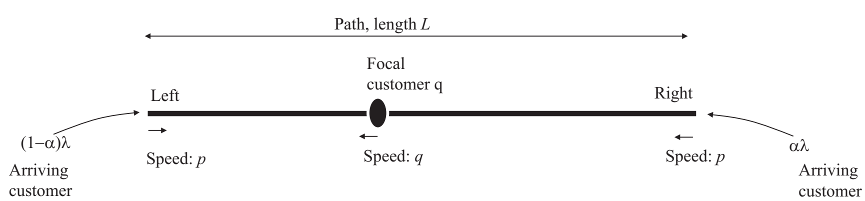

Fig. 1. Model setup: the focal customer q in the retail area.

each other in the same direction (one-way direct exposure) is $\pi_i(1-\pi_n)[\alpha^2+(1-\alpha)^2]\lambda^2 D_1$, where

$$D_1 = \int_{\underline{p}}^{\bar{p}} \left\{ \int_0^{L/q - L/\bar{p}} \bar{F}\left(\frac{L}{L/q-\tau}\right) d\tau + \int_0^{L/\underline{p} - L/q} F\left(\frac{L}{L/q+\tau}\right) d\tau \right\} f(q)\, dq. \quad [3]$$

Now, we find the rate of direct exposure due to customers passing each other in opposite directions. A susceptible customer arriving on the right and traveling at speed q will spend L/q time traveling. This customer will see two types of infectious customers passing in the opposite direction: 1) those traveling left to right who were in the area of the store when customer q arrived and 2) those who arrive on the left while customer q is traveling. In the following expression, the two terms correspond to the expected number of these two types of infectious customers seen by customer q:

$$\pi_i(1-\alpha)\lambda \left\{ \int_0^{L/\underline{p}} F\left(\frac{L}{\tau}\right) d\tau + \frac{L}{q} \right\}. \quad [4]$$

To find the overall rate of direct exposure due to customers who pass each other in opposite directions, note again that susceptible customers who travel at speed q arrive on the right (left) at rate $(1-\pi_n)\alpha\lambda f(q)$ ($(1-\pi_n)(1-\alpha)\lambda f(q)$). Therefore, the rate of exposure due to customers passing each other in opposite directions (two-way direct exposure) is $2\pi_i(1-\pi_n)\alpha(1-\alpha)\lambda^2 D_2$, where

$$D_2 = \int_0^{L/\underline{p}} F\left(\frac{L}{\tau}\right) d\tau + \int_{\underline{p}}^{\bar{p}} \left(\frac{L}{q}\right) f(q)\, dq. \quad [5]$$

Finally, recall that c is the probability of disease transmission, given that infectious and susceptible customers intersect. The rate of total disease transmission due to direct exposure for any distribution of speeds is

$$c\pi_i(1-\pi_n)\lambda^2 \left\{ [\alpha^2+(1-\alpha)^2] D_1 + 2\alpha(1-\alpha) D_2 \right\}. \quad [6]$$

We now show that disease transmission due to direct exposure is minimized when all customers move in the same direction (see *SI Appendix 1* for proofs of propositions).

Proposition 2.1. *For any distribution of speed, disease transmission due to direct exposure is minimized when there is only one-way traffic* ($\alpha = 0$ *or* $\alpha = 1$) *and is maximized when two-way traffic is greatest* ($\alpha = 1/2$).

We will see below that for our base case parameters, direct transmission with full two-way traffic ($\alpha = 1/2$) can be more than three times greater than direct transmission when there is only one-way traffic.

If customer speeds are distributed uniformly between $\underline{p}$ and $\bar{p}$ (i.e., $f(p) = 1/(\bar{p}-\underline{p})$), using straightforward calculus it can be shown that

$$D_1 = 2L \frac{(\bar{p}+\underline{p})\ln(\bar{p}/\underline{p}) - 2(\bar{p}-\underline{p})}{(\bar{p}-\underline{p})^2}$$
$$D_2 = 2L \frac{\ln(\bar{p}/\underline{p})}{\bar{p}-\underline{p}}. \quad [7]$$

Note that direct exposure is proportional to the facility size, L. This is not surprising as, all else equal, the number of other customers one encounters is higher when the store has longer aisles. The variance in speed also has an impact on direct exposure:

Proposition 2.2. *For a uniform distribution of speed, if we hold the mean speed,* $(\underline{p}+\bar{p})/2$, *constant, the direct exposure increases as the spread* $\bar{p}-\underline{p}$ *around that mean increases.*

In general, the rate of direct transmission increases as the variation in speeds rises. It can easily be shown that in absence of variability in speed, one-way exposure tends to zero but not two-way exposure. As we mentioned in the Introduction, some stores dedicate certain hours for elderly customers to shop. This may limit their risk of infection by reducing their exposure to other demographic groups. Our results show that these dedicated hours may have an additional benefit. By reducing the variance in customer speeds, the store reduces the risk of direct exposure. Speed variance reduction is particularly effective when paired with one-way traffic but cannot eliminate exposure due to two-way traffic. Analysis of a two-point speed distribution with "slow" and "fast" customers produces the same results; see *SI Appendix 2*.

Analysis of Wake Transmission. Recall that the function $h(d)$ is the infection risk per unit time for a susceptible customer who is d distance behind an infectious customer. We can find the total rate at which customers are infected by wake exposure by using an approach similar to our direct exposure analysis above; e.g., examine the wake each time customers interact with each other. For example, it can be shown that the wake transmission rate experienced by a susceptible focal customer moving at speed q who is passed in the same direction by a faster infectious customer moving at speed p who arrived at time t is

$$\int_{pt/(p-q)}^{L/p+t} h((p-q)\tau - pt)\, d\tau. \quad [8]$$

The total transmission rate for this one type of interaction, then, is found by taking expectations across all possible t, p, and q. This approach, however, can become quite involved. In particular, the expressions must also take into account the fact that wake exposure occurs when customers do not directly pass each other.

There is, however, a simpler approach that calculates the transmission rates at each location in the retail area and then finds total transmission rates by accumulating exposure as susceptible customers travel. Specifically, consider a susceptible focal customer who arrives from the right with speed q and has reached time t in the customer's journey. Therefore, the customer is at location qt from the entrance. Consider the wake at that location left behind by an infectious customer going speed p who has previously traveled through that spot in the same direction. In fact, customer q will encounter the wake of any infectious "customer p" who has passed through that spot at time τ, $0 \le \tau \le (L-qt)/p$ earlier, and that infectious customer is $p\tau$ away from customer q. Define $W_{R1}(t,q)$ as the wake transmission rate experienced at time t by a susceptible customer with speed q who arrives on the right, due to infectious customers traveling in the same direction. Because infectious customer p arrives on the right at rate $\pi_i\alpha\lambda f(p)$,

$$W_{R1}(t,q) = \pi_i\alpha\lambda \int_{\underline{p}}^{\bar{p}} \int_0^{\frac{L-qt}{p}} h(p\tau) f(p)\, d\tau\, dp. \quad [9]$$

Now consider the wake transmission rate experienced by susceptible customer q due to infectious customers traveling in the opposite direction. Assume that customer q has time t remaining in the journey. Therefore, customer q's current position is $L-qt$ from the beginning of the aisle. Customer q will again encounter any virus left by an infectious customer traveling at speed p in the opposite direction who has passed that spot at any time τ, $0 \leq \tau \leq (L - qt)/p$ earlier, and that infectious customer is $p\tau$ away. Therefore, the wake transmission rate $W_{R2}(t, q)$ at time t for customer q who arrived on the right, due to customers going in the opposite direction, is identical to the expression for $W_{R1}(t, q)$ except that α is replaced with $1 - \alpha$ because customer q is encountering the wake of customers who arrive on the left.

As a consequence, the wake transmission rate at time t for customer q, who arrived on the right, is

$$\begin{aligned} W_R(t, q) &= W_{R1}(t, q) + W_{R2}(t, q) \\ &= \pi_i \lambda \int_{\underline{p}}^{\bar{p}} \int_0^{\frac{L-qt}{p}} h(p\tau) f(p)\, d\tau\, dp. \end{aligned} \quad [10]$$

Expression **10** also calculates the wake transmission rate for a susceptible customer q who arrives on the left rather than the right. Susceptible customer q arrives on the right and left at rate $(1 - \pi_n)\lambda f(q)$ and the duration of customer q's journey is L/q. Therefore, the total rate of COVID-19 transmission due to wake exposure is

$$(1 - \pi_n)\lambda \int_{\underline{p}}^{\bar{p}} \int_0^{L/q} W_R(t, q) f(q)\, dt\, dq = \pi_i (1 - \pi_n)\lambda^2 \times W \quad [11]$$

where

$$W = \int_{\underline{p}}^{\bar{p}} \int_0^{L/q} \int_{\underline{p}}^{\bar{p}} \int_0^{\frac{L-qt}{p}} h(p\tau) f(p) f(q)\, d\tau\, dp\, dt\, dq. \quad [12]$$

Note that the rate of transmission due to wake exposure is independent of α: The quantity of wake exposure is not affected by the proportion of customers who travel in either direction.

Proposition 2.3. *For any distribution of speed, wake exposure is independent of the traffic direction.*

Recall that in *Proposition 2.1*, we found that two-way traffic increases direct exposure, and therefore one might have thought that two-way traffic would also increase wake transmission, as there are more opportunities for customers to be close to each other (recall that $h(d)$ rises as d falls). The increased number of close interactions, however, is balanced by the increased speed of two-way interactions: When customers pass each other going in opposite directions, they spend less time close to each other and this reduces wake exposure. The two effects—increased interactions and increased speed—balance each other out.

Virologists (20) find that SARS-CoV-2 decays according to a negative exponential function and therefore as a baseline wake infection risk function we define $h(d) = k_0 e^{-k_1 d}$. Here, at a distance of $1/k_1$ (what we call wake length), the intensity of the wake function is a factor $e^{-1} = 0.37$ of the maximum intensity. The strength of the wake function is captured by k_0. If speed is distributed as a uniform random variable, then

$$W = \frac{k_0}{k_1^2}(Lk_1 + e^{-Lk_1} - 1)\frac{\ln(\bar{p}/\underline{p})^2}{(\bar{p} - \underline{p})^2}. \quad [13]$$

It is easy to see that the rate of transmission due to wake increases in the wake strength (k_0) and squared wake length ($1/k_1^2$). Interestingly, the facility size (L) does not play a direct role; wake transmission increases according to $n - 1 + \exp(-n)$, where $n = L/(1/k_1)$ is the "number of wakes" in the aisles. When that number is large, wake transmission is proportional to it. Now, we analyze the impact of spread in speed:

Proposition 2.4. *For a uniform distribution of speed, if we hold the mean speed, $(\underline{p} + \bar{p})/2$, constant, wake transmission increases as the spread $\bar{p} - \underline{p}$ around that mean increases.*

As was true for direct transmission, increased variability in customer speeds increases wake transmission. It is easy to see that, as for direct two-way transmission, even if we eliminate variability in speed, wake transmission remains positive. Therefore, restricting store hours for customers with similar behavior, such as elderly customers, reduces but does not eliminate wake transmission. Again, the same result is true for a two-point speed distribution with slow and fast customers.

Total and Individual Transmission Rate. From the retailer's perspective, the total transmission rate is the sum of direct and wake transmission: $\lambda^2 \times T$, where

$$T = \pi_i(1 - \pi_n)(c[\alpha^2 + (1 - \alpha)^2 D_1 + 2\alpha(1 - \alpha)D_2] + W). \quad [14]$$

Note that transmission due to both direct and wake exposure increases with λ^2, so that restricting throughput, and therefore the density of customers in the store, is an effective method to reduce transmission. We examine this approach in more detail in *Throughput Control*.

From an individual susceptible customer's perspective, transmission risk depends on that individual's speed of travel. Fig. 2 shows the probability that an individual customer is infected via direct transmission while traveling through the retail area. Fig. 2 shows how this probability varies as the speed of the customer varies. For this plot we set $\alpha = 1$ and customer speed is uniformly distributed, $p \sim U[6, 18]$ (other parameters are described in *Model Parameters and Sensitivity Analysis*). Traffic engineers call this plot a "Solomon curve" after Solomon (29) demonstrated that the probability of an accident has this shape as the speed of the focal car varies (30, 31). In ref. 32, the author points out that a driver (or, in our case, customer) who wants to minimize the number of accidents (probability of direct transmission) should travel at the median speed. Fig. 3 shows how for the same set of parameters, the probability of infection from wake exposure decreases in the focal customer's speed. This makes intuitive sense: The slower the customer,

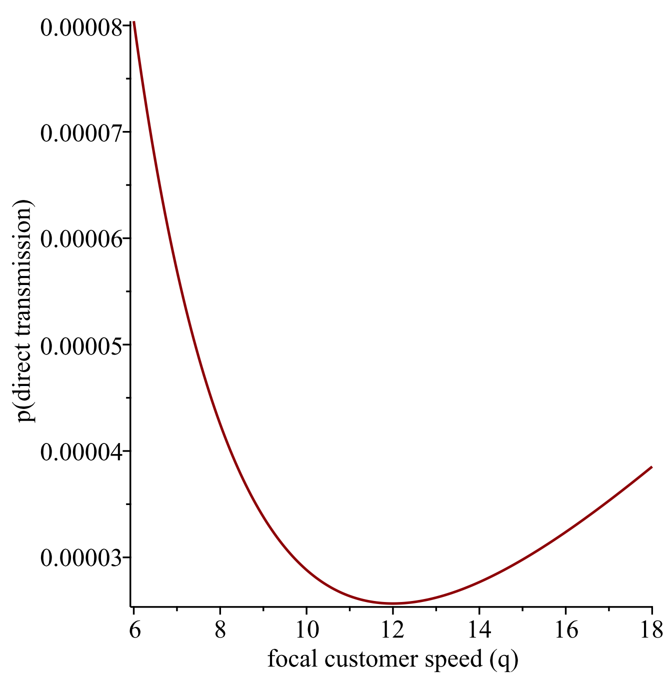

Fig. 2. Probability of infection due to direct exposure as speed q of the focal customer varies.

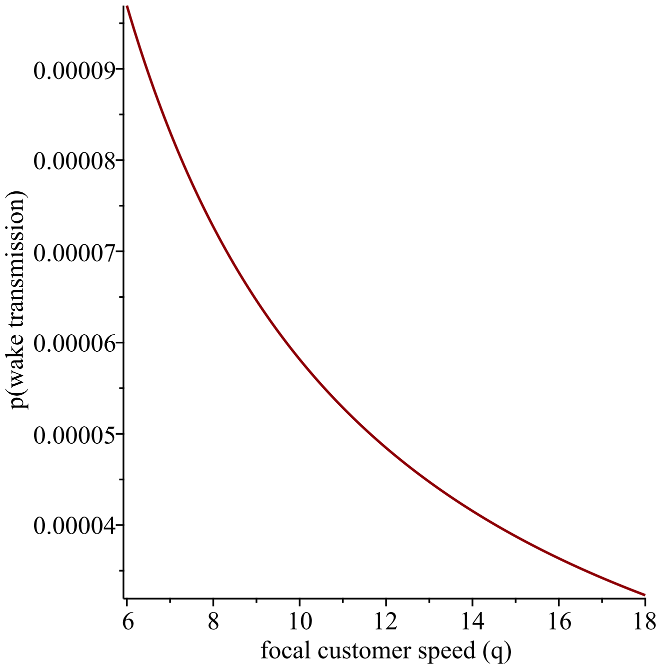

Fig. 3. Probability of infection due to wake exposure as speed q of the focal customer varies.

the longer the customer spends breathing in the wake of other customers.

Even though in our model the speed distribution F is exogenous, these results highlight how individual behavior may change, given the fear of contagion. If it is well known that direct transmission is the greater risk, then individuals may choose to walk closer to the median speed to avoid other customers. If customers know that wake transmission is dominant, some may choose to walk through the retail area as fast as possible.

Model Parameters and Sensitivity Analysis

In this section we determine parameters for the model, given our current understanding of retail customer flows and how COVID-19 is transmitted. Assuming that our store is a midsized supermarket, we use the following parameters:

- $L = 80$ m. Grocery store aisles can be up to 30 m long (33). Here we assume that our traffic area has a few commonly used aisles that customers visit in sequence, e.g., four aisles each 20 m long.
- $p \sim U[6, 18]$. Ref. 34 identified three categories of grocery shoppers based on their speed of movement through a store (table 1.1 in ref. 34). Sorensen's slowest, middle, and fastest categories move at average speeds of 9.5, 12, and 18 m/min, respectively. We first assume that customer speed is distributed as a uniform random variable from $\underline{p} = 6$ to $\bar{p} = 18$. This implies that a customer moving at the average speed $p_a = 12$ m/min spends 6.6 min in our area of the store. Below we vary the width of this distribution.*
- $\lambda = 2.23$ customers per minute. To obtain a base case value of λ, we observed traffic within a midsized grocery store during evening peak hours. Specifically, we collected data on the movement through four adjacent aisles of pasta, canned goods, cereal, and baking supplies. During the peak hour, customers arrived to the area at the rate 2.23 customers per minute.
- $\alpha = 0.7$. The midsized grocery store had signage and floor stickers to encourage one-way traffic within each aisle. During the peak evening hour, 70% of customers complied.
- $\pi_i = 0.006$. The parameter π_i represents the percentage of retail customers who are infectious at one point in time. As the pandemic waxes and wanes, this number can vary over time. We will assume that the general population is in the midst of a significant outbreak. Ref. 22 found that 2.6% of the population of an Italian town tested positive for the virus at the beginning of a lockdown, while 1.2% tested positive at the end. Ref. 23 found that 1.7% of a random sample of Indiana residents had an active infection in late April 2020. A multicenter study of asymptomatic surgical patients during a quarantine period in The Netherlands found a point prevalence of 1.5% (35). We assume that the overall prevalence of infection in the local population is 1% but that the proportion of infectious customers in a retail store is lower because symptomatic people are less likely to visit the store and asymptomatic people may be less infectious. Based on parameter estimates in ref. 36, we multiply the overall population prevalence by 60%.
- $\pi_n = 0.03$. The Centers for Disease Control and Prevention (24) collect data from ongoing seroprevalence studies that estimate the proportion of the population that was infected with SARS-CoV-2. Estimates span a wide range, from 1 to 23% in some parts of New York City, although there is a significant cluster around 3%. A seroprevalence study of grocery store customers throughout New York State from late March to April 2020 found rates of exposure from 3.6 to 22.7% (37). A cross-sectional study throughout the United States from July to September found wide variation in exposure, from less than 1% to 23% (38). Note, however, that there is still some uncertainty over the extent to which exposure to the virus provides immunity (39).
- $c = 0.001$. The probability of COVID-19 transmission due to direct contact between infectious and susceptible customers is equivalent to the secondary attack rate in the epidemiological literature. Secondary attack rates are usually estimated via contact tracing. Ref. 25 cites a range of 0.7 to 16.3% for this rate, with the higher values for contacts within households. The value in a particular retail store will depend on many factors. As Bazant and Bush write in ref. 40, p. 1, transmission risk "depends on the rates of ventilation and air filtration, dimensions of the room, breathing rate, respiratory activity and face-mask use of its occupants, and infectiousness of the respiratory aerosols." To be conservative we use $c = 0.001$, and the overall transmission rate for our model is linear with respect to c so that the following results can be linearly adjusted up or down for different estimates of c. We also conduct sensitivity analysis, below, to examine how c interacts with another highly uncertain parameter, π_i.
- $k_1 = 1.15$. Ref. 27 suggests a maximum transmission distance of 4 m due to aerosols. We interpret this to imply that aerosol risk drops by 99% when moving from 0 to 4 m away from another person. Therefore,

$$\frac{h(4)}{h(0)} = e^{-4k_1} = 0.01. \qquad [15]$$

Solving this equation gives us $k_1 = 1.15$, and the wake length $1/k_1 = 0.87$ m.

The remaining parameter to define is k_0, which governs the rate of wake transmission. Rather than setting k_0 directly, we

*Numerical experiments using an asymmetric triangular distribution that more closely corresponds to Sorensen's distribution (utilizing Monte Carlo integration to evaluate the model) produce similar results.

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work with a more intuitive parameter that has a one-to-one correspondence with k_0. Imagine that you are a susceptible customer and you are walking down an aisle of infinite length at speed p_a and you pass an infectious customer going in the opposite direction, also walking at speed p_a. You risk direct transmission from that customer the moment you pass, and you risk wake transmission as you walk behind the customer. We define the parameter r as the ratio of the wake and direct transmission probabilities in this scenario:

$$r = \frac{\int_0^\infty h(2p_a\tau)\,d\tau}{c} = \frac{k_0}{2ck_1p_a}. \quad [16]$$

Therefore, $k_0 = 2ck_1p_ar$. Given that $c = 0.01$, $k_1 = 1.15$, and $p_a = 12$, choosing r determines k_0. For our base case we set $r = 0.25$ (and therefore $k_0 = 0.069$); the risk of wake transmission in this scenario is 25% of the risk of direct transmission. Given the difficulty quantifying the relative importance of droplet vs. aerosol exposure, we examine results for $0 \le r \le 2$.

We could now use our model to calculate the rate of transmission per minute in one area of the store. A more intuitive and useful output, however, is the rate of infections transmitted per day within the entire store. Therefore, we scale up our model with the following parameters:

- The parameter λ described above is the peak arrival rate. Following the customer volume patterns shown in figure 5 of ref. 41, we assume a linear increase in the arrival rate from the store's opening at 6 AM until the peak at 6 PM, followed by a linear decline until the store closes at midnight.
- Our model focuses on one area of the store, which takes on average 6.6 min to traverse. According to ref. 42, the average time spent in a Safeway, a similar midsized grocery, is 18.1 min. Therefore, we assume that an average store consists of $18.1/6.6 = 2.7$ similar areas, and we multiply the results from the model by 2.7.[†]

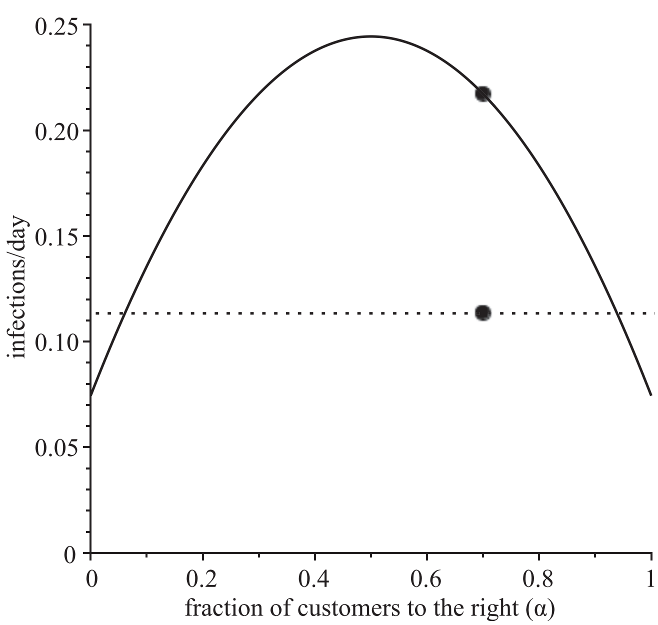

Fig. 4. Direct and wake transmission rates as the proportion of one-way traffic (α) varies.

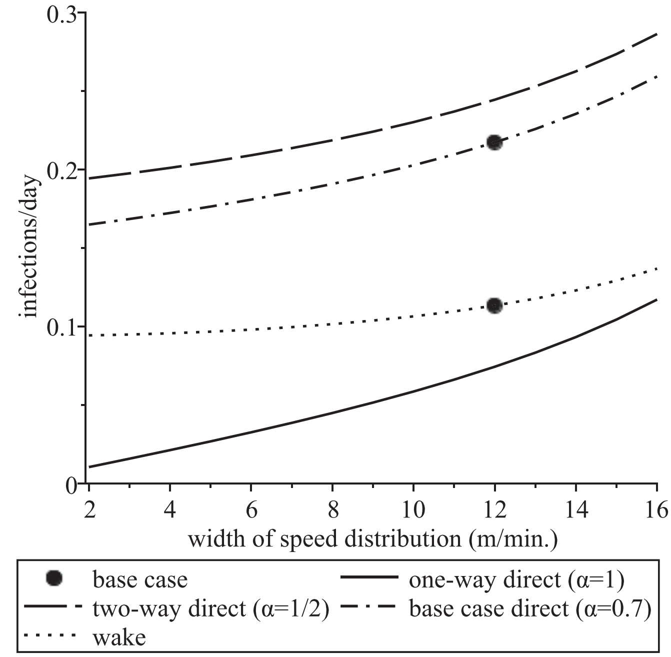

Fig. 5. Direct and wake transmission rates as the variation in speed increases.

With these base case values, we find that among all customers in the store there are 369 direct encounters per day between susceptible and infectious customers. The overall transmission rate due to both direct and wake exposure is 0.33 infections per day. Fig. 4 shows how the transmission rate varies with the proportion of one-way movement. With strict one-way traffic ($\alpha = 0$ or $\alpha = 1$), there are just 0.074 infections per day due to direct exposure, and this increases by more than three times, to 0.24/d, for two-way traffic ($\alpha = 0.5$). Thus, one-way flow reduces direct transmission by 70%. In the supermarket we observed, partial compliance with traffic signage did help a bit: With $\alpha = 0.7$, direct transmission is 11% lower than it would be with $\alpha = 0.5$.

It is useful to compare these transmission rates with the rates estimated in ref. 5, who use mobility data collected from early March to early May to estimate the rate of COVID-19 transmission at selected "points of interest." In their Exhibit 3e, we see a range in transmission rates for grocery stores from 0.15/h to 0.45/h. Our base case model produces a significantly lower transmission rate of (0.33/d)/(18 h/d) = 0.018/h. The data for ref. 5 were collected before mask wearing was widespread, and we believe that our lower rate reflects current conditions. In addition, note that the relative impact of operational interventions such as directing flow (one-way vs. two-way), or placing limitations on flow, does not depend on the specific values of the infection and transmission parameters π_n, π_i, and c.

Fig. 5 shows how both direct and wake transmissions increase as variation in speed increases while the mean speed p_a remains 12 m/min. On the left-hand side of Fig. 5, customer speed is

[†]Rather than modeling the store as many separate areas, we might model it as a single, longer area. These two options, however, produce virtually the same results. The direct transmission rate is linear in L (see the expressions for $D1$ and $D2$), and the wake transmission rate is almost linear in L (see the expression for W). Therefore, a store with 2.7 areas each of length L has almost the same transmission rate as a retailer with one area of length $2.7L$.

distributed as $p \sim U[11, 13]$, and on the right-hand side $p \sim U[4, 20]$. The rates of direct transmission given the base case, one-way and two-way traffic, increase relatively rapidly with increases in speed variation, compared to the increase in wake transmission. This highlights the value of reducing speed variance, particularly with one-way traffic. As mentioned above, retailers could allocate specific hours for similar shoppers. Managers may also want to design areas for shopping at different paces: one region for fast shopping for staples, another for preprepared baskets of goods, and a third for slower browsing. The general idea is to separate customers into groups who move at similar speeds.

Recall that the parameter r represents the relative risk of wake vs. direct exposure. For our base case we assume $r = 0.25$. The overall rate of wake transmission is linear in r, and Fig. 6 shows that for higher values of r (say, 200%) wake transmission can dominate direct transmission. The practical implication is that if aerosols are the primary contributors to disease spread, then retailers should focus on improving mitigation strategies such as better ventilation rather than directing traffic flow.

Two of the base case parameters described above are particularly uncertain. The rate of infectious customers π_i varies with local conditions, and the probability of transmission c depends on mask usage and store ventilation. Fig. 7 shows how the transmission rate varies with these two parameters. Each has a linear effect, but the two are multiplicative. For example, if $c = 0.002$ rather than the base case value of 0.001, and $\pi_i = 0.02$ rather than 0.006, there would be on average 2.2 infections per day rather than 0.33/d.

One early response to the pandemic by grocery stores was to reduce hours of operation to limit panic purchasing (43). Our model demonstrates how this can be counterproductive. As we adjust the number of hours a store is open, we assume that both the overall number of customers and the arrival pattern (with a peak at 6 PM) remain constant. Fig. 8 shows that reducing hours from a 24-h day to a 12-h day can nearly double the number of infections, as shorter store hours increase customer density.

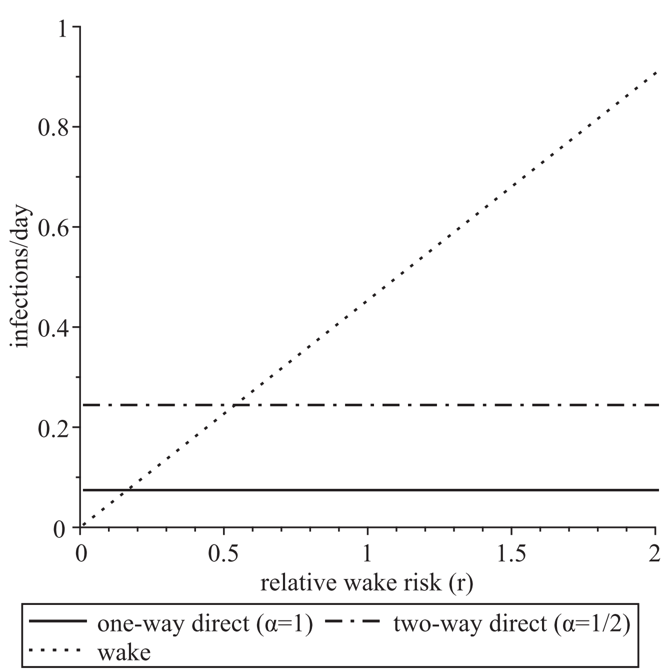

Fig. 6. Direct and wake transmission rates as the relative risk of wake exposure rises.

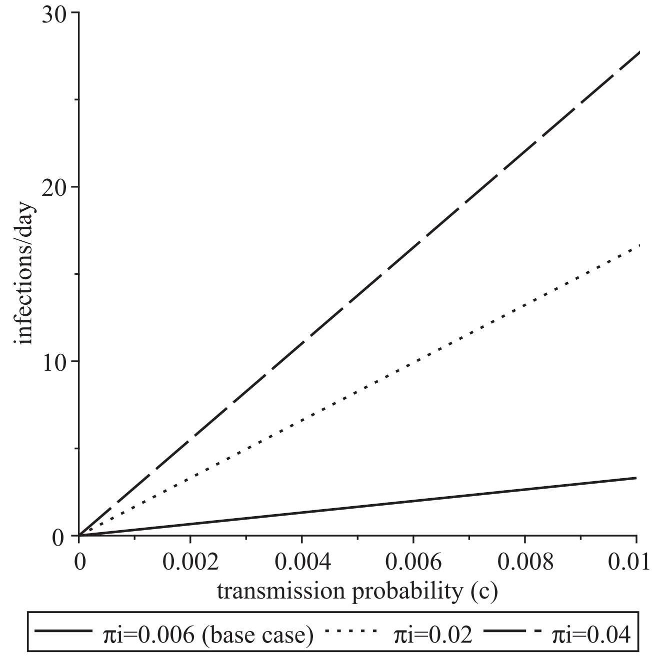

Fig. 7. Impact of π_i and c on daily transmission rates.

Finally, this analytical model of transmission predicts the expected number of infections per day, but does not capture variability around this average. To explore this variability we created a discrete event simulation of customers traversing the retail area (details in *SI Appendix 3*). Given a simulation with the base case parameters, the average infection rate clustered around 0.33/d, as expected. In one set of simulations we assume that all infectious customers have a probability of transmission $c = 0.001$. In that case, 73% of all days have no infections, 21% have one infection, and the maximum number infected in 1 d is usually four customers. We also ran a "superspreader" simulation, in which 1% of infectious customers have a 10% chance of transmitting the virus when in close proximity with a susceptible customer, while all other infected customers do not transmit the virus at all (producing an overall $c = (0.01)(0.1) = 0.001$). Again, the average infection rate is 0.33/d, but 85% of days have no infections, while there are rare days with larger numbers of infections, e.g., 1 d with seven infections. In general, the simulation demonstrates that more variation in the infectiousness of customers increases the clumping of cases, even as the average number of cases remains the same.

Throughput Control

To help customers maintain social distancing many retailers are limiting the number of customers who enter stores. Many state regulators are also attempting to balance the financial health of retail stores (and their tax base) with public health concerns by specifying reduced occupancy limits. For example, ref. 44 describes maximum retail densities implemented in April in North Carolina.

To comply with these limits, some stores use work in process (WIP) control, placing a cap on the number of people in the store (45), while others control throughput, e.g., by using reservation systems (46). Here we examine a throughput control system, allowing us to explore the trade-off between retail sales and the risk of exposing customers to COVID-19. Assume customers arrive according to a Poisson process with rate Λ customers per minute. We consider randomized access control in which only a fraction of the arriving customers are admitted to the area.

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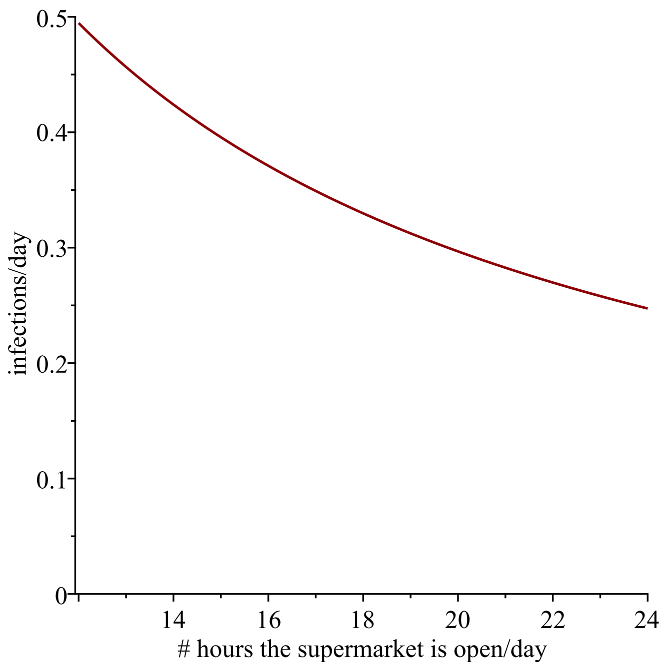

Fig. 8. Daily transmission falls as store extends hours.

We introduce two new parameters that allow us to examine the trade-offs. We assume that the average gross profit per customer who passes through the retail area is v and that there is a cost m per customer who is newly infected in the retail area (we do not penalize the retailer for existing infections). If the decision maker is the retailer, the parameter m may be an indirect cost, e.g., reputational risk if infection occurs in the store. If the decision maker is a social planner or regulator who is balancing the viability of the store with public health concerns, parameter m may take into account the costs of infection in health care resources, illness, and mortality. Therefore, the objective is

$$\max_{0\leq\lambda\leq\Lambda} \; v\lambda - m\times\lambda^2\times T. \qquad [17]$$

Assuming an interior solution the optimal throughput rate is

$$\frac{1}{2}\frac{v/m}{T} \qquad [18]$$

and the corresponding optimal profits are

$$\frac{1}{4}\frac{v^2/m}{T}. \qquad [19]$$

Clearly the higher the profit is, the higher the optimal throughput; the higher the cost of infection is, the lower the throughput. Fig. 9 shows how the optimal throughput rate varies as the fraction of infectious COVID-19 customers varies from 0 to 2%. To generate Fig. 9 we use the base case parameters, and we take the perspective of a regulator with a ratio of profit to infection cost of $v/m = 0.001$. Fig. 9 shows that the optimal throughput is sensitive to the disease prevalence. Given the base case of the midsized grocery store described above, the throughput $\lambda = 2.23$ customers per minute is optimal when prevalence is 0.007. When prevalence has risen above 1%, the optimal throughput has dropped significantly below the base case throughput. Fig. 9 also shows how the use of one-way movement to reduce contagion can increase the optimal throughput. The benefits of this intervention are greater for retailers with high margins and, somewhat surprisingly, greater in areas with lower spread of the virus.

Conclusions

By integrating knowledge about virology, epidemiology, and the physical flow of customers in retail stores, we develop and analyze a model that connects the biology of COVID-19 with operational interventions to reduce the spread of the disease. The model calculates the disease transmission rate in a retail environment and determines how the rate depends on the customer flow policy (one-way versus two-way), the travel speed distribution, and store size. We find that one-way restrictions are useful for reducing direct transmission but have no effect on wake transmission. Eliminating speed variability can reduce or even eliminate direct transmission when traffic is one-way but can only reduce (but not eliminate) transmission in two-way traffic. Finally, we show that the optimal admission rate to a store falls as the disease prevalence rises and the ratio of profit to infection cost falls.

We also calibrate our model using published epidemiological data. For a medium-sized retailer in an area with a relatively high prevalence of COVID-19, our model predicts a total transmission rate (via direct and wake exposure) of 0.33 infections per day. Complete customer compliance with one-way flow reduces the direct transmission rate by 70%, while the partial compliance observed in one store reduces the transmission rate by 11%. We also compare the impact of direct and wake transmission by first defining a ratio between the wake and direct transmission probabilities for a single encounter between an infectious and a susceptible customer. Given two-way traffic, if this ratio is 200% or more, then wake exposure dominates direct exposure in its contribution to virus transmission. When retailers can control customer throughput, the optimal throughput drops significantly as COVID-19 prevalence increases up to 1%. Because estimates of some parameters vary substantially from region to region and will change over time, we conduct sensitivity analysis to assess the robustness of our findings.

Now we discuss some of our modeling assumptions and possible extensions. In the model of customer flow, we ignore variation in both the speed and path of each customer, e.g., stopping to examine and pick products off shelves. Adding this additional variability would increase the number of customer

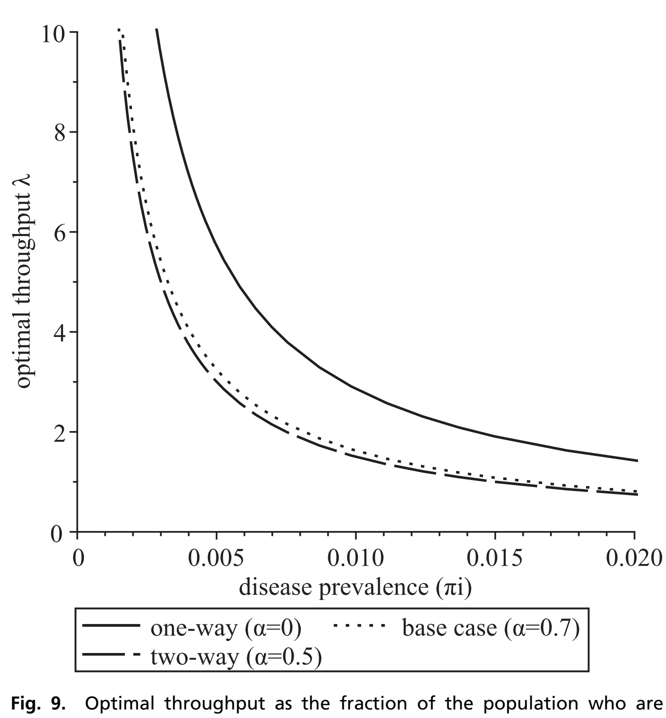

Fig. 9. Optimal throughput as the fraction of the population who are contagious varies.

interactions and direct exposure, although quantifying its impact and understanding the impact on wake exposure would require a more complex analytical model and/or simulation. We also assume Poisson arrivals, a reasonable assumption during short periods in many retail areas, but not a reasonable assumption in other contexts such as school hallways, where a fluid model may be more appropriate.

In addition, we assume that wake exposure ends as soon as an infectious customer leaves the area. This is a simplification, for infectious aerosols may remain in the air after customers depart (20). If the area is large, however, and if customers spend a significant amount of time on their journey, then the impact of edge effects when customers leave the area is small. For the numerical experiments described above, these edge effects are not significant.

Our model focuses on customer movement through store aisles and ignores interactions among customers and employees. Front-line workers for essential retailers, in particular, can face a high risk of exposure (47). Cashiers, for example, face both direct and wake exposure in checkout areas. Many stores now enforce social distancing standards around these areas and provide guidance such as floor stickers to indicate spacing between customers. While this can nearly eliminate direct exposure, wake exposure would be a concern around checkout areas. Incorporating a queuing model that includes customer movement and airflow may be a useful extension.

The specific infection rates predicted by our model depend upon many environmental variables, including ventilation systems and the proportion of customers who use masks. Given this uncertainty, the model highlights where gaps in the scientific knowledge of COVID-19 transmission need to be filled so that we may redesign service operations to reduce spread. In particular, the effectiveness of these interventions is highly dependent on whether the virus is transmitted through heavy droplets or aerosols. In addition, the model may be adapted to analyze COVID-19 transmission in other service settings such as restaurants, airplanes (supplement to ref. 48), and hotels in which customer flow can be regulated.

Data Availability. All data are available in this article and *SI Appendix*. Code is publicly available at https://doi.org/10.5281/zenodo.4427097.

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