THE BACKWARD ART OF SLOWING THE SPREAD?
CONGREGATION EFFICIENCIES DURING COVID-19

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ABSTRACT

Were workers more likely to be infected by COVID-19 in their workplace, or outside it? Although both economic models of the pandemic and public health policy recommendations often presume that the workplace is less safe, economic theory predicts that group cooperation significantly increases the per capita demand for public goods. Disease prevention may also have scale economies in supply. The available data from schools, hospitals, nursing homes, warehouses, grocery stores, food processing plants, hair stylists, and airlines – covering more than a million employees and students – show employers adopting mitigation protocols in the spring of 2020. Coincident with the adoption, infection rates in workplaces typically dropped from well above household rates to well below. When this occurs, the sign of the disease externality from participating in large organizations changes from negative to positive, even while individuals continue to have an incentive to avoid large organizations due to the prevention costs they impose on members. Rational cooperative prevention sometimes results in infectious-disease patterns that are opposite of predictions from classical epidemiology.

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I.   Introduction

The spread of COVID-19 in the United States has prompted extraordinary, although often untested, steps by individuals and institutions to limit infections.   Schools, restaurants, entertainment venues, and many other places of business were required to close under the compelling theory that infectious diseases spread more quickly when people congregate.   More than a year into the pandemic, public officials were still advising their populations to "stay home" and paid unprecedented unemployment benefits in part to encourage home over work even for healthy persons.[1]   However, for centuries many accomplishments were achieved by leaving home to work and learn in teams.   As Wesley Mitchell (1912) put it, "the business enterprise … made possible more elaborate specialization and machinery, more perfect coordination of effort and greater reduction of waste than could be attained by the family."   Is home also the wrong place to slow the spread?   The purpose of this paper is to assess the relationship between group size and private efforts to avoid infections.

An emphasis on private incentives and prevention behaviors is the hallmark of economic epidemiology (Philipson & Posner, 1993; Kremer, 1996; Geoffard & Philipson, 1997; Gersovitz, 1999; Gersovitz & Hammer, 2004; Philipson T. J., 2008), as distinct from classic epidemiology models of infectious disease.   Economic epidemiology contrasts individual incentives with social returns and examines how they interact with disease prevalence, but so far without much discussion of how individuals seeking protection might cooperate on scales smaller than the entire polity.   Disease prevention is an industry whose organization is a topic especially suitable to economic analysis, including strong quantitative predictions that derive from the public-good element of infectious-disease prevention.

Economics more generally provides many results regarding voluntary associations, such as the theories of the firm from Viner (1932), Coase (1937) and Alchian and Demsetz (1972);

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[1] In April 2021, the Canadian province of Ontario was under a stay-at-home order (Office of the Premier of Ontario 2021). The essential assumption that staying at home slows the spread is featured in many economic models of the pandemic, including Greenstone and Nigam (2020), Eichenbaum, Rebelo and Trabandt (2020), Kapicka and Rupert (2020) and Birinci, et al. (2021).

theories of local-externality management ("clubs") such as Buchanan and Tullock (1962) and Buchanan (1965); and cooperative game theory in general (Shapley, 1953; Telser, 1994). People voluntarily join groups outside their household, despite travel costs and other constraints a group imposes on its members, in part because they value the group's management of local externalities and public goods.[2] Even though an infectious disease would spread more rapidly in congregations of people who prevent the same way they do in households, the groups may be enough more productive at prevention that the disease spreads more rapidly at home where there are fewer people.

Section II of this paper extends the Viner framework to describe determinants of group size, prevention efforts, and their correlation with infection rates. It assumes that, absent costly prevention activities, larger groups naturally have more infections per member. However, prevention demand per member tends to increase with group size, even if transmission risk were the same, to the extent that members of larger groups cooperate and have a greater fraction of their interactions that are internal to the group. Over some range, larger organizations also have greater supply of prevention due to scale economies in production. These large-group incentives to engage in costly prevention measures may be enough to reverse the natural infection-size gradient. Nevertheless, individuals may shift their time allocation away from large groups with low equilibrium infection rates toward smaller groups (such as families) with higher rates because doing so avoids costs of prevention. In this case, "staying home" may have a negative externality especially when community prevalence is high.

A widely-reported study of COVID-19 hospitalizations in New York in early May 2020 found that 66 percent were patients who had been sheltering at home (Fink, 2020). Although it was a first clue that staying at home might not be safer, the finding can also be explained by a correlation between staying at home and the harm from infection or by an especially high fraction of New Yorkers who stayed at home.[3] Sections III presents a measurement framework that distinguishes between marginal and average infection rates, helping to organize the various

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[2] One of the group's management techniques may be to price local elements of the externality, in which case it may more properly be called a "priced spillover."

[3] Bayes' Rule reveals that most of the hospitalized could have sheltered at home even while the relative risk of hospitalization is less among those sheltering at home. If those sheltering at home had the same propensity to be hospitalized conditional on infection, then the relative risk of being infected for those sheltering at home would be essentially $\frac{66}{100-66}\frac{100-s}{s}$ where s is the percentage of New Yorkers who sheltered at home.

academic studies that offer estimates of the latter and to relate the estimates to time allocation issues. Together Sections II and III embrace two key disease-transmission premises of the stay-at-home orders: people should not change locations and that large groups are more infections at given levels of prevention.

However, neither prevention effort nor prevention results are constant. Using original place-specific estimates of COVID-19 prevalence and transmission as well as estimates from the published literature, Section IV shows how businesses and other large organizations implemented and enforced prevention measures ranging from mask wearing to improved ventilation to testing. Coincident with those measures, per-capita transmission rates on site fell dramatically, usually to levels below household transmission. Section V reviews additional types of statistical evidence that permit comparisons of COVID-19 transmission in households, schools, and various types of businesses. Section VI concludes.

II.   Economies and Diseconomies of Scale: Theory

Before the pandemic, the economy consisted of many voluntary organizations of various sizes n and types of interpersonal interactions. The organizations include employers, large-group consumption activities such as concerts and sporting events, and households. They possess organizational capital that helps members relate to each other and enjoy the local public goods produced by the organization, group, or firm, which are terms hereafter used interchangeably. The model that follows addresses the question of which organizations will, in addition to their normal operations, provide infection-prevention services to their members while they are engaged with the organization.[4] It predicts that the privately-rational prevention activities of organizations may reverse their epidemiology fundamentals, with larger organizations that might be more dangerous absent prevention ending up safer because of scale economies in prevention activities. A wide range of organizations may ultimately have infection rates below those of the smallest organizations, such as households.

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[4] The model does not address the formation of new organizations, which may be especially important when infections are a serious concern over a long period of time.

I then turn to time allocation from an individual perspective. In the model, stay-at-home orders are partly redundant to individual incentives even though, under testable conditions described below, the orders may increase aggregate infections. The model reveals quantitative relationships between the marginal effect of time allocation on infection rates, which is relevant for decision making, and the average number of infections per unit time that is more readily measured.

II.A. Prevention by an Organization

The presence of an infectious disease adds infection and prevention costs to the costs of the organization's normal activities. I assume that the infection costs are proportional to the number of people infected, which itself is proportional to the number pairwise interactions involving a group member. Absent prevention activities, which may involve reductions in the number of interactions, the actual number of pairwise interactions in a firm sized n is $nf(n)$. For example, if the n members interacted only with other members and engaged in all such pairwise interactions, then $nf(n)$ would be the familiar pairwise combination formula $(n-1)n/2$. Because some of the potential pairwise interactions may not occur, especially in large firms, I assume that f is increasing and concave.

An organization's decisions are based on costs experienced by its members, as distinct from costs experienced by non-member counterparties to interactions involving at least one of the organization's members.[5] The fraction $s(n)$ of counterparties that are members tends to increase with the size of the organization. That fraction ranges from one half at $n = 1$ to one for an organization in which the entire population is a member.

Absent any protection by the organization, the per-member infection costs would be $vs(n)f(n)$, hereafter "baseline infection costs," where v converts pairwise interactions into health costs (via infections). The relationship between organization size n and baseline costs is shown in Figure 1 as the upper dotted curve. The parameter $v > 0$ reflects infection rates per interaction (related to, among other things, disease prevalence in the community), infection fatality rates, and the value of life. Industries may differ in infection rates with, for example, meat-packing businesses and indoor choirs having especially high rates because infections are easily

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[5] See also Leeson and Rouanet's (2021) distinction between "on-site" transmission and "cross-site externalities."

transmitted during their normal activities. Other industries, such as hospitals, may have high baseline infection rates even without high transmission rates because infections are especially likely to come into the workplace with patients. Still other industries, such as nursing homes, have high v values because (among other things) each infection imposes a greater health cost. For brevity, I often refer to v as the "disease-severity" parameter.

Figure 1. Equilibrium Prevention and Organization Size
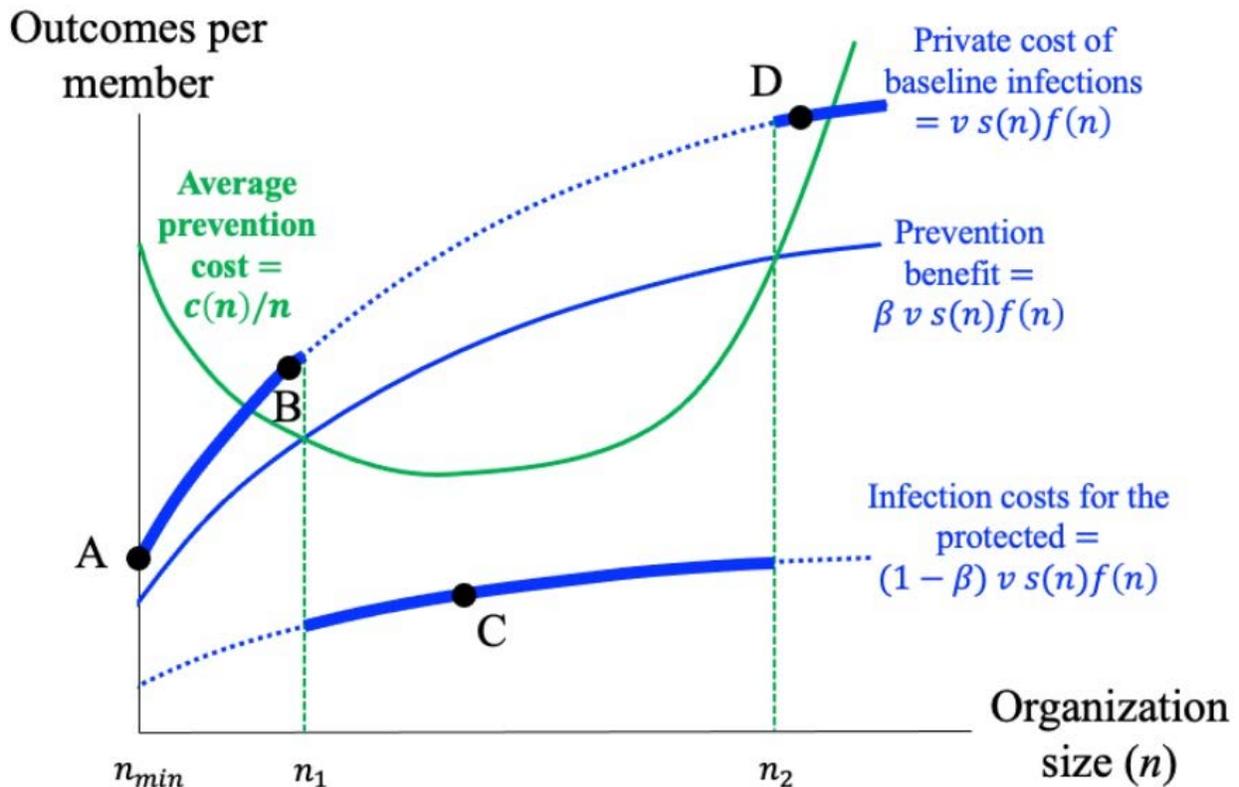
Figure 1 illustrates the choice to make an organization-wide prevention effort with cost $c(n)$ that reduces infection costs from $vs(n)f(n)$ to $(1-\beta)vs(n)f(n)$, which is the lower dotted curve in the figure. One of the prevention activities may be to reduce the number of pairwise interactions, for example, by maintaining members in cohorts or reducing the number of workers on site. The resulting pairwise interactions are, in my notation, reflected in the product

$(1-\beta)f(n)$; I interpret n as the pre-pandemic organization size. I assume that $c(n)$ increases with group size because at least some of the prevention efforts have a per-member element, such as the nuisance of wearing masks or being subjected to quarantine.

The prevention costs include interruptions of, and resource allocation away from, the group's normal operations. The costs also include inconveniences experienced by members as they participate in group activities that involve prevention protocols. Organizational capital accumulated by the group prior to the pandemic may be reflected in values of $c(n)$ that are lower than they would be without that capital. As an example, organizations may have cultivated a degree of group loyalty. Especially when group membership is voluntary, loyal members are willing to incur some personal costs when they expect a corresponding benefit to accrue to the other members or the group as a whole. In this case, $c(n)$ reflects the organization's costs net of the value that members place on making a contribution to the organization. My notation $c(n)$ emphasizes the relationship between prevention costs and organization size n, discussed further below.

II.B. Economies and diseconomies of scale

The cost function $c(n)$ reflects potentially important economies of scale in prevention. Large organizations can gather larger statistical samples, which are critical when the condition being prevented is prevalent in only a small fraction of the population. A COVID-19 infection entered a household of three an average of less than once per year, which makes it impossible for a household to infer (before the pandemic is over) from its data alone whether its prevention efforts are effective.[6] Organizations could pool data, but the organizations might not have common measurement instruments or infection rates. Understanding and trusting data from outside sources, or using theory to extrapolate from prior pandemics, are themselves fixed costs.

A reluctance to use, or a prohibition from using, markets also disadvantages small organizations because normally the market is the primary mechanism that the owner of a specialized skill services multiple organizations and households. Take the large organization University of Illinois, which developed its own rapid COVID-19 testing operation far beyond the

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[6] Throughout the pandemic, daily confirmed cases per person in the U.S. were always less than 1/1000 and often less than 1/5000.

capabilities of any one household (Deliso & Bhatt, 2020). Law prohibited the university from selling testing services in the marketplace until authorized by the U.S. Food and Drug Administration, which was not obtained (and then only on an emergency basis) until February 24, 2021 (Food and Drug Administration, 2021). By that point, the university had been using the test within its organization for almost eight months (Cherney, 2020).

Monitoring compliance with organization rules is an important part of managing local externalities and local public goods. Any prevention effort at the individual level has a benefit for the other employees that differs from the individual benefit unless the individual is monitored and faced with reward or punishment.[7] Monitoring has elements of economies of scale, such as designating specialists to do the monitoring and administer the rewards and punishments. It can help for members to perform their activities in line of sight of each other, which is an economy of scale at small group sizes but a diseconomy at large sizes. In other words, the scale of a firm may not only facilitate the discovery of new prevention methods as with the University of Illinois but also monitoring the use of well-known prevention techniques. The household sector is at a particular disadvantage with monitoring (across households) because privacy is one of the important goods produced by households in free societies.

For these reasons, and in parallel with modeling costs of an organization's normal operations (Viner, 1932), I assume that average prevention cost $c(n)/n$ slopes down with n at smaller values of n, as illustrated by Figure 1's green curve. Figure 1 also allows that average cost slopes up at higher values, although that assumption is not needed for many of the results in this paper. Arguably the rising marginal costs that create the u-shape average prevention cost have some relation with the rising marginal costs for the organization's normal operations, so that industries that normally have large organizations would have their average prevention costs turn up further to the right than in other industries.

II.C. Rational behavior may invert epidemiology fundamentals

An organization of size n facing a disease with severity v has a discrete choice $\min\{vns(n)f(n), (1-\beta)vns(n)f(n) + c(n)\}$. Even if average and marginal prevention costs

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[7] The monitoring may be probabilistic (Becker 1968, Becker and Stigler 1974). In firms such has hospitals that value a reputation for safety, disease prevention efforts by individual employees (recall that I use employees broadly to include customers) also benefit the owners of the firm.

were constant – a horizontal green curve in Figure 1 – firm size would still play a role in prevention decisions because the prevention benefit curve $\beta vs(n)f(n)$ slopes up with n. One reason is that each member of a larger organization is engaged in more interactions ($f'(n) > 0$). Second, a larger group internalizes a greater fraction of the infection costs created when one of its members passes on his infection ($s'(n) > 0$). In other words, group activity may not only enhance the supply of prevention as represented by $c(n)$ but also increase demand because a cooperative group's demand for any member's prevention exceeds that member's demand for his own prevention.[8]

The organizations voluntarily engaging in prevention efforts are sized between n_1 and n_2 as indicated in Figure 1 where average prevention cost is no more than the average prevention benefit. The equilibrium infection rate is proportional to the (disjointed) thick blue curve. The curve slopes up among the smaller organizations for which average prevention costs are too high, from the organization's perspective, to justify prevention. At size n_1, the equilibrium infection rate jumps down. The infection rate for the organization at C is below the rates for those at A and B, even though A and B have fewer pairwise interactions per group member and therefore more favorable epidemiology fundamentals than C does. In this range, privately rational prevention efforts more than offset the epidemiology fundamentals, rendering C the safest of the three.

At the same time, the pandemic harms C more than it harms A and B because C is the only one of the three paying the prevention cost $c(n)$. Members of A and B are not necessarily tempted to join group C, despite C's being the safest of the three.[9] A hospital with COVID patients may prove to be safer for healthcare workers than the wider community is, but nevertheless be a costly place to work because of unpleasant or disruptive prevention protocols. Using A, B, C subscripts to denote the groups, the private cost comparisons are:

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[8] To the extent that low disease prevalence is a public good, this second effect is related to Samuelson's (1954) conclusion that larger groups have a larger marginal benefit from public goods. This is also why Lindsay and Dougan (2013) conclude that the private provision of public goods increases with group size.

[9] To the extent that prevention has more scale economies than normal operations, individuals may wish that they had formed larger groups before the pandemic.

$$(1-\beta)vs(n_C)f(n_C) < vs(n_A)f(n_A) < vs(n_B)f(n_B) < (1-\beta)vs(n_B)f(n_B) + \frac{c(n_B)}{n_B}$$

$$< (1-\beta)vs(n_C)f(n_C) + \frac{c(n_C)}{n_C} < vs(n_C)f(n_C)$$

(1)

The final inequality says that group C prefers prevention to none. The second- and third-to-last inequalities in (1) show that (i) C is harmed by the pandemic more than B is and (ii) B prefers not to engage in the prevention activity. The first two inequalities show that C is the safest of the three.

Little of C's harm is a health harm, which is relevant for predicting how an infectious disease will spread. Members of small groups may have too little incentive to participate in larger groups – and larger groups too little incentive to attract such individuals – because the larger groups are engaged in costly prevention that also benefits the broader population.[10] If the outside-organization externality from infections is great enough, Group C membership is socially preferred to Group B membership even though the private costs of the former are greater than the costs of the latter, as shown by the second- and third-to-last inequalities in (1).

In drawing Figure 1, I have ruled out solitary confinement where baseline infections would be zero. This assumption is reflected in that, according to the figure, the prevention activities (masks, temperature checks, etc.) still has an effect at the minimum organization size. Having people "stay home" (A) does not necessarily stop infections. At the same time, homes with somewhat more residents (B), such as intergenerational living quarters or even nursing homes, may not prevent enough to overcome the natural disadvantage of their density.

My model focuses on a binary prevention decision by the organization. It could be extended to include multiple prevention decisions, each with its own size threshold n_1 that is required to privately justify it. This suggests that organizations with higher fatality rates, transmission rates, etc., represented with a greater value for the disease-severity parameter v would engage in more prevention, all else the same, than low-v organizations. A similar result

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[10] A social benefit can occur to the extent that members of the large group spend some time in the broader population, or that their prevention activities provide some valuable information to other groups considering such activities. It must also rule out situations that can occur at the end of a pandemic where infections have a positive externality by putting the population closer to natural herd immunity (Mulligan, Murphy and Topel 2020, Bourne 2021). Hereafter I assume that these conditions hold, so that an infection acquired inside an organization would have a negative externality on the broader population. I no longer refer to "externalities" within organizations.

would relate organization size to the amount of prevention, at least over the range that average costs are falling. Appendix I shows these results for a continuous-choice version of the model with only two organization sizes.

II.D. Super-spreading among the largest groups

Figure 1 assumes a u-shaped cost curve, which means that prevention costs eventually increase on the group-size margin. As drawn in the figure, they may increase enough to surpass the private benefits of prevention. Therefore a particularly large group may engage in less prevention due to its high average costs. Such a group would have an especially high infection rate both due to the number $f(n)$ of pairwise interactions in the group and also the lack of prevention by comparison to groups sized between n_1 and n_2.

II.E. Allocation of time across locations

Consider an individual who visits L locations during a typical day. Let t_i denote the time spent at the ith location, where $f(n_i)$ contacts are made. Anyone entering the location uninfected will leave it infected with probability $P_i(t_i)$. The nondecreasing infection function P varies across locations not only because locations differ in terms of number of contacts but also in terms of the prevalence of index cases, transmission rates, and the fraction of time at the location spent making no contact.

We expect that the infection function P is concave because a person infected during the first few minutes of contact can maintain that contact indefinitely without further changing his infection status. For someone uninfected entering the first location, the probability of being infected upon exiting the Lth location is (2):

$$1 - \prod_{i=1}^{L} [1 - P_i(t_i)] \tag{2}$$

Because this "any-location" infection probability is also concave in the time spent at any one location, an individual's infection probability is minimized by allocating her entire day to a single location, which would be the location attaining the minimum among $\{P_i(1)\}$.[11] A stay-at-home order (SAH) is in fact a directive for individuals to remain at a single location that is expected to have relatively few contacts. If the low number of contacts is enough by itself for home to achieve near the minimum $\{P_i(1)\}$, then a fully-enforced SAH would come close to minimizing infections.

Indeed, mobility data, discussed further below, show that much of the population sharply and voluntarily reduced the number of locations they visited (Goolsbee and Syverson 2021). Nevertheless, to the extent that workplaces might be safer, the disease externality from allocating more time to work could be positive, even if home were the alternative location for that time.[12]

The marginal rate of transformation between t_i and t_j in (2) is the ratio of their hazard functions:

$$MRT_{i,j} = \frac{P_i'(t_i)}{P_j'(t_j)} \frac{1 - P_j(t_j)}{1 - P_i(t_i)} \tag{3}$$

Therefore, even without going to the extreme of requiring individuals to remain at a single location, infections would be reduced by a small reallocation of time from a location with a high hazard ratio to a low one.

II.F. Staying at home has an externality that changes from positive to negative as the disease gets more severe

If disease severity v were low enough, then Figure 1's baseline-cost curve, and therefore its prevention-benefit curve, would be everywhere below the u-shaped cost curve. With no private incentive to prevent, the equilibrium infection rate curve would coincide with the base-

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[11] Here time is measured in days, so that $t = 1$ is a full day. Infection would be maximizing at a potentially interior solution that equates marginal infection hazards across locations.
[12] The model does not capture another possibility: that fully-enforced SAHs potentially increase the number of contacts at home – social distancing is more difficult to maintain – because the jurisdiction's nonresidential real estate is required to remain vacant.

line cost curve. An individual reallocating time from a large organization to a small one would confer a positive externality as long as smaller organizations, which have fewer infections per member, had a lower infection hazard as defined in (3). Her individual incentive would be in the same direction, because there would be no prevention costs to offset the private infection-cost gradient.

As disease severity increases, the baseline-cost curve shifts into a higher position such as the one shown in Figure 1, inducing larger organizations to prevent while smaller ones do not. If their prevention is effective enough, as the case shown in Figure 1, then a relatively large organization like C has fewer infections per member, and potentially a lesser infection hazard, than A even while the disease creates fewer total private costs (infection plus prevention) for A. The latter comparison shows how the severe disease distorts individual choice between A and C in the direction of A, as would be the case with a less severe disease. However, in Figure 1 individual choice is distorted toward A to avoid the costs of prevention, which has a positive externality. To the extent that stay-at-home orders move individuals to A from organizations like C, they are partly redundant to individual incentives at the same time that they may increase aggregate infections.

III.   Data and Measurement Framework

A disease transmission measurement framework should help organize the various academic studies that offer estimates of components of average infections rates. It should also help connect average infection rates with the marginal rates that are relevant for decisions. In this spirit, I decompose the number of new infections at a gathering location during a time interval into five components, many of which are commonly measured in epidemiology studies:[13]

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[13] This formula infinitesimally exaggerates the infection rate because it assumes that a person could be infected twice during the time interval. Algebraically, it approximates $(1-p)p$ with the infection rate p. Recall that, for COVID-19, daily incidence is less than 1/1000.

(new infections)

$$= \text{(infectious members)} * [1 - \text{(screening rate)}]$$
$$* \text{(avg number of close contacts per member)}$$
$$* \text{(secondary attack rate per unit time)} * \text{(duration of gathering)}$$

(4)

The first two terms on the RHS reflect the entry of infectious members into the location at the beginning of the time interval, such as a school day. As indicated in the formula, such entry can be low either because few members are infectious or because the location screens them before entry.[14] Infectious members who gain entry ("index cases") make close contacts (e.g., teachers and students who share a classroom), each of whom becomes infected with probability equal to the secondary attack rate per unit time multiplied by the duration of contact. The product of the final two terms is itself often called the secondary attack rate (SAR).[15] Prevention activities involve some combination of increasing the screening rate, reducing close contacts, or reducing the SAR. A small class size is an example of reducing the average number of close contacts. Masks, physical barriers, regulated traffic flows, and pods can reduce the secondary attack rate.[16]

The location-specific rates in (4) are averages, as distinct from the marginal infection probabilities $\{P'(t_i)\}$ that are central to time allocation questions. My purpose here is to show how relative marginal probabilities can be partially identified from average infection probabilities in the case that time is continuous and infection hazards h are constant over time within location. Let p_i denote the prevalence rate among the members who gather at location i, after the location has applied its screen. Each member passing the screen is present at the location for t_i units of time, which is divided into $f(n_i)$ intervals each involving a pairwise interaction with another member. The infection probability for a person who entered the location uninfected is:

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[14] To the extent that households do not deny entry to any of its members, households are unusual in having a zero screening rate.

[15] Many epidemiology studies do not emphasize the time dimension; see also Thompson et al.'s (2021) definition of SAR as the "probability of onward infection from an index case among a defined group of close contacts." Studies that do investigate time durations find, unsurprisingly, that infections are more likely for long-duration contacts with an index case (Thompson, et al. 2021).

[16] Regulated traffic flows and pods (a.k.a., "quaranteams") are examples of positive assortative matching, which reduces disease transmission on the principle that a person cannot be infected twice (at least not before recovering). Assortative matching is treated extensively in economic epidemiology, e.g., Philipson and Posner (1993), Kremer (Kremer 1996), and Philipson (2000).

$$P_i(t_i) = 1 - \left[1 - p_i + p_i e^{-h_i t_i / f(n_i)}\right]^{f(n_i)} \tag{5}$$

where the square bracket term is the probability that an uninfected individual remains uninfected after one interaction at location i. In the constant-hazard environment, each index case makes $f(n_i)$ close contacts, which are of three types: another index case, uninfected both before and after the interaction, and infected as a result of the interaction (secondary infections). By definition, the share of the latter is the SAR:

$$SAR_i(t_i) = (1 - p_i)\left[1 - e^{-h_i t_i / f(n_i)}\right] \tag{6}$$

The ratio of marginal and average infection probabilities at a location can be expressed as function of three observables: the number $f(n_i)$ of close contacts, the prevalence p_i of index cases, and the SAR:

$$\frac{P_i'(t_i)}{P_i(t_i)} = \frac{p_i}{\left(\dfrac{1 - p_i}{1 - p_i - p_i SAR_i}\right)^{f(n_i)} - 1} f(n_i) \frac{1 - p_i - SAR_i}{1 - p_i - p_i SAR_i} \ln \frac{1 - p_i}{1 - p_i - SAR_i} \in [0,1] \tag{7}$$

where for brevity the notation in (7) suppresses the dependence of *SAR* on duration of time at the location. The ratio (7) of marginal to average is decreasing in the number of close contacts and the prevalence of index cases. Of particular interest is the limit as index prevalence goes to zero because it proves useful for inferring marginal infection probabilities from averages:

$$\lim_{p_i \to 0} \frac{P_i'(t_i)}{P_i(t_i)} = \frac{1 - SAR_i}{SAR_i} \ln \frac{1}{1 - SAR_i} \in [0,1] \tag{8}$$

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This limit also varies from zero to one and is monotonic decreasing in the *SAR*. Therefore, in locations where the *SAR* is, say, no greater than ½, the constant-hazard model bounds the marginal probability below by the average probability times ln(2).[17] If the workplace had an average infection rate less than ln(2) times the infection rate at home, then equation (8) says that the marginal infection rate at work must be less than the marginal infection rate at home.

Studies vary according to which components of (4) are measured and the comparability of the measures across contexts.[18] An ideal study would count within-group infections among the same group of people before and after the implementation of organization-wide prevention protocols while measuring infections members acquired when they were outside the group. Having studies for a single country (say, the U.S.) would also help for comparing across settings. In searching Google Scholar and surveys found therein, I found one study close to this ideal (Seidelman, et al., 2020), which looked at healthcare workers. Two other studies of U.S. primary and secondary schools, also listed in Table 1, came close to the ideal except in having no "before-prevention" data (Zimmerman, et al., 2021; Falk, et al., 2021). The next-best type of study measures infection rates among members of an organization relative to prevalence in their local community, falling short of the ideal in failing to specify where members acquired their infection. I found data for these comparisons for meat processors (which is also enough for before-after comparisons), on-campus university students, students and staff in primary and secondary schools, and airline pilots. These studies are listed in the second panel of Table 1 and discussed on Section V below. Finally, I included studies that estimated SAR in U.S. households or workplaces. These also usually included estimates of number of contacts. Because none of the U.S. school studies (recall Figure 3) estimated a SAR, I broadened my article search to schools in Europe and Australia. The SAR studies are listed in Table 1's third panel.

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[17] Conversely, a marginal infection rate that is far below the average rate indicates either a SAR near one, a large number of index cases, or a large number of close contacts. This situation is sometimes referred to as fatalism (Kremer 1996, Akesson, et al. 2020). Note that the SAR in equation (8) refers to transmissions resulting from contacts made by an index case in a single day, which is a shorter time horizon than used in the studies cited in what follows.

[18] The empirical averages are usefully compared across settings by dividing both sides of (4) by the number of group members and the duration of gathering to arrive at per-capita infection rate per unit time.

Table 1. Studies Measuring Setting-specific COVID-19 Infection or Transmission Rates
Studies have U.S. subjects unless noted otherwise

Description	Time Frame	Citation
Worker/student infections traced to source (Figure 3)		
Duke Health workers	Mar 15 - Jun 6	Seidelman at al. (2020)
NC schools	Aug 15 - Oct 23	Zimmerman et al. (2021)
Wood County, WI schools	Aug 31 - Nov 29	Falk et al. (2021)
Worker/student infection rates compared to local community (Table 3)		
Meat processing workers	Apr 1 - Jul 31	Hernstein et al. (2021)
On-campus university students	Sep 18 - Nov 20	[This paper]
Primary & secondary students & staff	Aug 31 - Nov 22	Mulligan (2021)
FEDEX pilots	Jan - Aug	Risher (2020)
Amazon/Whole Foods front-line workers	Mar 1 - Sep 19	Amazon Staff (2020)
Secondary attack rates (Table 4)		
Hair stylists, masked	May 12 - May 20	Hendrix et al. (2020)
Healthcare with PPE	January	Burke et al. (2020)
Office workplace	January	Chu et al. (2020)
Households	March - April	Dawson et al. (2020)
Households	March 2 - 12	Rosenberg et al. (2020)
Households	March 22 - April 22	Yousaf et al. (2020)
Students & staff, Australia	March 5 - April 9	Mccartney et al. (2020)
Students & staff, France	Jan 24 - Feb 7	Danis et al. (2020)
Students & staff, Ireland	March 1 - 12	Heavey et al. (2020)
Students & staff, Italy	Sep 1 - Oct 15	Larosa et al. (2020)

Note: All dates are for the year 2020.

In addition to the published studies identified in Google Scholar, I also obtained data for University of Chicago on campus-students as measured by an ongoing surveillance survey (The University of Chicago, 2021) and data published by Amazon on its blog.[19] The university data is compared with contemporaneous positivity and confirmed-case rates reported by the City of

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[19] Amazon's data pertains to "all 1,372,000 Amazon and Whole Foods Market front-line employees across the U.S. employed at any time from March 1 to September 19, 2020" (Amazon Staff 2020).

Chicago (2021). I supplement these and other data sources with overall prevalence data from Our World in Data (Global Change Data Lab 2021) and duration of exposure data from Mulligan (2021). I also estimate pre-pandemic rates of flu prevention in the workplace using the Behavioral Risk Factor Surveillance System for 2019 (Centers for Disease Control and Prevention 2021), which is an annual survey of more than 400,000 U.S. adults regarding their "health-related risk behaviors, chronic health conditions, and use of preventative services."[20]

A transparent but useful result is that COVID prevalence at a point in time is far closer to zero than it is to one. With an average of 250 daily new confirmed cases per million persons in the U.S. during the twelve months beginning April 1, 2020, prevalence of active cases would be about 1/400 if cases were active an average of 10 days. Even if there were three unconfirmed cases for every confirmed case, that would still put prevalence at about 1/100. This low prevalence is why the limiting marginal-average ratio (8) is particularly useful.

IV. Large-group prevention activities and their possible efficacy

Businesses, schools and other organizations implemented protocols to slow the spread of COVID-19 that were rarely, if ever, implemented in households. For two industries I found before-after estimates of either within-organization spread or prevalence among the workforce. For other industries, COVID-19 prevalence is measured among the workforce (or student body) and compared to prevalence in the surrounding community. Both the spread data and the prevalence data suggest that the prevention efforts worked, or at least that something about the organization keeps infection rates below what they are outside the organization. The study authors also emphasized the role of prevention efforts in shaping these outcomes.

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[20] I used variables FLUSHOT7, EMPLOY1, IMFVPLA1, _AGEG5YR, _SEX, _LLCPWT, and EDUCA.

IV.A. Prevention activities by businesses and schools

Table 2 lists the prevention activities I found cited in the academic articles (Table 1) about the spread of COVID-19 within organizations. Universal masking was cited in all of them, although the type of mask cited only in the hospital and hair-stylist context. Seidelman at al.'s (2020) study of Duke Health specifically cited universal masking as defining the before and after time periods. Hospital studies also cited other personal protective equipment such as eye protection (Seidelman, et al., 2020; Paltansing, et al., 2021). Yale University's Emergency Department described "structure[ing] into distinct pods...staggering breaks or using portable computers…taping off or removing chairs" and "individually packaged meals" (Sangal, et al., 2020). Clinical staff conducted a single exam with "supervising providers present outside the room on telephone or at a computer workstation on video." Airborne Infection Isolation Rooms are not new to hospitals (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2020) but many new ones were built during the pandemic (Dyer, 2020) as well as taking other steps to manage air flow. Airlines also emphasize air filtering systems (Pombal, Hosegood, & Powell, 2020).

Table 2. Prevention Measures Cited in Papers about Within-organization Spread

Physical barriers
Universal masking (all organizations studied)
Other PPE such as eye protection (hospitals)
Airflow or filtering (hospitals, airlines)
Other physical barriers (hospitals, food processors)

Positive assortative matching
Screening/quarantining potentially sick (hospitals, schools, food processors, airlines)
Pods or limits on interdepartmental contact (hospitals, schools)
Develop and administer its own testing service (University of Illinois, Amazon)
Video-based contact tracing (Amazon)

Social distancing
Spacing (hospitals, schools, airlines, Amazon)
Closed lunch rooms (hospitals)
Handshakes prohibited (hospitals)

Organizations also took active steps to separate their uninfected members from the infected ones. Various screening devices were used at worksite entrances, especially by hospitals, airlines, and schools. Hospitals and schools also noted how they put coworkers and students in pods and prevented interdepartmental contact, which helps maintain positive assortative matching on infection status. As previously noted, the University of Illinois developed and administered its own rapid, saliva-based, test for COVID-19. Amazon also built its own testing capacity, "testing regularly and broadly [to] help identify people who have contracted the coronavirus but are asymptomatic and therefore might not otherwise be tested" and costing "hundreds of millions of dollars" (Amazon Staff 2020). Amazon/Whole Foods also reports that it "introduced or changed over 150 processes to ensure the health and safety of our teams." Hospitals, schools and airlines also noted other steps they took to keep coworkers, patients, clients, and students spaced apart. For quarantine purposes, Amazon/Whole Foods also used video-based contact tracing. These are all examples of what Mitchell (1912) referred to as "more elaborate specialization and machinery."

Although households likely did not implement many of the prevention protocols cited in Table 2, they did reduce their geographic mobility (Chetty, Friedman, Hendren, & Stepner, 2020).[21] Measures of infection rates in the household sector are therefore equilibrium rates that reflect reduced mobility. Interpreting the results that follow is therefore facilitated by seeing them in context of household mobility. For that purpose, I display Google Mobility data as Figure 2. For each week of 2020 after February 14, it shows the time individuals spent in various locations as compared to the time spent in the baseline period January 3 – February 6, 2020.

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[21] As noted previously, staying away from the workplace may have been an act of prevention early in the pandemic, but was likely prevention avoidance later.

Figure 2. U.S. Weekly Mobility, 2020
Percentage change from Jan 3 - Feb 6
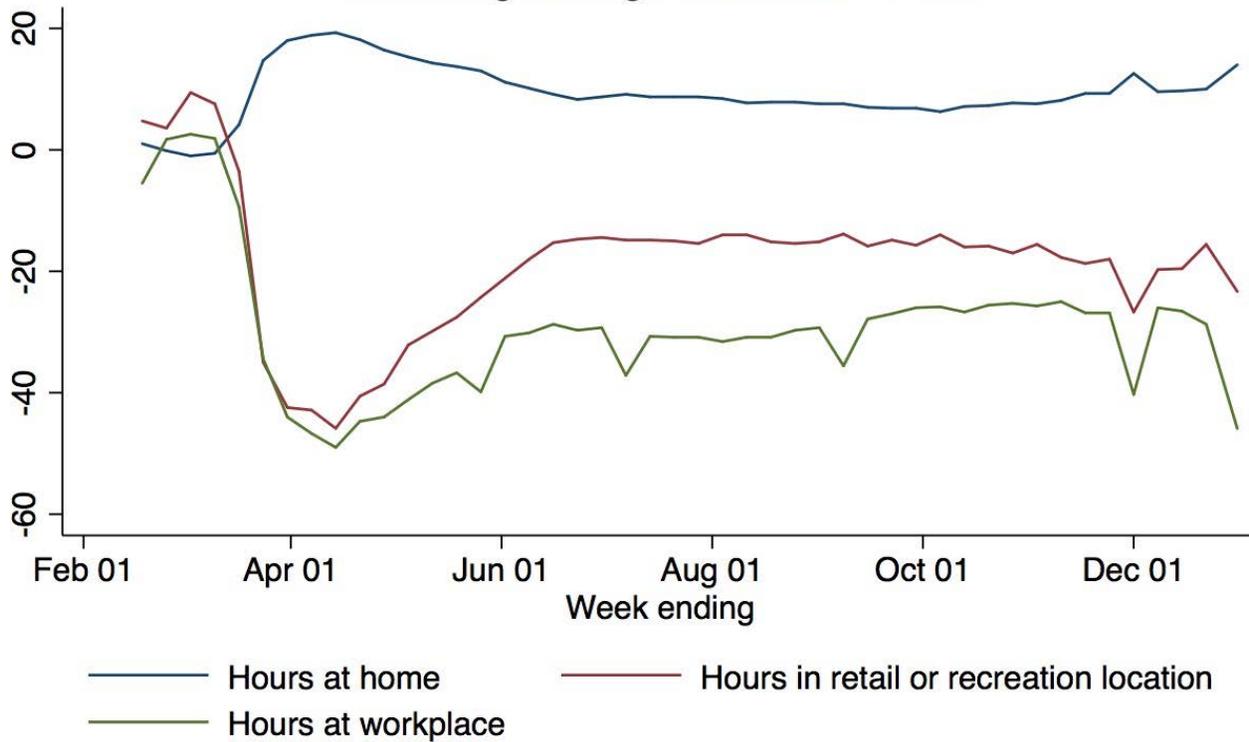
Source: Google Mobility

Prior to the pandemic, prevention during annual flu seasons was less, but not absent. Tens of millions of flu shots were given annually, with the workplace an important distribution point (Centers for Disease Control and Prevention 2019). 60 to 70 percent of employers offered on-site flu shots (American Management Association 2004, SHRM 2020). Using data from the 2019 Behavioral Risk Factor Surveillance System (Centers for Disease Control and Prevention 2021), I estimate that the workplace is the most common location for employed adults to receive their flu shot, with a doctor's office a close second. I also find that self-employed are less likely than other employees to receive a flu shot. Conditional on receiving a flu shot, it is rare for the self-employed to have received the shot on site at work. If we interpret self-employed status as a proxy for working at a small business, these two findings suggest that smaller businesses are less likely to offer a flu shot on site. Employees at such businesses are less likely to prevent in this way because, inclusive of time and hassle costs, getting the flu shot is more expensive for them.

Paid sick leave is another pre-pandemic prevention tool utilized especially by larger businesses. Using the National Compensation survey, the Wiatrowski (2015) finds that half of

small-business employees have access to paid sick leave as compared to 81 percent of employees at large businesses.[22]

IV.B. Employees of Duke Health and meat processors, before and after prevention protocols

Figure 3 shows the before-after results for the Duke Health system, which "consists of a tertiary care academic hospital, 2 community hospitals, 21,014 HCW, and more than 180 primary care and specialty clinic practices in 10 counties in North Carolina, providing approximately 70,000 inpatient hospitalizations and 2.4 million outpatient visits annually." Between March 15, when Seidelman et al.'s data begins, and April 14, 2020, Duke Health observed 1.3 community-acquired infections for every thousand of its healthcare workers [HCWs] as compared to 1.2 acquired at work.[23] At rates per 100,000 hours present in each setting, they are 0.37 and 0.62, respectively.[24] This is the 1.67 ratio shown in red in Figure 3.[25] Over the next six weeks, the ratio is only 0.31 because work-acquired infections almost stopped while community-acquired cases continued as did prevalence in the broader community. From the point of view of being infected with COVID-19, these two ratios suggest that an hour worked in the Duke Health system went from being more dangerous than an hour outside work to being more than three times safer. Moreover, that the change coincides with implementation of new prevention efforts by the employer suggests that those efforts were effective.[26] The schooling data also displayed in Figure 3 is discussed in the following section of this paper.

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[22] Here small and large businesses are defined as less than 50 employees and more than 500 employees, respectively.

[23] Duke Health implemented a universal mask mandate on March 31. April 14 is two weeks after implementation, to allow time for workers acquiring before the mandate to be screened or recovered. Figure 1 of Seidelman et al. (2020) shows a cumulative work-acquired incidence curve that turns sharply between April 7 and April 14.

[24] I assume 45 weekly hours at work for HCW. The hours denominator for community-acquired infections are all of the remaining waking hours of the week (i.e., what remains from 18 hours per day).

[25] Seidelman et al. (2020) also have a residual category of "unknown-etiology," which is about the same number of cases as the other two categories. If this unknown category were allocated proportionally between community- and work-acquired, the ratios shown in my Figure 3 would not change.

[26] Another study of a hospital in the Netherlands (Paltansing, et al. 2021) measured in-hospital transmission using whole-genome sequencing. It found only one in-hospital transmission after April 30, 2020, which was the seventh day after implementing universal masking of healthcare workers. By comparison, the small sample has 11 community-acquired cases. Also note that Figure 3's 0.31 is measured in April and May when household prevention efforts were, at least as measured in Figure 2, greater than they would be the rest of the year.

**Figure 3. COVID-19 Infections Acquired at Work or School
as a Ratio to those Acquired in the Community**
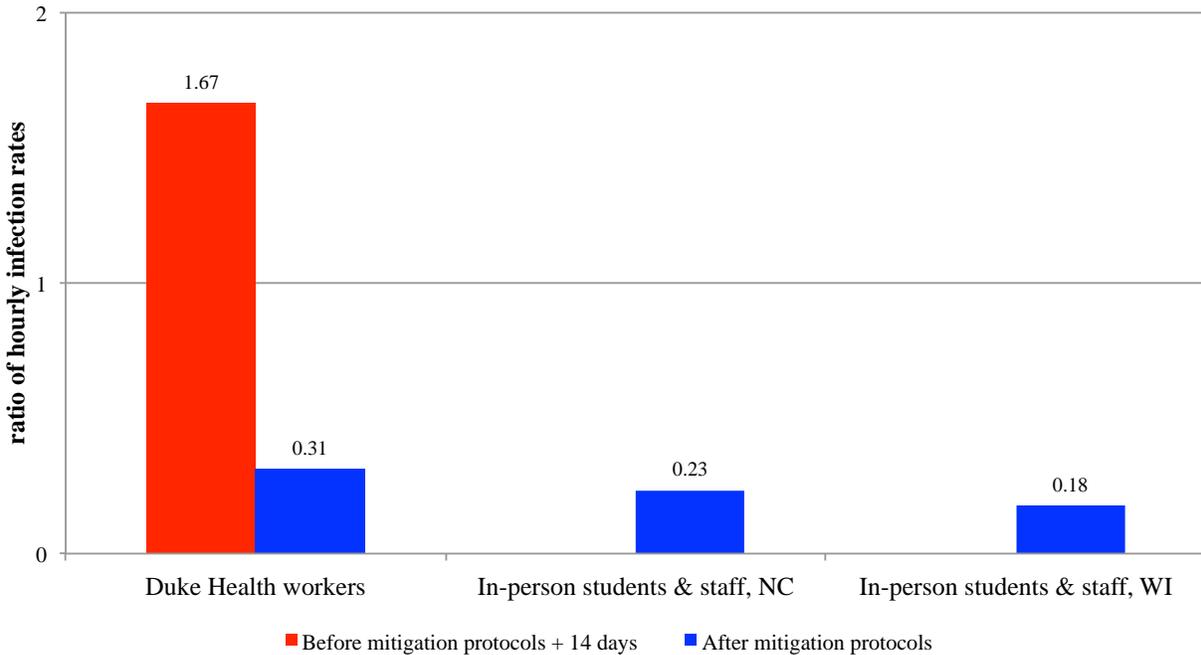
Sources: Seidelman et al (2020), Zimmerman et al (2021), Falk et al (2021), Mulligan (2021), author's hours calculations.
Notes: Before-mitigation school data unavailable. Each of the four ratios in the chart has the same sample for its numerator as its denominator.

In late March 2020, a few governors ordered nursing homes in their states to accept COVID-19 patient transfers from hospitals.[27] These orders are believed to have accelerated the spread of COVID-19 among the elderly (Hammond & Kingsbury, 2021). They are of economic interest because of, among other things, the differences in size and prevention efforts between nursing homes and hospitals. Using facility-level data from Centers for Medicare and Medicaid Services (2021), I find that the interquartile range for nursing-home employment is 91 to 187 with an average of 151.[28] By comparison, the average employment of a non-teaching hospital was more than 600 and the average employment of a teaching hospital more than 1,500 (Shahian, et al., 2012). Before the pandemic, nursing homes were routinely cited for infection-prevention failures, such as failures to screen new employees for infections or failing to isolate

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[27] The New York state order is New York Department of Health (2020). New Jersey's was Governor Murphy's Executive Order 103.
[28] I assume two employees per resident, which is consistent with the employee-hours-per-resident data shown in the CMS data.

infected patients (United States Government Accountability Office, 2020). Negative pressure rooms were rare in nursing homes.[29]

Perhaps due to their relatively small size, a number of nursing home personnel are contractors at multiple facilities. Using anonymized cell phone data, Chen, Chevalier and Long (2021) found that the average nursing home facility is connected with seven others through at least one cell phone that was present both in the facility and one of the connected facilities. Across facilities, their connectedness measure is positively correlated with COVID-19 infection rates. Perhaps, on a per-worker basis, managing infections between work locations is more difficult for a smaller business such as a nursing home that relies on outside contractors as compared to larger organizations such as hospitals, which actively manage the interdepartmental connections within their organization.

Food processing plants were notorious for spreading COVID-19, partly because "the high density of workers required for operations, prolonged close contact of personnel on the production line, indoor work environments with compact cafeteria and locker room areas" (Herstein, et al., 2021). Based on their county-level data for the first half of 2020, Taylor, Boulos, and Almond (2020) conclude that "livestock processing poses a particular public health risk extending far beyond meatpacking companies and their employees." Hernstein et al. (2021) measured infections at eleven meat processing facilities in Nebraska before and after facilities both mandated masks and installed physical barriers.[30] Unlike the Duke Health study, Hernstein et al do not distinguish infections acquired at work from those acquired in the community. However, I have supplemented their data with surrounding-community data in order to compare prevalence among employees with prevalence among community members who are not employees as described in Appendix II. The top two rows of Table 3 shows the results. Before the companies' mitigation protocols, Nebraska meat-processing employees were being infected with COVID-19 at 15 times the rate that other residents of the surrounding counties were. After the protocols, that ratio drops to about three. Interestingly, the before/after comparison for meat processing is a factor of about 5.4 (15.1/2.8) as it is for Duke Health (1.67/0.31). However, the

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[29] Diamond (2020). The first facility in Pennsylvania to accept COVID patients was much larger than average and had just built a negative pressure wing (Miller, et al. 2020).

[30] The timeframe was April through July 2020. Including two additional facilities that did not install physical barriers, the average employment per facility was 1,675.

meat-processor infection rate needs to fall even further before it would be below the rate for the other residents of the surrounding community.[31]

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[31] Another study of meat processing plants suggests that some of the transmission among meat-processing employees occurs outside the plant, such as "shared transportation to and from the workplace, congregate housing, and frequent community contact with fellow workers" (Waltenburg, et al. 2020).

Table 3. COVID-19 Prevalence Among Employees or Students Compared to the Surrounding Community

Employer/organization	Time frame	Community definition	Infection rate as ratio to community's
Nebraska meat processors, before mitigation	Apr 1 - May 17	Other residents of surrounding counties	15.1
Nebraska meat processors, after mitigation	May 18 - July 31		2.8
Univ. of Chicago on-campus students	Sep 18 - Nov 20	Chicago	0.09
Primary and secondary in-person students	Aug 31 - Nov 22	U.S. ages 5-17	0.77
Primary and secondary in-person staff	Aug 31 - Nov 22	Reweighted U.S. age-specific infections	0.81
FEDEX pilots	Jan - Aug	Reweighted U.S. age-specific infections	0.92
Amazon/Whole Foods front-line workers	Mar 1 - Sep 19	Reweighted state and age-specific infections	0.58

Sources: See Table 1.

Note: Each numerator includes infections that employees or students acquired in the community. Age-specific infection rates are from CDC. State and age-specific baseline for Amazon/Whole Foods was calculated by Amazon Staff (2020). Occupation-specific age distributions are from Jan - Mar Current Population Survey hosted by IPUMS. Both numerators and denominators are expressed per capita.

V. Comparisons between homes, businesses, and other organizations

Enough data has been published in academic papers to assess infection rates for various organizations and compare them to households, without necessarily indicating whether the results are due to prevention efforts or other factors. For these additional organizations this section shows either the infection-source results akin to Figure 3, prevalence rates relative to the surrounding community akin to Table 3, or rates of within-organization transmission ("secondary attack rates"). All of these sources suggest that unlike some of the food processing plants, many businesses and schools have a work environment that is substantially safer than the surrounding community.

V.A. Infections of organization members by source

Eleven of the North Carolina's school districts offered in-person schooling and participated in the study by Zimmerman et al (2021). The authors explain how "case adjudication of within-school transmission was performed via contact tracing by the local health department." Of the 77,446 students plus thousands of staff present in person during the study period (August 15 through October 23), 773 acquired COVID-19 from the community during that period. The same group of students and staff acquired 32 cases at school. As explained further in Mulligan (2021), I estimate that the average staff and student was, especially due to hybrid scheduling, present at school only somewhat more than half of the school days. Taking a full school week to be 30 hours, that puts the average student and staff outside school almost six times more hours than they were in school. Therefore Figure 3 shows a ratio 0.23 for North Carolina schools, which is even closer to zero than Duke Health's.

The Wood County, Wisconsin study (Falk, et al., 2021) involved about 5,500 students and staff attending school in person for at least part of the week.[32] Seven cases were acquired in

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[32] Most of the students and staff were in secondary schools, which Falk et al (2021) define as grades 7-12.

school during the study period (August 31 to November 29), as compared to 184 outside. The outside-inside hours ratio is about five because the sample had more full-time schooling than North Carolina did. The inside-outside ratio of hourly infection rates is 0.18, as shown in Figure 3.

On an hourly basis, the schools studied were more than four times as safe as the places frequented by students and staff when not in school. By April 14, Duke Health was more than three times as safe.[33] Figure 3 begins to cast doubt on the hypothesis that regulations or subsidies that require or encourage workers to spend more time outside their place of work or school help slow the spread of COVID-19. Rather, it raises the question of whether such actions might hasten the spread by keeping people away from prevention measures that large organizations use but households do not.

"Before" COVID-prevention protocol data are not available for North Carolina and Wisconsin schools. An Israeli high school, selected for study because it had an outbreak, was conducted without masks or open windows due to hot weather. The study authors also note "crowded classes...distancing among students and between students and teachers was not possible" and that "air conditioning functioned continuously in all classes" (Stein-Zamir, et al., 2020). The large number of cases occurring in the school suggest that COVID can spread rapidly in a school that does not implement prevention measures.[34]

V.B. Prevalence of employees and students compared with community prevalence

Comparing prevalence among employees or in-person students with the wider community (Table 3) confounds the source-specific analysis (Figure 3) with at least two additional factors. One is that employees may be different than other adults, or in-person students different than other children their age, in the community in terms of the types of

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[33] Note that Figure 3, Table 3, and Table 4 (which follows) all adjust for community prevalence in the sense that the results shown are unaffected by anything that increases the numerator's infection rate in the same proportion as the denominator's.

[34] On the other hand, another study of several Irish schools with community-acquired cases (Heavey, et al. 2020) found zero in-school transmission early in the pandemic (March 1 through March 12), which presumably preceded many prevention efforts that would come later.

interactions they have in the community. This confounding factor might be dwarfed in cases where the workplace infection rate is especially different from the community rate, as appears to be the case for meat processing plants before their mitigation protocols.

Another confounding factor is that, as discussed in connection with Figure 3, even in-person employees and students spend most of their waking time outside their place of work or school. Their prevalence rate is a blend of infection rates at work and rates in the wider community with most weight on the latter. For example, mixing the NC-school relative rate shown in Figure 3 (0.23) with the community relative rate (1) with weights 1/6 and 5/6 results in a relative prevalence of 0.87. Mixing the "after" Duke Health rate with weights 1/3 and 2/3 results in a relative prevalence of 0.77. Conversely, relative prevalence estimates of 0.8 or 0.9 may suggest relative source-specific infection rates of about 0.3.

The second confounding factor is less important for workers or students who spend less time in the wider community. Table 3's third row is interesting in this regard, because it refers to students on a college campus, which is both school and living quarters. Infection rates among on-campus students are measured as part of a surveillance-testing program and therefore pick up infections that are not associated with symptoms or obvious close contact with an infected person (The University of Chicago, 2021). By contrast, I measure infections in the City of Chicago where tests are initiated based on symptoms or possible close contacts. Nevertheless per-capita student infection rates were only nine percent of Chicago's (City of Chicago, 2021). On-campus living quarters are also interesting because of their large scale compared to single-family households, intergenerational households, or even nursing homes.[35]

A potential policy question for many occupations might be the health effects of lengthening the workday during a pandemic. Recall from equation (3) that marginal time allocation changes depend on marginal infection rates, as distinct from the average infection rates that have been measured. Because the campus is both living quarters and "workplace" for

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[35] A nursing-home facility typically has less than one hundred residents, and sometimes as few as a dozen (Centers for Medicare and Medicaid Services 2021). As discussed further below, my conceptual framework is about organizations with voluntary participation, and therefore does not describe correctional facilities. An inmate's surplus from living in prison is negative, which means that "threats" to screen out infected persons are by themselves an incentive for an inmate to seek infections. Of course, correctional facilities also have other disadvantages when it comes to controlling infectious disease (Williams, et al. 2020).

university students, relevant policy questions such as the number of students to have at home or on campus are more likely to depend on the average infection rates.

Emily Oster (2020a; 2020b) has led a "COVID-19 School Response Dashboard" project gathering attendance and prevalence data from participating schools in almost every U.S. state. The prevalence measures are only for school students and staff but do not distinguish infections acquired in school from those acquired at home or in the community. For community comparison purposes, I use the CDC's national case counts for the 5-17 years age group. Oster's prevalence estimates for in-person students is 77 percent of the prevalence for all persons aged 5-17. As discussed above, this may suggest that community-acquired infections of in-person students may significantly outnumber school-acquired, even on an hourly basis. Alternatively, or in addition, Oster's sample of schools may not be representative or in-person students may not be representative of other persons their age in terms of infection rates.

The penultimate row of Table 3 shows results for FEDEX pilots. Through August 2020, 100 of more than 5,000 FEDEX pilots tested positive for COVID-19, according to their pilots' union (Risher, 2020). Reweighting the age-specific infection rates from CDC to reflect the age distribution of pilots as indicated in the January through March 2020 Current Population survey, I estimate that 2.13 percent of the comparable community was infected, putting the ratio at 0.92. This directionally agrees with other studies of airlines that find only a few dozen airline-acquired cases out of millions of passenger hours. As Pombal, Hosegood and Powell (2020) put it, "the risk of contracting coronavirus disease 2019 (COVID-19) during air travel is lower than from an office building, classroom, supermarket, or commuter train."

Amazon tracked and reported infections for its front-line employees, including those at subsidiary Whole Foods Market grocery stores. Out of 1,372,000 of those employed at any time between March 1 and September 19, 2020, 19,816 tested positive or were presumed positive. Surveillance testing was an important part of their prevention program. Amazon Staff (2020) estimated that the number positive would have been 33,952 had their employees been infected at the average rate for their geography and age as measured by Johns Hopkins University. The ratio of these two, 0.58, is shown in the final row of Table 3.[36] Amazon also reported the numerator and denominator for each of the 41 states and DC where it had more than 1,000

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[36] Herrera (2020) and Simon (2020) calculated a ratio of 0.66 by using a nationwide denominator that does not reweight according to the geography and age of Amazon's employees.

employees. 39 of the 41 ratios were less than one. Note the likely upward bias in the ratios due to including asymptomatic infections at a higher rate in the numerator than the denominator.

V.C. Secondary attack rates

The secondary attack rate (SAR) is perhaps the most common context-specific measure of COVID-19 infections. It is the "probability of onward infection from an index case among a defined group of close contacts" (Thompson, et al., 2021). As shown in equation (4), reproduced below for the reader's convenience, the SAR is only part of the overall infection rate. Other parts include the number of close contacts, the rate that infectious members are screened out of the group location, and the fraction of group members that are infected. Of these three, SAR studies at most indicate the number of close contacts.

$$
\begin{aligned}
\text{(new infections)} \\
= \text{(infectious members)} * [1 - \text{(screening rate)}] \\
* \text{(avg number of close contacts per member)} \\
* \text{(secondary attack rate per unit time)} * \text{(duration of gathering)}
\end{aligned}
\tag{4}
$$

Table 4 shows the results from U.S. studies of household or workplace SAR that I found on Google Scholar or in surveys cited therein. Studies of healthcare were excluded unless they provided enough information to calculate SAR for healthcare personnel wearing personal protective equipment (PPE).[37] Because none of the U.S. school studies (recall Figure 3) estimated a SAR, I broadened my article search to schools in Europe and Australia. In six of the settings – hair stylists, healthcare with PPE, office workplace, students and staff in France and

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[37] In healthcare contexts "close contact" is often defined to be within six feet for several minutes with at least one of the parties not wearing a mask (Baker, et al. 2020, Heinzerling, et al. 2020). Burke et al. (2020) have a healthcare sample of close contacts with a mix of PPE dispositions. By this close-contact definition, estimation of SAR is impossible after universal masking. Conversely, we see that so far studies of healthcare SAR use data from early in the pandemic before masking became universal in that sector (e.g., the survey by Thompson, et al. (2021) finding four U.S. studies of healthcare SAR, all of which use data from January through March 2020).

Ireland, and school staff in Italy – zero were infected out of a total of 1,527 close contacts.[38] The two hair stylists in particular have been widely cited because each of them worked with COVID for about eight days and a combined 139 clients, who are obviously within arm's length for an extended period. Both stylists and clients wore masks, which were either cloth or surgical masks.

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[38] Although the Wood County, Wisconsin study does not report numbers of close contacts required for the SAR's denominator, it does note that the numerator is zero among staff in the study. That is, SAR = 0 for staff in that study, as with the studies of schools in Italy, France, and Ireland.

Table 4. Secondary Attack Rates in Various Settings

Occupation/location	Country	Time Frame	Index cases	Close contacts per index	Reproduction rate	SAR Raw	SAR per 8 hours
Hair stylists, masked	U.S.	May 12 - May 20	2	69.5	0	0	0
Healthcare with PPE	U.S.	January	2	81.5	0	0	0
Office workplace	U.S.	January	1	11	0	0	0
Households	U.S.	March - April	26	2.5	0.62	25.0%	0.89%
Households	U.S.	March 2 - 12	155	2.2	0.85	38.2%	1.36%
Households	U.S.	March 22 - April 22	N/A	[195 contacts]	N/A	24.1%	0.86%
Students	Australia	March 5 - April 9	9	62.7	0.11	0.2%	0.01%
School staff	Australia	March 5 - April 9	9	7.3	0.11	1.5%	0.07%
Students & staff	France	Jan 24 - Feb 7	1	86	0	0	0
Students & staff	Ireland	March 1 - 12	6	154	0	0	0
Students	Italy	Sep 1 - Oct 15	48	20.75	0.79	3.8%	0.19%
School staff	Italy	Sep 1 - Oct 15	48	4.25	0	0	0

Sources: See Table 1.

Note: All school subjects are in person. The reproduction rate is the product of close contacts per index and raw SAR. Household contact hours are assumed to be 14 days times 16 hours per day. School contact hours are assumed to be 3.4 days (avg. presence of index case) times 6 hours per day.

In contrast, none of the three household studies found zero secondary infections. The pooled household (raw) SAR is 32.2 percent of 602 close contacts. A small number of secondary infections were found among Australian students and staff as well as Italian students. In order to compare the nonzero SARs for schools with household SARs, I divided raw SARS by an assumed number of contact hours. For households, I assumed 16 hours per day for a full 14 days because infections can potentially last two weeks. For schools, I assumed six hours per day for 3.4 days, which is the average number of days that the index cases were present in the Australian schools and presumed infectious. I then multiplied all hourly rates by eight so that the numbers were not so small. Table 4's final column shows that, even when they are not zero, the hourly school SARs are an order of magnitude less than the hourly household SARs.

On the other hand, Table 4's close-contact column confirms at least an element of the conventional wisdom, namely that more close contacts are made in schools and workplaces than at home. The household studies show between two and three close contacts whereas the average number of close contacts in the nonhousehold contexts averages twenty-five. From equation (4)'s perspective, a factor of ten advantage for households in terms of close contacts is more than offset by its higher hourly SAR. The household disadvantage is further widened to the extent that it does not screen out infections as much as the workplaces and schools do.

VI. Conclusions

During China's Great Leap Forward, villagers were required to manufacture steel in their backyards to help their country accelerate its transition to an industrialized nation (Dikötter, 2010). Non-steel production suffered for lack of inputs, while the resulting steel output proved useless. One reaction is that the villagers should have been more careful with quality control. Another is that the efficient scale for steel production, reflecting advantages of specialized physical and human capital, is too large for the backyard. This is one of the first papers to pose

the question of whether households also fall short of the efficient scale for preventing infectious disease.[39]

Consistent with economic theory, real-world workplaces and schools (hereafter, workplaces) engaged in more COVID-19 prevention than households did. Workplaces required and enforced masking, and often wearing other personal protective equipment, dividing personnel into pods, and screening entrance to the site. A number of workplaces administered their own testing services and adjusted and filtered air flow. These seem to be clear cases of decentralized supply of a public good. This observation by itself does not say that voluntary supply is efficient or even that stay-at-home orders harm public health. It does show that voluntary supply is significant and that carefully crafted public policy would not unknowingly undermine it.

An unsurprising observation, consistent across studies, is that people have many more close contacts at workplaces than they do at home. However, each household contact is far more likely to result in transmission, even on an hourly basis. Households are not even close to the public-health "ideal" of solitary confinement and zero transmission. Instead, the evidence suggests that "households show the highest transmission rates" and that "households are high-risk settings for the transmission of [COVID-19]."[40]

Something at workplaces greatly reduced the spread, as suggested most clearly in the infection-source data from hospitals and health clinics as well as prevalence data from meat-processing plants (Figure 3 and Table 2 in this paper). Infections of in-person primary and secondary students and staff were more than twenty times more likely to be traced to the community rather than someone else in their school. COVID-19 prevalence measured among more than a million people who were on-campus university students, in-person primary and secondary students and staff, wholesale or grocery front-line workers, or airline pilots was below the prevalence of comparable populations not engaged in these activities. To the extent that

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[39] See also Mulligan (2020), which observed in April that "some of the most valuable innovation can be the discovery and implementation of ways to reduce infections in the workplace" and that a stay-at-home order "can be a significant barrier to these kinds of progress because it closes the workplaces where many of the new practices would be administered." In more abstract terms, Buchanan and Tullock (1962) observed that "the business firm or enterprise is the best single example of an institutional arrangement or device that has as its purpose the internalization of external effects" adding that "If care is not taken…, the comparison that will tend to be made is between the costs of collectivization on one hand and the costs of purely individual organization on the other, with the [business enterprise], and possibly most efficient, alternative being overlooked…."

[40] Thompson, et al. (2021) and Madewell, et al. (2020), respectively.

these findings are due to prevention activities that took organizations time to devise and implement, the sign of the public-health effects of stay-at-home orders may have reversed during the first few weeks of the pandemic (Figure 3).

These results apparently contradict what has been assumed in economic models of the pandemic. Eichenbaum, Rebelo and Trabandt (2020) assume that less transmission occurs in households based on what was observed during flu seasons, when businesses were not implementing any of the prevention measures cited in Table 2. Kapicka and Rupert (2020) calibrate a similar parameter based on a 1997 finding that the majority of personal contacts normally occur at work. Birinci, et al. (2021) quantify the relative safety of households as an "internal calibration" exercise, which refers to an effort to match aggregate disease dynamics. At best, the assumptions made by these papers describe how the economy would evolve if employers and other organizations did little to reduce the spread at their locations. They are not grounded in either microdata during the pandemic or on any analysis of the differential incentives of households and firms to engage in prevention activities.

Data on more workplaces is needed to more precisely estimate gaps between transmission at home and in workplaces, and whether transmission varies systematically across workplaces or personnel according to specific prevention efforts and other factors. Short of additional data, it would help to have weights that could be applied to the existing data in order to better represent populations of interest.

The model in this paper emphasizes cooperation and scale economies in both natural disease spread and prevention. More attention could be given to heterogeneity among group members in their incentive to stick with the group and the constraints it imposes on members for the purpose of managing an additional local externality in the form of infectious disease. As emphasized in the theory of the core, group success comes easier when members enjoy a significant surplus from their membership.[41] Infection-prevention groups may therefore not form anew upon the arrival of a pandemic but rather closely resemble longstanding enterprises that maintain some of their previous surplus-creating activities. Shutting down such enterprises amounts to an in-kind tax on disease prevention.

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[41] Telser (1994), Klein and Murphy (2008), Murphy, Snyder and Topel (2014) and Jaffe, et al. (2019).

Reallocating some of a person's time from a group with a high average infection rate per member per unit time, such as a household, to a large group with a low rate does not in principle necessarily confer a positive externality on the broader community. In theory, at least, averages can differ from the marginals relevant for cost-benefit assessments. However, due to the low prevalence rates and low secondary attack rates (SARs), the gap between marginal and average infection rates appears to be significantly less than the average-infection rate gaps between locations. More direct measurement of marginal infection rates would be an interesting and valuable topic for future research.

Another shortcoming of assessing externalities with organization averages is that averages do not reflect the degree of assortative matching that occurs outside the organization. Infecting two people at school may increase total community infections less than infecting just one if the two exit school into a home where the residents are already infected or immune whereas the one goes to a home with susceptible residents. This is one reason that network models are sometimes used both in economics (Karaivanov, 2020) and epidemiology (Christley, et al., 2005). With that said, shifting time to an organization with a zero SAR does confer a positive externality on the broader community because it does not introduce any infections into the broader community and may avoid an infection from the foregone alternative. Presumably reallocating time to a location with SAR sufficiently close to zero also has a positive externality, especially when the outside-group average infection rate is several times greater (Figure 3).

A pandemic may still distort individual behavior toward households even when, as in Figure 1, they are less safe than larger organizations because the latter impose prevention costs on members that households do not. Hospitals intentionally rid themselves of opportunities for employees to socialize (Sangal, et al., 2020), which from an employee perspective makes work less attractive at the same time that it likely contributes to the low infection rate in hospitals compared to the community. A number of University of Chicago students chose not to return to a campus with remarkably low infection rates because on-campus living quarters were more heavily regulated than before the pandemic with no commensurate reduction in residential fees. These are good examples of how a pandemic can encourage individuals to stay home even while public health would be enhanced by spending more time in groups with effective prevention protocols.

VII. Appendix I: Continuous Prevention Choice

Figure 1 in the main text illustrates a discrete prevention choice from the perspective of organizations with a range of sizes. The purpose of this appendix is to show the analysis for just two firm sizes but with a continuous prevention choice, following the excess burden approach used by Philipson (1995) and Mulligan (2020). In that model, firms value their activities, which have a normal pre-pandemic cost plus an infection cost during a pandemic. Here I add that the activities generate infections at different rates in large versus small firms because of the potential number of pairwise interactions. As a result, the infection-weighted per-member quantity of those activities in their pre-pandemic amounts is greater for the large firm (q_4) than for the small firm (q_3), as shown in Figure A1.

Figure A1. Infections and Prevention for Small and Large Organizations

Marginal private value

- A = infection costs per large-org member
- $A + B + C$ = infection costs per small-org member
- $E - C - D$ = extra per-member cost in large org

Normal cost + disease cost v

C D

A B

E

Normal cost

Large organization demand

Small org. demand

q_1 q_2 q_3 q_4

Infection-weighted quantity per member

As in the main text, the parameter v reflects (up to scale) the private monetary cost of each infection. To the extent that $v > 0$, the marginal costs of the firm's activities are greater than normal as indicated by the higher of the two horizontal lines in Figure A1. Each firm rationally reduces the number of infections from its activities, with large reducing to q_1 from q_4 and small to q_2 from q_3. The excess burden of the disease is the opportunity cost of the activities that are not conducted normally, which is calculated in the usual way in Figure A1 as areas defined vertically between demand and supply curves and horizontally between q_1 and q_4 and q_2 from q_3, respectively.

Figure A1 assumes that larger firms reduce infections at a higher rate, for the reasons discussed in the main text, as represented in the figure by their more elastic demand curve. Even so, if v were small enough, equilibrium infections per member would be greater for the larger firm because its rational choice would be close to q_4 while the small firm's choice close to $q_3 < q_4$. As drawn in Figure A1, the cost v per infection is great enough that the large firm has fewer infections, and therefore lower infection costs, per member than the small firm does. Nevertheless, the large firm has greater total private cost, which is the sum of the private infection costs and the prevention costs represented as an excess burden. The difference between large- and small-firm total private costs is shown in the figure as the difference between the area E and the combined area $C + D$. This is the seemingly paradoxical case in which the per-capita private costs of participating in large-group activities exceeds the costs of participating in small-group activities even though the small group activities are less safe. Still further increases in v (not shown in the figure) generates a third case in which the large firm has lower equilibrium total private costs than the small firm does.

To facilitate comparison of Figures 1 and A1, Figure A2 shows the discrete prevention case. The large firm can reduce only to, say, q_1 or not at all. The small firm can only reduce, if anything, by the same proportion $\frac{q_1}{q_4} = 1 - \beta$. As drawn, the large firm prefers to prevent. The small firm prefers not to prevent because $H + I > F + G + J + K$.
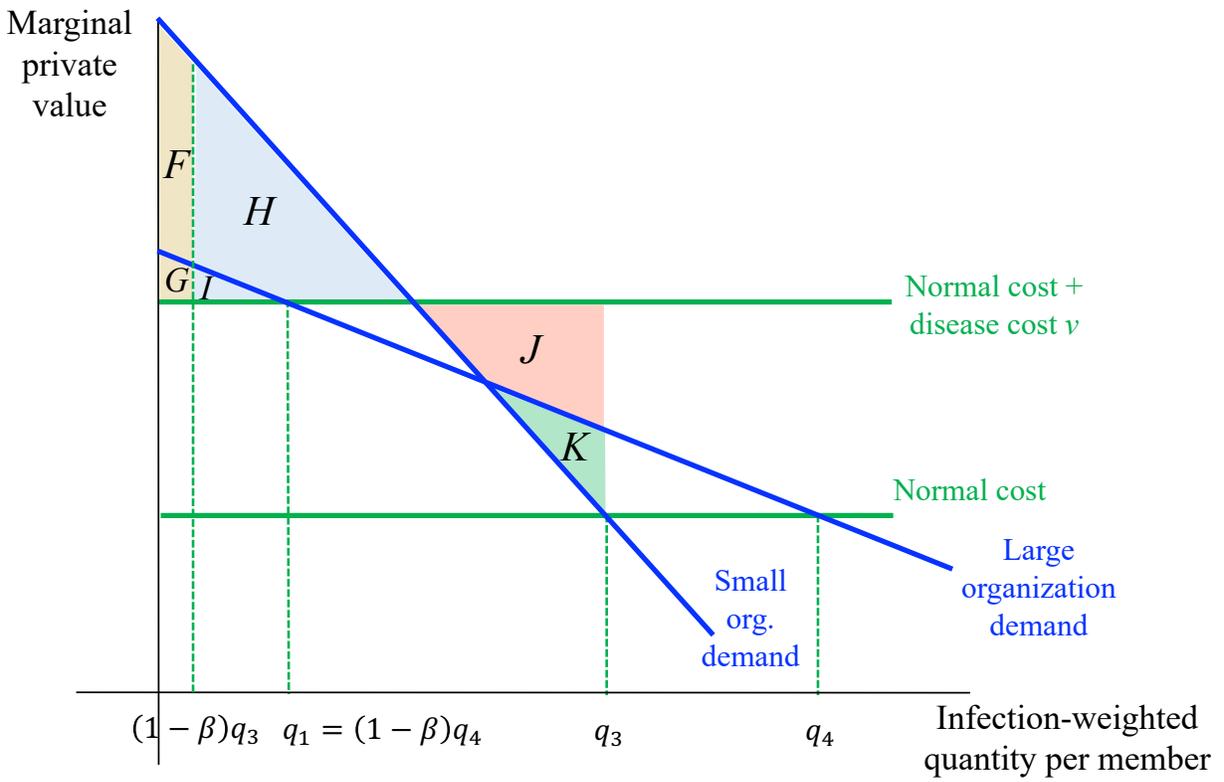

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Figure A2. Discrete Protection

Marginal private value

F

H

G I

J

K

Normal cost + disease cost v

Normal cost

Large organization demand

Small org. demand

$(1-\beta)q_3$ $q_1 = (1-\beta)q_4$ q_3 q_4

Infection-weighted quantity per member

VIII. Appendix II: Data Related to Nebraska Meat Processing Plants

I identified 28 of 93 Nebraska counties, plus one county from South Dakota and three from Iowa, within a 15-mile radius of a Nebraska meatpacking plant using the map prepared by the Environmental Working Group (2020).[42] I reviewed on-line news articles about the outbreaks, which reported plant-level prevention activities including mandatory masks, workstation dividers, social distancing in breakrooms, and expanded testing. They also noted difficulties in obtaining prevention supplies in April. Three Nebraska plants were closed, with reopenings ranging from May 8 to May 18. I take May 18 as the beginning of the "after" period for the purposes of measuring community prevalence for comparison to plant-employee prevalence.

The 32 counties recorded 11,588 new cases between April 1 and May 17, 2020, of which 6,015 were in the state of Nebraska through May 6. Because the Environmental Working Group identifies 1,263 Nebraska cases through May 6 as meatpacking workers, I attribute 21 percent (=1263/6015) of the 11,588 to meat packing, and the remaining 9,155 cases to other members of the community. The average daily number of new cases during this period is therefore 52 for meat packers and 195 for the remaining community in the 32 counties.

Herstein et al. (2021) found that the eleven meatpacking facilities implementing universal masking and workstation dividers had 5.4 times the daily rate of new cases before implementation than after. Applied to the 52 daily cases cited above, that puts the average daily number of new cases May 18 – July 31 ("after") among meat packers in the 32 counties at 10. Because average daily cases overall May 18 – July 31 is 202, these estimates imply 193 average daily cases for the remaining community in the 32 counties during that period. These counties have about 26,000 meat packing workers and 1,473,000 other residents.

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[42] The county FIPS codes are 19133, 19149, 19193, 31001, 31025, 31035, 31037, 31043, 31047, 31051, 31053, 31055, 31063, 31067, 31073, 31079, 31081, 31093, 31109, 31119, 31121, 31131, 31137, 31141, 31151, 31155, 31159, 31167, 31173, 31177, 31181, and 46127.

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