Mask Economics

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* A note on this paper. This paper was prepared for discussion in: ECO 3930: Contemporary Issues in Economics. It is written to illustrate how one might start to apply economic benefit-cost reasoning to a contemporary issue in an undergraduate class—namely the role of policies related to mask wearing. It is not intended for distribution to, or consumption by, other audiences. Think of it as a very detailed set of notes (still in progress) to support a week of undergraduate lectures.

** A note on data and sources. I throw out various statistics below to justify various model assumptions. Due to time, I was not able to go back and add the sources at all in many cases, and in others there is just a link with no other info. Even so, unless otherwise stated, every number herein is based on some reasonable source (CDC or published research or data from a government agency).

1. Introduction

The basic model used by epidemiologists to study the spread of diseases like Covid-19 is the dynamic SIR model, and variants thereof. In the model, the population is divided into groups that are susceptible (S), infected (I), or removed (R) due to death or immunity acquired after recovery, thus the name SIR. Variations are possible allowing births, other deaths, children born with immunity, and so on. We will see more about how these models work below and in one of the assigned readings.

While the disease will spread through the population until herd immunity is achieved, either through natural immunity or vaccination, the potential for exponential growth opens up the possibility for heightened costs as healthcare and other systems are pushed temporarily beyond their capacity. Thus, the economic and human costs of epidemics may be mitigated by steps to reduce the rate pf spread, prolonging the epidemic but spreading out the infections more evenly so they can be better dealt with.

Wearing a mask in public is one such potential mitigation measure. Not only are masking expectations in response to Covid-19 a new phenomenon in the U.S., but they are also controversial. Some people feel passionately about masking in ways apparently unrelated to any systematic consideration of its role in the pandemic.

The governor of Florida prohibited mask mandates were it is within his authority to do so, for example at state universities. This is so even though Florida is a state with a disproportionately large elderly population that is at high risk from Covid, and even though the rhetoric of the Republican party has traditionally opposed to centralized authority. In opposition to mandates, ostensibly to support freedom, Florida is imposing a statewide mandate against mandates that deprives local governments, institutions, and businesses of their freedom/property right to decide for themselves what to do within their own jurisdiction or on their own property. Generally, such actions have been considered by conservatives to be both authoritarian and anti-business. Truly, we live interesting times.

Anyway, universities, including Poly, and some communities, in Florida responded to the "no mandate mandate" by saying they "expect" masking indoors, even though they cannot enforce it. Does masking make enough difference for this to matter? Is so, can such a non-enforced masking expectation capture much of the benefit of masking, or does disallowing enforcement impose large net costs on society?

This is the sort of question economic and policy analysis generally, and benefit-cost analysis in particular, is used to sort out. Attempting to analyze that question was the basis of a class assignment. The purpose is to structure our thinking in a way that can help avoid errors that arise from letting extraneous factors and biases influence our decisions, and also to practice framing arguments in a way that may avoid slipping into a contest to score political points rather than understand the issues and tradeoffs involved in making effective public policy. A sketch of such an analysis is presented below. We will pick it up in class as well.

We would like to work towards a model that could provide a quantitative estimate of optimal masking and its evolution over the epidemic in a world where agents are endogenously modifying their behavior as the pandemic evolves. To do that, we would need to integrate a model of masking into a dynamic SIR model and calculate the optimum time path of masking and enforcement thereof. We won't get there—it is very complex! Instead, first we will focus on a simple static model, myopically focused on a single point in time. Then we will look at a simple dynamic model where behavior is exogenously determined and consider enforcing a constant, rather than evolving, level of masing over the pandemic. Then we will consider, in a handwavy way, what might happen if other things are accounted for; things like including endogenous behavior, disease seasonality, randomly arising variants, or waning immunity. While the modeling will be somewhat abstract, at the end we will also briefly consider just how we might get data to operationalize such models. My hope is that together these models will give you some feel for what is involved in such modeling, and the sorts of things you might learn to do with graduate training and more time. Of course, it should also give some insight into the value of masking and the cost of mandating that there be no mask mandates.

2. Keeping it (too) Stupid Simple

Assume we simply inherit some fraction of the population that is infected from the previous period, i_0, that do not yet know they are infected and so interact freely with others. That endowment of infected, in conjunction with other parameters, gives rise to the probability an uninfected individual gets sick in the period under study, i. Assume those already infected are not susceptible to being infected again, so the share of the population currently susceptible is $s=1-i_0$

Let us think of the benefits of masking as resulting from saving on the cost of illness. Let i be the probability someone who is not already sick gets sick. Let us assume this fraction depends on the fraction that mask, m, the fraction of the population that is initially sick, i_0, the average number of interactions from each infected person if they do not mask, q, which would transmit the infection if the person they are interacting with is susceptible and did not mask. It depends on the share of those infectious transmissions that are transmitted by those that do mask, $(1-g)$, where $g\in(0,1)$ reflects the effectiveness of masking in reducing transmission. Finally, it also depends on the share of infectious transmissions received by the susceptible population if they are masked, (1-h), where h∈(0,1) reflects the effectiveness of masking in reducing transmission.

Yes, an essentially one period static model is far too simple to get at much related to an ongoing pandemic. But, it is a useful starting point at which to understand some of the mechanics that we will later build into a dynamic model. Even though it is too simple to be worth much, other than as a starting point, it turns out that if we are restrained in our willingness to generalize, we can draw some useful insights from this exercise.

We should try to get a feel for the likely magnitudes of these important parameters. In this model, q is the analog of the basic reproductive rate, or R_0, in dynamic epidemiological models. Estimates of R_0 are almost all over 2 and tend to cluster around 3.

Covid may spread by droplet or aerosol. How important each is is still an open question. Masks are more effective against droplets than aerosols. Masks also interfere more with transmission than reception. The Pee test, https://srhd.org/media/documents/PeeTest.pdf, does a reasonable job of explaining the basic mechanics of why the most important effects of masking have to do with reducing transmission, not reception. Masks vary in their ability to stop aerosols, but the evidence seems to suggest that high quality masks stop considerable aerosols and that low quality masks block some aerosol reception but far less than high quality masks, but still block considerable droplet reception. So, the evidence seems clear that for an average mask, 1>g>h>0, but as far as I can tell just what those values are is still pretty open.

With these assumptions and notation, the average infections from an infectious individual if the entire population is susceptible, is $q(1\text{-}gm)(1\text{-}hm)$. If we assume uniform mixing, the number of new infections per capita is $i=q(1\text{-}gm)i_0s(1\text{-hm})$ or $i=(1\text{-}i_0)i_0q(1\text{-}gm)(1\text{-}hm)$. The benefit of masking comes from reducing the fraction sick. This benefit is reflected by the derivative of i with respect to the fraction masking, m, $i' = -\left(1-i_0\right)i_0q\left(g+h-2ghm\right)$.

The benefit of masking increases with the number of potential transmissions, q, and falls with the effectiveness of masking, g and h. Neither g nor h need be anywhere near 1 (100% effective) for there to be considerable benefit from masking. The benefit of masking is small if the infected population is small, so that i_0 is near 0, because encounters with the infected are very rare, or if the infected population is large, because encounters with the susceptible are very rare. Indeed, the impact of masking is greatest when i_0 is 0.5.

This is a bit oversimplified, since with a richer model the effects of masking might be nonlinear (think of each exposure as a Bernoulli trial, and infection as a binomial process). But, if the share of the population initially infected is relatively small, q is not too large, the population is large, and mixing is relatively uniform, it should be a reasonable approximation. Importantly, it simplifies matters greatly, making the model tractable.

If c_i is the average cost of a covid infection, the cost of new infections per capita is $c_i i(\cdot)$. The direct costs of masking include the monetary cost of masks, the discomfort from wearing them, and things like communications difficulties and the value of lost human interaction from having our faces covered. Let c_m be the average direct costs of masking per person wearing a mask. Per capita direct costs of masking are then $c_m m$.

There would also be costs associated with enforcing an involuntary mask mandate. If people are asked to wear masks, by stating that masks are expected indoors in public places, but mask

$[0, m_v]$ where $m_v < 1$.

Pushing masking above m_v requires monitoring and enforcing penalties for non-compliers. Let $e(m;m_v)$ represent the per capita variable costs of enforcement. Once we try to enforce masking beyond $m=m_v$, getting higher masking compliance costs more, so the marginal enforcement cost is positive. Let $e' \geq 0$ be the first derivative of $e(\cdot)$. It makes sense to assume getting m=1 is impossible, so that the marginal cost increases without bound as m becomes approaches some upper limit, $m_v < \bar{m} \leq 1$. It makes sense to assume that with very minimal threat of enforcement at least a few people would be more likely to wear a mask, so that the marginal cost goes to 0 as m approaches m_v from the right. There may well be significant quasi-fixed costs associated with enforcement. Let k be the value of these costs per capita. Define E to equal 0 if the mandate is not enforced and 1 if it is. Enforcement costs per capita are $Ek+e(m;m_v)$.

Our goal is to characterize the mask policy that minimizes costs. The choices are no masking, an unenforced mask expectation, or enforced masking higher than m_v. Since n is constant, we may minimize cost per capita and get the same answer as minimizing total cost. Having summed the components, the optimization problem is:

$$\min_{E\in\{0,1\},m\in[0,\bar{m})} \quad c(m) = c_i(1-i_0)qi_0(1-gm)(1-hm) + mc_m + EF + e(m;m_v). \tag{1}$$

If the optimal value of masking is higher than m_v, it must satisfy this first order condition:

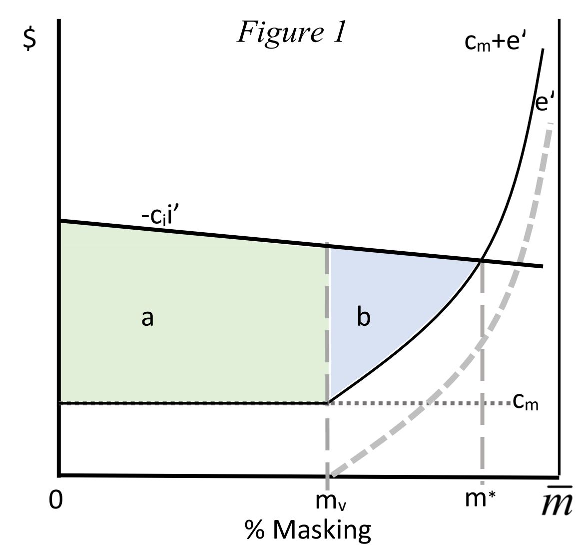
$$-c_i(1-i_0)qi_0(g+h-2ghm) + c_m + e' = 0. \tag{2}$$

It is more insightful to write is this way:

$$c_i(1-i_0)qi_0(g+h-2ghm) = c_m + e'. \tag{3}$$

The left side of equation 3 is the marginal benefit (MB) of increasing m, and the right side is the marginal cost (MC). The interpretation of this condition is straight forward—the rate of increase in cost from increasing m, c_m+e', must equal the rate of health cost savings from increasing m, $-c_i i'$. If increasing m saves more (less) health cost than it creates enforcement and masking cost, we should enforce a higher (lower) value of m. At the optimum, the two are in balance, and no improvement is possible locally. However, keep in mind that the global solution, m**, may be at m_v, not m*.

Figure 1



Let us consider the first order condition graphically. Figure 1 is drawn so MB crosses MC to the right of m_v, with m* representing an optimal local solution at which MC crosses MB. If we integrate the area between marginal cost and marginal benefit up to m*, we get the net benefit of the (locally) optimal mask mandate; area a plus area b.

Area a is the benefit we would get from an unenforced mandate; $m_v(-c_i i'-c_m)$. Area b is the additional net gain from enforcement. To be worth enforcing a mandate, area b must be larger than the quasi-fixed cost of enforcement, k. If k larger than b, the global solution, m**, is m_v, otherwise it is m*. If the MB was below c_m, we would obviously optimally have no masking, since the avoided cost of sickness is not higher than the cost of wearing a mask, so that $m^{**}=0$.

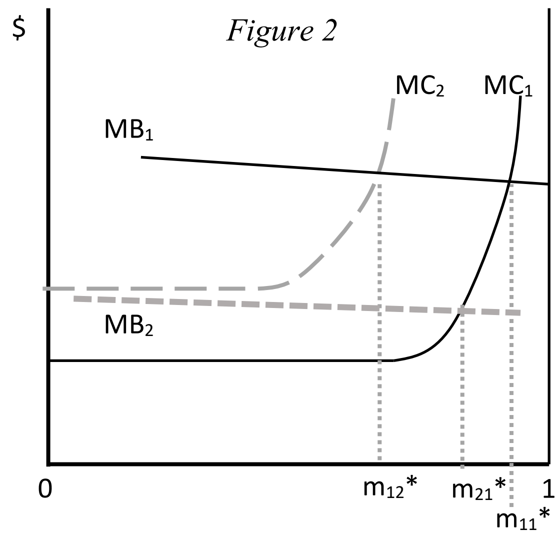
Thinking a bit more about area *a* can help drive home an important insight that may or may not have otherwise occurred to you: masking need not be highly effective individually to be very valuable in the aggregate. This is because c_i is a large number and c_m is not, as we will see below.

How do changes in the parameters i_0, q, g, h, c_s, c_m, m_v, or F impact the solution? Consider figure 2, which shows an initial solution at m_{11}*. Assume k is small enough so that m_{11}* is the global solution initially. What happens to the solution when the marginal benefit shifts? The figure shows a decrease in MB to MB_2 decreases masking to m_{21}* if k is small enough, or to m_v if k is large enough. This could result from a decrease in q, f, or g, or from i_0 moving farther from 0.5.

Figure 2 also shows an increase in MC results in a decline in masking to m_{12}* if k is small enough, and to m_v otherwise, keeping MB at MB_1. This change shown reflects both an increase in c_m and a decrease in m_v. So, if we were to find out, say, that masking causes more communication breakdowns or mental isolation than previously thought, meaning c_m is higher, m^* would decline, and perhaps m^{**} would fall to m_v or to 0.

If voluntary compliance is lower, the level of enforced masking would be lower too. This perhaps is a useful insight that we would not get without thinking through a model like this. Relatively low voluntary compliance DOES NOT mean we should enforce compliance. It might be a signal that enforced compliance is too expensive to be worth it. When we couple this with the earlier observation that when voluntary compliance is high, enforced mandates are likely to improve matters little if there are non-trivial quasi-fixed enforcement costs, this suggests that voluntary mask compliance may usually be nearly as good as, or better than, enforced making, even if voluntary compliance is not high.

Figure 2



Finally, we see that MB_2 is below MC_2 throughout. In this case, the impact of the increase in MC is to move m^{**} to 0.

We were able to analyze the model above in the same way you have analyzed other models in economics courses, practicing modeling skills and perhaps gaining a little insight into masking. For example, it shows that even is masking is not highly effective individually it can still be very impactful in the aggregate, and so not being able to enforce mask mandates *might* have left some potential gains unrealized relative to unenforced mandates. It also showed that those may well be small since unenforced mandates are likely to be nearer the optimum than you might have otherwise thought.

But it largely misses any important matter because it is too simple to reflect enough of reality to be useful. Why? Without vaccinations, almost everyone would get covid; with the epidemic ending only when natural herd immunity is reached (if it is). Herd immunity occurs when the population of susceptible has dropped so low that the disease either becomes endemic (continuing at a background level in steady state) or dies out. If immunity is not perfect and permanent, that is only temporary. Variants will occur regularly that get around existing immunity too. Unless an effective vaccine is developed and deployed and annual boosters are given very widely, Covid-19 may be a presence for the rest of our lives. It is likely most all of us will eventually have Covid, likely more than once in our lives. Like we have colds—only with much worse potential costs.

The problem is that avoiding sickness at one point in time does not mean it has been avoided indefinitely, only postponed, unless something else happens. Thus, we have not properly modeled health savings. Savings in the model are, except for the small preference to get sick next month instead of this month, illusory. If we assume for a moment that a more or less fixed share of the susceptible get covid before the outbreak ends, and that as immunity wanes that share will approach 100% of the population, unless something else happens anyway, is there any health benefit to masking?

The answer is of course yes. As one example, if we can delay most people getting sick for long enough, namely until the vaccine has been widely administered and effective treatments for the ill have been developed, we might well have many individuals avoid potential serious infection after all. But again, this requires dealing explicitly with epidemic dynamics, so we can model how many sicknesses may be avoided for long enough to reach widespread vaccination at any given cost.

As another example, outbreaks are dealt with locally and local healthcare capacity is limited, or more accurately congestible. Hospital rooms are not mobile and cannot go where they are most needed, but outbreak severity fluctuates a lot locally. Moreover, the US has fewer doctors per capita than many other industrialized countries and is always amid nursing shortages. Thus, hospital beds are not the only, or even the most limiting, supply factor. When a local outbreak spikes, congestion in the healthcare system will likely cause costs, including reduced quality of outcomes for non-covid patients, to rise considerably relative to what would have happened had the same number been sick over the course of the epidemic, but at a lower infection rate for a longer period of time. This is the gist of the argument about flattening the curve. Modeling the impact of masking on the costs of such situations of temporary capacity limits and congestion costs takes explicit dynamic modeling of a developing epidemic. We build a rudimentary model along these lines in the next section.

3. An SIR Model with Masking and Health System Congestion

3.1 The Dynamics of the Epidemic and the Objective

Following the earlier model, let i_t and s_t represent the infectious and susceptible portions of the population. The initial level of infection is i_0 , the initial susceptible share is $1-i_0$. In addition, let r_t be the share of the population that has been infected but is no longer infectious, with $r_0=0$. Let x

be the rate at which infectious individuals exit the infectious population. Counting time in days, since people are infectious for about 10 days on average, if they were asymptomatic x is about 0.1.

Let q be the average number an infected person would infect in a day if everyone they interacted with were susceptible neither were masked. When the whole population is susceptible, the average infectious person will infect q/x others. This rate, known as R_0 in epidemiological modeling, has been estimated many times for Covid. While the range of such estimates is large, most seem to cluster around 2 to 4. We set it to 3. If x is 0.1, this means q is 0.3.

Again following the earlier model, the average number of infections stemming from a single infectious individual in one day is q(1-*gm*)(1-*hm*), with *m* representing the fraction masked, and *g* and *h* reflecting the effectiveness of masking in disrupting transmission and reception respectively. This gives the following system of three equations governing the evolution of the epidemic.

$$i_t = i_{t-1} + q\left(1-gm\right)\left(1-hm\right) i_{t-1} s_{t-1} - x i_{t-1}. \tag{4}$$

$$s_t = s_{t-1} - q\left(1-gm\right)\left(1-hm\right) i_{t-1} s_{t-1}. \tag{5}$$

$$r_t = r_{t-1} + x i_{t-1}. \tag{6}$$

We need explicit quantitative models of health, masking, and enforcement costs—hopefully ones that replicate qualitatively reasonable features even if it is not particularly realistic quantitatively.

For health costs, let $\tilde{i}$ denote the level of infectiousness at which the system begins to become congested. Define a switching variable, C_t, that is one if infections are above that threshold and 0 otherwise. Then we model the daily health cost incurred for a single sick person as

$$c_{it} = \alpha + C_t \beta \left(i_t / \tilde{i} - 1\right)^2. \tag{7}$$

The parameter α has the same interpretation as c_i in the earlier model, the average cost of a covid sickness, now per day infected, when the system is not congested. Note that the additional congestion cost goes to zero as the infection rate approaches the threshold from the right (that is $\beta\left(i_t/\tilde{i}-1\right)^2 = 0$ if $i_t = \tilde{i}$). In the congested region, the rate the cost associated with a sick individual rises with the infectious rate is $c'_{it} = 2\beta\left(i_t/\tilde{i}-1\right)/\tilde{i}$. This also goes to zero as the infection rate approaches the threshold from the right, and the parameter β governs the rate per capita costs rise with congestion.

Following the earlier section, daily masking costs for an individual are still simply c_m, and daily enforcement costs are:

$$E_t F + \gamma\left(\left(\frac{m_t - m_v}{\bar{m} - m_t}\right) + \ln\left(\frac{\bar{m} - m_t}{\bar{m} - m_v}\right)\right). \tag{8}$$

E_t is 1 if masking expectations are enforced and 0 otherwise. This form is chosen because it has a vertical asymptote at $\bar{m}$ --cost explode as masking approaches 1. The parameter γ governs how fast enforcement costs rise with the desired level of required masking.

With these definitions, the sum of all costs per capita per day is

$$c_t = i_t s_t q(1-gm)(1-hm)\left(\alpha + C_t\beta\left(\frac{i_t}{\tilde{i}}-1\right)^2\right)+c_m m + E_t F + \gamma\left(\left(\frac{m_t - m_v}{\bar{m}-m_t}\right)+\ln\left(\frac{\bar{m}-m_t}{\bar{m}-m_v}\right)\right). \quad (9)$$

The idea is to choose a masing policy to minimize the present value of these costs over some time period. We will focus on one year, 365 days, since, with the model we have with permanent immunity and no social distancing, the disease will have exhausted itself in that time. Since we are looking at only one year, we ignore discounting, and so simply minimize the sum of costs over a year.

We define an enforced mask policy as a set of four dates, $t_{U1} \leq t_E \leq t_{U2} \leq t_N$, and a level of masking, m*, defined as follows.

t_U: Time at which unenforced mask expectations are expressed.
t_E: Time at which masking becomes enforced.
t_{U2}: Time at which masking moved from enforced to expected but unenforced.
t_N: Time at which all masking expectations are dropped.
m*: The level of masking enforced during the enforcement period.

We define an unenforced mask policy as a set of two dates, $t_U \leq t_N$, defined as follows.

t_U: Time at which unenforced mask expectations are expressed.
t_N: Time at which all masking expectations are dropped.

Related to these policies, define the switching variable U=1 if we are in a period of unenforced masking expectations and 0 otherwise.

3.2 Choosing Reasonable Parameter Values

Let us assume the average person is indifferent between losing \$10 or wearing a mask in public for a day, so that c_m=10. We don't have any evidence for this value, it just seems not unreasonable. You could do some research to help inform a guestimate here. There is a large research literature on compensating differentials—how much is pay impacted by the desirable or undesirable aspects of a job. You could try to find how much more people who must wear protective gear are paid, all else equal. You could also conduct a survey, but such self-reported values are notoriously problematic. Since we don't do that, I suggest you do some sensitivity analysis using the spreadsheet provided below to show changing this does not change anything important in the analysis to follow.

I don't really have any idea how large F, the daily quasi fixed cost of enforcement per capita might be. Let us just assume F=1, so that in a jurisdiction of 1 million, it would cost \$1 million per day to administer the mask mandate, aside from direct enforcement costs. To do better you could look up public finance research on the fixed and variable costs of enforcing various other legal requirements, and just make your best guess based on the most similar enforcement problems you

$\overline{m}$ =1. These just seem to work reasonably well; I have no particular evidence for them, and looking at equation 9 there is no reason to think changing them a little would matter much. Again, you can verify for yourself that small changes in these do not change things enough to worry about for our purposes—that is small changes do not induce qualitative changes or overwhelming quantitative changes in outcomes.

What about the cost of a typical covid sickness? On one hand, many cases are near asymptomatic, and many more are symptomatic but minor. You could look up studies of the health cost of common viruses as a starting point to represent the cost of minor cases. The lost value of the work is the minimum cost, usually valued at the wage rate, the average of which is about $25 in Florida. Suppose a symptomatic case keeps one out of work for 5 days. If an infection is 10 days, the lost productivity for symptomatic infections will be (over) $100 per day; 5×8×25/10. In addition to the productivity cost, people would pay more to avoid feeling nasty, too, increasing that considerably, let us say to $200. However, about a third of cases are asymptomatic, see for example https://www.sciencealert.com/over-a-third-of-covid-infections-are-truly-asymptomatic-says-massive-new-analysis, so let us call it $130.

What about the cost of lost life? The value of a statistical life is estimated by examining how much people are willing to pay to reduce the probability of death slightly. Estimates vary, but adjusted to 2020 dollars they will be in the ballpark of $10 million in the US. https://www.epa.gov/environmental-economics/mortality-risk-valuation. The median age in the US is about 38, https://www.census.gov/library/stories/2019/06/median-age-does-not-tell-the-whole-story.html, with average remaining life expectancy of 41 years, https://www.cdc.gov/nchs/data/vsrr/VSRR10-508.pdf, meaning the statistical value of a life year is around $250,000. How many life years are lost on average to a covid death? The average death is at around age 73, and the average life expectancy is about 14 years, so about $3,500,000 per statistical covid death. Estimates of the infection fatality rate vary, but it probably has been around 0.007 in the US, https://www.medrxiv.org/content/10.1101/2021.05.12.21256975v3.full, Let us round it down to 0.005 to be conservative, making the statistical cost of the loss of life about $18,000 per infection or $1,800 per infection day.

We are now up to a cost of at least $1,930 per infection day. Then there are the costs of the very serious but not fatal infections, and also the actual hospitalization costs and costs of treatments and doctor visits. Hospital costs are thousands of dollars per day, and about 4% of infections are hospitalized. Hospitalization alone will add at least another $200 in expected cost per infection day. A significant number of infections turn into long covid, perhaps 5% of non-hospitalized cases and the majority of hospitalized cases. https://www.healthline.com/health-news/these-groups-are-at-higher-risk-of-developing-long-covid-19 These extend the productivity and misery costs over a much longer time period. Expected cost per infection day will almost certainly exceed $2,500 in uncongested conditions. So, let us assume α is 2,500 as a benchmark.

What is a reasonable value for $\tilde{i}$? The US has about 0.0028 hospital beds per capita. There is always some extra capacity. The occupancy rate is around two-thirds, which means about 0.001

open beds per capita, or one in 1,000. Some open beds are required to deal with patient turnover and normal variability in hospitalizations. Some beds will be on wards where there are few sick people at any given time and are not easily moved to other locations within the hospital. Useable open beds may be more like 1 per 2000 residents, 0.0005 per capita.

New reported hospital admissions have seemed to average a bit less than a tenth of new reported daily infections. The CDC estimates about 25% of covid infections and 50% of covid hospitalizations are reported. So, for 100 new infections, 25 are reported, with about 2 reported hospitalizations, meaning about 4 total hospitalizations, which will last 10 days each, so about 0.4 occupied beds per new infection. The infected are infectious for about 10 days, so the share of the population hospitalized will be about 0.04 times share of the population that is infectious (of course operating with some lag in reality). So, if the infectious share of the population approaches and goes over about 1 in 80, or 0.0125, covid hospitalizations would start to approach and exceed 1 in in 2000 residents. Since hospital beds are not the only factor limiting supply, and probably not even the most limiting factor, we round this down a bit to 1 in 100, or 0.01.

We set β to 1—again noting that varying it from a bit less to somewhat larger makes only modest changes in optimal masking policies, and you can do sensitivity analysis yourself to verify that. Finally, let i_0=0.0001 and r_0=0.

We will consider mask policies for two scenarios: 1) masks are somewhat effective (g=0.4 and h=0.2) and 2) masks only modestly effective (g=0.2 and h=0.1). We choose the policy variables (dates and m*) to minimize the sum of masking, enforcement, and health costs over 365 days from time 0. Since we are looking at only one year, we ignore adjusting for the time value of money. We discussed evidence suggesting masks are at least somewhat effective in the previous section.

3.3 The Parameterized Model

With these parameter values, the objective is as follows.

$$\min_{t_{U1},t_E,t_{U2},t_N,m^*} \begin{array}{l} \sum_{t=1}^{365} i_t s_t q\left(1-gm_t\right)\left(1-hm_t\right)\left(2500+C_t\left(100i_t-1\right)^2\right) \\ +\sum_{t=1}^{365}\left(10m_t+E_t+\left(\frac{m_t-0.6}{\overline{m}-m_t}+\ln\left(\frac{\overline{m}-m_t}{\overline{m}-m_v}\right)\right)\right) \end{array} \tag{10}$$

The optimization is subject to the following constraints that must hold for all values of t.

$$i_t = i_{t-1}+3\left(1-gm\right)\left(1-hm\right)i_{t-1}s_{t-1}-0.1i_{t-1} \tag{11}$$

$$s_t = s_{t-1}-3\left(1-gm\right)\left(1-hm\right)i_{t-1}s_{t-1} \tag{12}$$

$$m_t = U_t m_v + E_t m^* \tag{13}$$

It is also subject to these initial conditions.

$$i_0 = 0.0001 \tag{14}$$

$$s_0 = 0.9999 \quad (15)$$

Equations 10-15 define a dynamic SIR model with health system congestion costs and given masking policy. Cost is optimized using excel solver (though some manual double checking is called for). The workbook is available below, so you can do sensitivity analysis and what-if scenarios for yourself.

Table 1 shows major results for four scenarios: no policy, unenforced expectations and enforced masking with somewhat effective masking, and unenforced expectations and enforced masking with slightly effective masking. The time paths of the infectious and still susceptible population with moderately effective masking are shown in Figure 3 and the time paths of the infectious and still susceptible population with slightly effective masking are shown in Figure 4.

Table 1: Impact of Mask Policies

Mask Effectiveness		Moderate: g=0.4, h=0.2		Slight: g=0.2, h=0.1	
Policy	None	Unenforced	Enforced	Unenforced	Enforced
t_{U1}		25	26	27	28
t_E			34		34
t_{U2}			187		96
t_N		143	278	99	112
m*			0.94		0.93
Cost	28,059	21,883	18,495	25,358	24,104
Peak Infection Rate	0.31	0.16	0.08	0.24	0.20
Not Infected	0.05	0.19	0.37	0.10	0.14

No masking (N) Infections spike at 31% of the population and costs rise to $28K per capita. By the time the infection dies out, all but 5% of the population has been infected.

Masking Policies with Moderately Effective Masking If masking is moderately effective, with optimal unenforced masking (V), masks are expected day 25 and the expectation is dropped day 143, infections spike at 16% of the population and costs rise to $22K per capita. When the infection dies out, only 19% of the population has not been infected. With optimal enforced masking (E), masks are expected starting day 26, enforcement starts day 34 with masking at 94%, enforcement ends day 187, all masking expectations are dropped day 278. Infections peak at 8% of the population, and costs are $18K per capita. When the infection dies out over a third of the population has not been infected.

Interestingly, optimal masking actually prevents a significant share of the population from ever getting sick. The reason can be inferred from Figure 3. Without masking, infections get so high so fast that nearly everyone is exposed before those infected at the peak become non-infectious, whereas with masking the curve is flatter so when those infected at the peak are no longer infections, many people have not yet been sick, and as the susceptible population falls, the infection spreads slowly until herd immunity occurs with “only” about 63% having been infected.

Figure 4: SIR Model with Health System Congestion and Moderately Effective Masking (g=0.4, h=0.2)

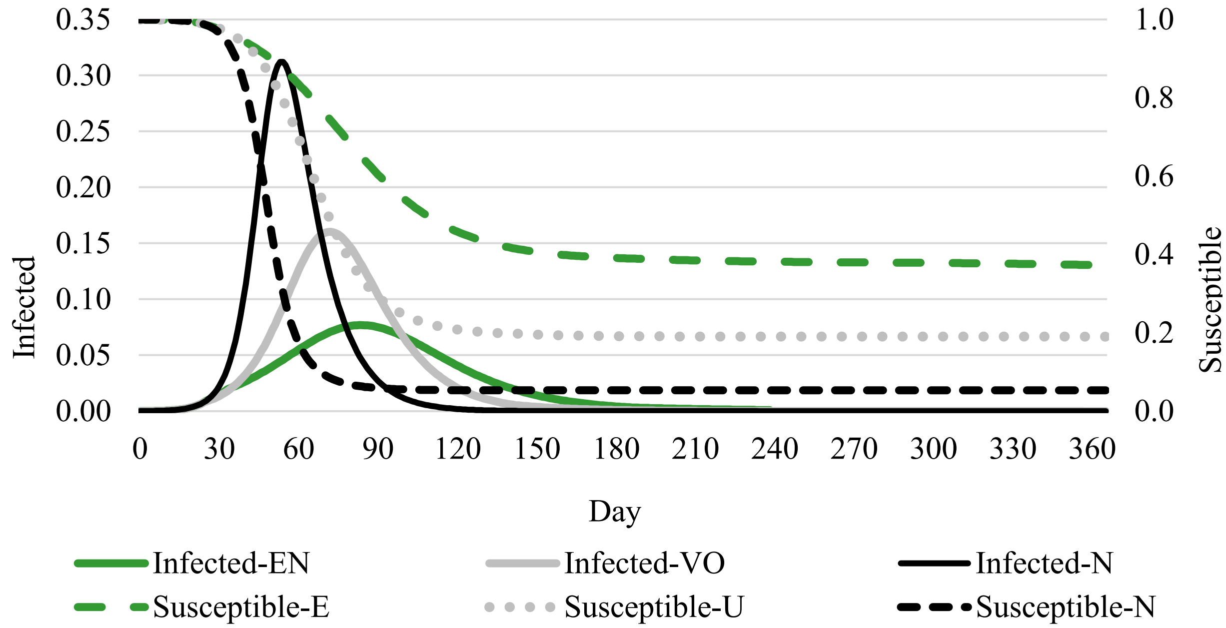
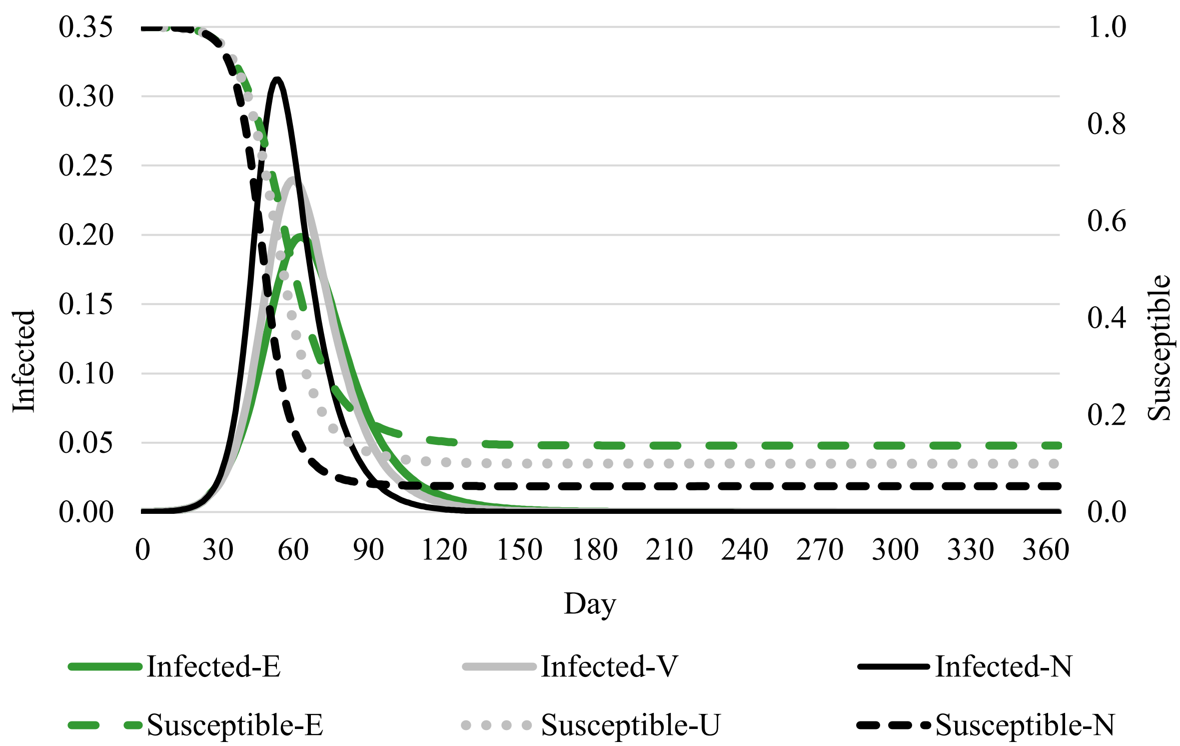


Figure 3: SIR Model with Health System Congestion and Slightly Effective Masking (g=0.2, h=0.1)



It is also interesting to note from Figure 3 that with enforced masking voluntary masking starts later, letting infections initially rise higher compared to unenforced masking, and infections stay high longer as well. This is because enforced masking can still flatten the curve, and letting infections rise sooner effectively allows more curve flattening, avoiding more congestion costs. Remember, in this model almost everyone is going to get sick, it is just optimal to spread it out so we can deal with it more effectively.

<u>Masking Policies with Slightly Effective Masking</u> With optimal unenforced masking (V), masks are expected day 27 and the expectation is dropped day 99, infections spike at 24% of the population and per capita costs rise to $25K. When the disease dies out only 10% of the population has not been infected. With optimal enforced masking (E), masks are expected starting day 28, enforcement starts day 34 with masking is at 93%, enforcement ends day 96, all masking expectations are dropped day 112, infections peak at 20% of the population, and per capita costs are $24K. When the disease dies out only 14% of the population has not been infected.

What did learn here? 1) Masking can result in substantial social cost savings even if individually masks are not very effective. 2) Optimal enforced masking to do much better than unenforced mask expectations, though that depends on how high voluntary compliance is and just how effective masking is. 3) Interestingly, enforced and voluntary masking optimally ends sooner with less effective masking. Why? Because we burn through the susceptible population faster because masks help less, so the benefits in terms of infecting prevention decline sooner. 4) Perhaps most importantly: even if masking is only modestly effective (but more than slightly effective), optimally enforced masking it can make a major difference in the share of the population that never becomes infected. If masks are even modestly effective, it is entirely possible that Florida discouraging enforced mask mandates literally killed a great many people.

Sensitivity analysis shows that moderate alterations in other parameters leaves the pattern unchanged—optimal masking is far better than no masking. Of course, just how much masking matters can be significantly impacted by these parameters. I suggest you open the included workbook by clicking on the icon below and experiment with alternative parameter values to get a better feel for the model.

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4. Still a too Simple—Behavior is Endogenous

The model in the previous section is more useful than the two-period model in section 2 did. It clearly demonstrates some things that are not necessarily completely obvious. However, it is at best suggestive, and any findings must be taken with a large pinch of salt, because it leaves out a number of things that are seemingly very central. Some of those things are exogenous, like seasonality or waning immunity. We discuss some of these in the next section. In this section we consider an important omission that has much more to do with economics—endogenous behavior.

Redressing this omission is particularly important for evaluating the impact of mask mandates, or of mandates that there be no such mandates. Why?

Here is the idea. Imagine some fraction, φ, costs, including congestion costs, are borne by individuals, where $0<\varphi<1$. In that case, delaying getting sick until a time when the system is uncongested has real benefits to the individual—it avoids the increased individual costs due to congestion. Further, if masking is effective enough, of one can delay being infected until herd immunity is reached, one will not be infected. Masking at the most infectious times does not guarantee one will not get sick when the system is congested, or make it to herd immunity without getting infected, but it makes it less likely that will happen, at least as long as h is not literally 0. If we were to add in that the cost of sickness falls over time as treatments and vaccines are developed, this argument is stronger. Note if h is 0, this does not occur at all, and it is minimal if h is very low. Yet, potentially, endogenous self-interested masking

Note that the individual does not receive all the benefits of masking—rather there are two sorts of externalities. First, not all congestion costs are private. Someone who gets hospitalized with covid may get treated, but displace someone who needs gall bladder surgery, causing their surgery to be done later when it is more risky and more serious, and so more likely to have bad outcomes including death. I personally know 2 people who have had exactly this occur. Second, masking does more to protect others than to protect the individual wearing the mask. So, endogenous masking will always be sub-optimal, but it does reduce the beneficial impacts of mask mandates. Saying anything quantitative about how much it changes the benefits and costs of mask mandated would require a really complicated model. Building one would be suitable for a PhD program, not this class.

Endogenous behavior has important implications beyond masking. In particular, the level of interactions each individual has can be self-moderated, at some cost, by social distancing and by cutting down on unnecessary trips or activities. This would work the same way. Individuals would have an incentive to reduce such things when infections are high, possibly making up for it when infections are low. This would endogenously dampen infection spikes, and also limit the size of the decline after spikes, potentially causing the reproductive rate accounting for such precautions to oscillate somewhere around 1.

5. Some Other Omissions

TO BE FINISHED ADDED LATER