Determining the optimal duration of the COVID-19 suppression policy: A cost-benefit analysis

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ABSTRACT

We investigate the optimal duration of the COVID-19 suppression policy. We find that absent extensive suppression measures, the economic cost of the virus will total over $9 trillion, which represents 43% of annual GDP. The optimal duration of the suppression policy crucially depends on the policy's effectiveness in reducing the rate of the virus transmission. We use three different assumptions for the suppression policy effectiveness, measured by the R_0 that it can achieve (R_0 indicates the number of people an infected person infects on average at the start of the outbreak). Using the assumption that the suppression policy can achieve $R_0 = 1$, we assess that it should be kept in place between 30 and 34 weeks. If suppression can achieve a lower $R_0 = 0.7$, the policy should be in place between 11 and 12 weeks. Finally, for the most optimistic assumption that the suppression policy can achieve an even lower R_0 of 0.5, we estimate that it should last between seven and eight weeks. We further show that stopping the suppression policy before six weeks does not produce any meaningful improvements in the pandemic outcome.

Keywords: COVID-19, Pandemic Curve, Attack Rate, Economic Damages, Public Health Policy, Suppression, Mitigation

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I. Introduction

The pandemic spread of COVID-19 poses an unprecedented threat to the U.S. economy, national security, and the quality of life in the United States. Experts agree that a vaccine will not become widely available until at least 18 months from now. In the absence of effective drug treatments, a non-pharmaceutical intervention is paramount. An intervention helps two-fold. First, by reducing transmission rates, it lowers the total number of infections and deaths. Second, it shifts the peak of the pandemic curve further out in time, and by then effective drug treatments may be available.

We assume that a non-pharmaceutical intervention will start with a suppression policy followed by mitigation until drug treatments become available. As discussed in Ferguson et al. (2020), a suppression policy "aims to reverse epidemic growth, reducing case numbers to low levels and maintaining that situation indefinitely" by restricting travel, closing schools, prohibiting gatherings, etc., while a mitigation policy "focuses on slowing but not necessarily stopping epidemic spread" and is less restrictive on the freedom of movement and less costly to the economy. The paper presents a cost-benefit analysis of extending the pandemic suppression policy to multiple weeks before eventually replacing it with a mitigation policy until pharmaceutical treatments become available, which we assume will happen 18 months from now.

Under the assumptions used in this paper, we conclude that the optimal public health policy would involve extending the suppression policy to at least seven weeks, but likely longer, depending on how effective it turns out to be at reducing infection transmission. We model the COVID-19 pandemic curve similarly to how the pandemic influenza[1] curve was modeled in a 2019 study by staff of the Council of Economic Advisers (CEA (2019)). The evolution of new infections is modeled at a weekly frequency. We assume that if no one in the U.S. population is immune, an infected person can infect R_0 other people over the two weeks that this person is sick.[2] The number of people infected in *each* of the two weeks equals $R_0/2$. We further assume that people who were

[1] Throughout the paper we will be using the terms "flu" and "influenza" interchangeably.

[2] R_0 measures how many other people an infected person infects on average at the start of an outbreak.

previously infected develop immunity that lasts at least two years and therefore would not be able to get infected again or pass the illness to others during that period.

Once a person is infected, they may be symptomatic or not. A symptomatic person will experience several possible outcomes. They may have mild symptoms and make an outpatient visit or recover from the illness without any professional help. A person may have severe symptoms and be hospitalized. Yet a smaller fraction of people may be hospitalized and then die. Each progressively more severe outcome entails higher economic costs associated with the illness. These costs are taken from the literature on seasonal flu. The probability of each outcome is taken from case studies on COVID-19, and these probabilities are adjusted for the likelihood that some cases were never diagnosed and, therefore, do not enter the study sample.

As discussed in Ferguson et al. (2020), the suppression policy helps reduce the total attack rate (AR) (defined as the fraction of the population that becomes symptomatically ill) by shifting the pandemic curve further out in time and closer to the vaccine availability date. The paper shows that the optimal duration of the suppression policy will depend on its effectiveness in reducing infection transmission rates, captured by R_0. Three different assumptions for R_0 of the suppression policy are considered: 1.0, 0.7, and 0.5. Once the suppression policy is lifted, it will be replaced by a mitigation policy. The paper assumes that the effectiveness of the mitigation policy can be improved through contact tracing but only if the number of new illnesses is relatively small. Otherwise, the system will be overwhelmed and contact tracing would not be possible. That critical value is set at 10,000 new infections per week. We assume that mitigation without contact tracing reduces the COVID-19 no-intervention R_0 by 30%, and if contact tracing is possible, mitigation will reduce the R_0 by half. Once a vaccine will become available, we assume that it will be highly effective, reducing R_0 to a very low value of 0.3.[3] At this time, all non-pharmaceutical intervention can be stopped. (The assumptions about R_0's used in this paper are detailed in Table I.)

The estimates in the paper show that shifting the pandemic curve forward in time by only a few weeks does not result in a substantial reduction in the attack rate because the entire pandemic

[3] In contrast, the effectiveness of the influenza vaccine is quite low because the virus constantly mutates.

scenario has a chance to play out before the vaccine becomes available. Even under the most optimistic assumption about the suppression policy's effectiveness, we show that it should be kept in place for at least seven weeks to produce optimal results. Under the more conservative assumptions, the policy should continue weeks longer in order to achieve noticeable results and prevent another steep acceleration in the number of new cases.

We find the optimal duration of the suppression policy by balancing its incremental benefits against the enormous costs the suppression policy imposes on the U.S. economy. Obviously, the longer the suppression period lasts, the further into the future it shifts the peak of the pandemic curve. If a policymaker's only objective was to achieve the lowest attack rate, the optimal solution would involve extending the suppression policy to 78 weeks, until the vaccine becomes available. However, after a certain point, the incremental benefits start to decline quickly. Hence, the policy should be kept in place only until the incremental benefit of an additional week of suppression still exceeds the costs it imposes on the economy. The optimal stopping time heavily depends on the policy effectiveness. The less effective it is, the longer suppression should be kept in place.

We would like to caveat the findings by pointing out that most of the inputs into our model are not yet precisely estimated. To the extent possible, we drew the model inputs from COVID-19 studies. When those were not available, we used the estimates from the seasonal influenza literature, and some assumptions were made by the author. We included some sensitivity analysis to check how the results would change in response to alternative parameter inputs. As more data on the COVID-19 outbreak become available, the model inputs can be easily changed and the optimal policy decisions re-estimated.

The rest of the paper is organized as follows: Section II models the pandemic curve under different assumptions and calculates the cost of the COVID-19 outbreak. Section III calculates the optimal stopping time for the suppression policy by estimating the point in time at which the incremental benefit from extending the suppression policy by one more week falls below the weekly economic cost of the policy. Section IV discusses the sensitivity of the results to alternative assumptions, and Section V concludes.

II. Estimating the cost of the outbreak

In this section, we closely follow the methodology of the CEA (2019) study that was done for a hypothetical pandemic flu outbreak to assess the economic cost of the COVID-19 pandemic.

A. Costs of the COVID-19 infection

The risks of possible outcomes for an infected person are described in Table II. The costs associated with different medical outcomes across age groups are described in Table III. For the calculation of the costs of lost productivity due to illness, we use the assumption in CEA (2019) that one missed work day represents a productivity loss of $151.88. Since COVID-19 is also a viral illness, we assume that using medical costs associated with seasonal influenza is appropriate. For the risks of different medical outcomes for various age groups, we use the estimates obtained from the COVID-19 outbreak when available. Otherwise, we use the probabilities associated with the seasonal flu. We furthermore assume that only 90% of the infected people develop symptoms that would need to be treated with medications, missed work, medical visits, or hospitalizations.[4] The other 10% do not suffer any loss in productivity and do not incur any medical costs.

The total cost calculations closely follow the studies of the costs of seasonal flu outbreaks (e.g., Molinari et al. (2007)). For each outbreak scenario, we first calculate the number of symptomatic people, and the number of sick people in each age group across different possible outcomes. We then multiple the number of people in each outcome category in each age group by the appropriate average costs and find the total cost of the pandemic by summing up the costs across possible outcomes and across all age groups. We perform two sets of the total cost calculations, with and without the value of statistical life (VSL) because VSL measures the value of a life and does not represent the actual cash outflow.

[4]For example, the WHO (2020) report states: "Symptoms of COVID-19 are non-specific and the disease presentation can range from no symptoms (asymptomatic) to severe pneumonia and death ... typical signs and symptoms include: fever (87.9%), dry cough (67.7%), fatigue (38.1%), sputum production (33.4%), shortness of breath (18.6%), sore throat (13.9%), headache (13.6%), myalgia or arthralgia (14.8%), chills (11.4%), nausea or vomiting (5.0%), nasal congestion (4.8%), diarrhea (3.7%), and hemoptysis (0.9%), and conjunctival congestion (0.8%)." (page 12)

B. Modeling the pandemic curve under different scenarios

In modeling the pandemic curve for COVID-19, we closely follow the methodology for modeling the pandemic flu used in CEA (2019), which was derived from the CDC models for pandemic influenza. Specifically, we model the number of new COVID-19 infections at a weekly frequency. We assume that the number of sick people is currently equal to 30,000 (source: CDC)[5] (this is week 0 in our model).

We will further assume that a certain fraction of the population will show no symptoms when infected and will not transmit the illness to others (the lack of asymptomatic transmissions is also sometimes assumed in pandemic flu models). While the CEA (2019) model assumes that 50% of the population is asymptomatic, we assume a much lower percentage of asymptomatic people, 10% across all age groups, as described in Table II. (In Section IV we relax the assumption that the asymptomatic people cannot pass the virus to others and also experiment with different proportions of asymptomatic people.)

Another assumption we use is that infected people are ill for two weeks, during which time they will infect R_0 other people at the start of the outbreak because no one yet has immunity. The number of other people a sick person infects is assumed to be spread evenly across the two weeks, with $R_0/2$ people infected in each week. (In Section IV, we change the assumption that the new infection transmission is spread evenly across the two weeks and instead assume that it happens entirely during the first week of the illness.) Additionally, we assume that the population who survived the illness will develop immunity to it for at least 24 months.

As the outbreak progresses, more and more people develop immunity, and an ill person is increasingly more likely to come into contact with someone who is already immune and not pass on the virus. The increasing immunity ratio is what explains the bell shape of the pandemic curve. At the start of an outbreak, the infection initially spreads at increasing rates[6] (the first sick person on average infects R_0 other people, the R_0 newly sick people infect another R_0^2 people and so

[5] `https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html`.

[6] Assuming $R_0 > 1$.

on). However the rate of increase in the number of new infections starts to slow as more people develop immunity. The number of new infections eventually peaks and then starts to decline to zero. Without any intervention, an infection will die out naturally after a sufficient fraction of the population develops immunity. What a public health intervention needs to minimize is the infection attack rate (AR), or the fraction of the population that becomes ill over the course of the outbreak.

B.1. The no-intervention scenario

A key question is what assumption to use for the no-intervention R_0 for COVID-19. We use the assumption of Ferguson et al. (2020) that COVID-19 has $R_0 = 2.40$, a number that is consistent with the COVID-19 studies.[7] This R_0 values is very high and, in fact, higher than typical R_0 assumptions used for modeling pandemic flu. In case of a pandemic flu strain, some older people may have experienced similar flu strains in the distant past, lowering the R_0 of the outbreak, and COVID-19 is an entirely novel virus to which no humans have immunity.

Figure 1 presents the shape of the COVID-19 pandemic curve in the U.S. without any interventions. The number of new infections peaks around the middle of July 2020. The attack rate (AR) is 79.5%, and the total number of deaths is estimated to be 1.9 million.[8] The economic cost of the pandemic, calculated as described above, is projected to be $13.2 trillion when VSL for the fatalities is taken into account and $1.2 trillion when it is not.

B.2. Suppression policy

Next, we plot the pandemic curve assuming that suppression policy is put in place starting in week 0. We assume that suppression reduces R_0 to 1.0 or below, in line with the discussion in Ferguson et al. (2020), and model three different scenarios for R_0 that the suppression policy can achieve: 1.00, 0.70, and 0.50. The latter two scenarios are rather optimistic in light of the fact that the

[7] For example, Zhang et al. (2020) estimate a similar value of 2.28.

[8] The fatality estimate is somewhat lower than the 2.2 million estimated in Ferguson et al. (2020) (page 7). Our population-weighted infection fatality ratio (IFR) is 0.74%, which is lower than the IFR of 0.9% in that paper—see Table 1 of Ferguson et al. (2020) for that paper's assumptions.

median R_0 for seasonal influenza is 1.28 (Biggerstaff et al. (2014)), and with seasonal influenza a large portion of the population is immune prior to the outbreak—some through vaccination, and some through prior exposure.

Pandemic curves for each of the three scenarios are plotted in Figure 2. With the assumption of $R_0 = 1.0$, even though each person on average infects one person at the start of the outbreak, the number of new infections declines over time because of the assumption that 10% of the population are asymptomatic and do not spread the virus further.[9] When the suppression policy is kept in place for the entire 78-week period until the vaccine becomes available, the outcomes are as follows. With the assumption of $R_0 = 1.0$, the AR is 0.10%, total fatalities reach 2,300, and total economic cost is calculated to be \$15.8 billion with VSL and \$1.4 billion without. With the middle scenario that assumes $R_0 = 0.7$, AR equals 0.03%, total fatalities reach 439 people, the the total economic cost equals \$3.0 billion with VSL and \$273 million without. Finally, under the most optimist scenario with $R_0 = 0.5$, AR is 0.02%, fatalities amount to only 211, and the total economic cost is \$1.4 billion with VSL and \$131 million without. All these numbers are orders of magnitude below the cost of the no-intervention policy. However, the suppression policy undeniably imposes a very high cost to the economy, and it may be optimal to stop it before a vaccine becomes available.

B.3. Modeling the suppression policy at different durations

We assume that once stopped, a suppression policy will be replaced by a less socially restrictive and less economically damaging mitigation policy, as described in Ferguson et al. (2020). While is it unclear how much a mitigation policy can reduce the no-intervention R_0, Ferguson et al. (2020) argue that this value will be above 1.00. We will assume that if the number of new infections stays above 10,000, mitigation measures can reduce R_0 by 30% relative to the no-intervention scenario,

[9] The decline is initially not smooth, as the number of new cases increases slightly in week 2 compared to week 1 due to how the outbreak is modeled. Because of the assumption that the ill infect others over a two-week period, and prior to week 0, the virus spreads at a much higher $R_0 = 2.4$, the number of the ill in week -1 is significantly below that in week 0, but the rate at which they spread the infection to others declines significantly in week 1 compared to week 0 due to a much lower R_0 at that time.

from 2.4 to 1.68. However, if the number of new infections falls below 10,000, contact tracing will become possible, and R_0 can be instead reduced by 50%, from 2.4 to 1.2.

For the ease of the exposition, the benefits from extending a suppression policy further in time are calculated relative to the baseline scenario, which is defined as keeping the suppression policy in place for only two weeks and then replacing it with a mitigation policy. Table IV presents statistics on the attack rate, fatalities, and total costs for each of the three suppression policy effectiveness assumptions, as measured by its R_0.

Figure 3 presents pandemic curves drawn assuming that suppression can achieve $R_0 = 1.0$. The upper-left chart plots the pandemic curve for the baseline scenario of keeping the suppression policy in place for two weeks and then replacing it by mitigation. From chart that follows to the right, it can be seen that extending the policy to 10 weeks shifts the peak of the pandemic curve further out in time relative to the baseline scenario. However, almost the entire pandemic curve has a chance to play out before the vaccine becomes available around September 19, 2021. The 20-week extension moves the pandemic curve even further out in time, but again not enough to have a strong effect on the course of the outbreak. Relative to the baseline scenario, AR is reduced by only 0.17 percentage points and the number of deaths, by 6,448. The total cost of the outbreak is reduced by $44 billion (unless specified otherwise, we will only mention total costs that include VSL). Extending the policy to 25 weeks produces a visible change in the shape of the pandemic curve: the right-hand tail of the curve becomes clipped because the vaccine availability substantially speeds up the rate of decline in new infections, which already started to happen on its own. The AR is reduced by 6.20 percentage points, the number of fatalities by 249,677, and total costs by $1.7 billion. When suppression lasts 30 weeks, the pandemic curve never fully materializes. The curve is pushed so far forward in time that its rise is clipped once the COVID-19 vaccine becomes available. The 34-week suppression policy shows a similar but a more pronounced effect. The smaller Y-axis scale of the graph additionally shows the initial fall int the number of new infections, which is also present on the other charts but visible because of the larger scale. Relative to baseline, the AR is reduced by 54.48%, the number of deaths by 1,325,722, and the total economic cost by $9.1 billion.

Figure 4 depicts pandemic curves for the assumption that suppression can achieve $R_0 = 0.7$. (We present shorter duration-change steps than on the previous figure because the suppression policy produces significant effects sooner.) The two-week baseline scenario presented in the upper-left chart looks about the same as in the previous figure. Similarly, extending the policy to seven weeks does not significantly change the course of the pandemic but simply shifts the peak of the curve forward in time. However, extending suppression to 10 weeks already starts to show visible results. The right-hand tail of the curve becomes clipped by the vaccine availability, and the AR is reduced by 44.07 percentage points, the number of fatalities by 1,164,949, and the total economic cost by $8.0 billion. With a 12-week suppression policy ,the pandemic curve has a much shorter rise. At 13-week suppression duration reduces the rise even further. The AR is 55.12 percentage points below the baseline, the number of deaths is reduced by 1,335,359 and economic cost is $9.1 billion lower. At 14 weeks the peak is reduced even further. Both chart clearly show the initial decline in the number of new cases that starts to pick up again once the mitigation policy is put in place. Again, this initial decline is also present in previous charts but not visible because of the scale.

Finally, Figure 5 plots pandemic curves for the suppression policy assumption of $R_0 = 0.5$. The patterns that emerge are very similar to the previous two figures, but visible a reduction in the number of new infections is achieved sooner.

III. Estimating the incremental economic benefits of extending the suppression policy

Given its high cost, the suppression policy should be kept in place only as long as its incremental benefit derived from reducing the number of new infections going forward exceeds its cost. To find the optimal duration for the suppression policy, in this section, we calculate the incremental benefit of extending the suppression policy by each additional week, before replacing it with the mitigation policy, and compare this benefit to the weekly cost that suppression imposes on the U.S. economy.

A. Estimating the incremental weekly costs of the suppression policy relative to mitigation

The suppression policy is likely to impose high incremental costs on the U.S. economy relative to our mitigation baseline. The economy would be hurt by both of these policies, but the suppression creates a larger damage. By prohibiting public gatherings, restricting travel, and closing schools, it disproportionately affects certain sectors of the economy and reduces the productivity of working adults with underage children, since the children need to be supervised and home schooled during work hours. We will provide a rough estimate of what these incremental costs may be.

The first component of the cost is the reduced productivity of adults with children under 18 years old. There are 158,130,000 working adults in the U.S., and 40.66% of U.S. households have children under the age of 18.[10] We assume that each adults in the household with children under 18 would will lose 35% of their productivity. Using the assumption that we used in the cost-of-the-outbreak calculation, that a productive work day contributes $151.88 to the GDP, we estimate the total weekly cost due to the lower productivity to be $17.09 billion.

The restrictions on social gatherings and travel would have a large negative effect on certain sectors of the economy. Using the sector definitions from the Census Value Added table, we assume that the negatively affected sectors will be (1) Arts, Entertainment, Recreation, Accommodation, and Food Services (4.2% of value added in 2018), (2) Retail Trade (5.5% of value added), (3) Transportation and Warehousing (3.2% of value added), and (4) Other Services, Except Government (2.1% of value added). We further assume that relative to the mitigation policy baseline, these sectors will experience an incremental decline in output equal to 50% for Arts, Entertainment, Recreation, Accommodation, and Food Services, and Transportation and Warehousing; 20% for Retail Trade and 10% for Other Services, Except Government. Multiplying these projected percentage declines by the 2018 output, we calculate that these sectors will be losing $18.70 billion per week when the suppression policy is in place. Adding together these costs, we estimate suppression has an incremental cost of $35.79 billion per week relative to the mitigation strategy

[10]Source: Statista.

baseline. If extended to a year, these incremental costs would amount to 8.7% of the 2019 GDP. (In Section IV do a sensitivity analysis to an even larger value for the incremental damage amount.)

B. Optimal stopping time for the suppression policy

Figures 3–5 show that extending the duration of the suppression policy beyond a certain point starts producing quickly diminishing returns. Figure 6 plots the incremental benefit produced by extending the suppression policy by each additional week, assuming that it was in place in all weeks prior, relative to the baseline that it is replaced by the mitigation policy until the vaccine is available. Each charts plots two lines, with and without the value of statistical life (VSL) factored into the cost calculation. The three charts present the plots for each assumption on the suppression policy's effectiveness. All charts show a similar pattern: Incremental savings rise to a maximum value and then start to decline. The charts also show that the suppression policy needs to be in place for a shorter period of time to achieve maximal results when it is more effective.

Given that incremental savings start to show a decreasing pattern after some point, it may be optimal to end the policy before the vaccine availability. Specifically, it should end before the incremental benefit of extending the policy by yet another week falls below the economic damages it imposes on the economy, which we estimated to be $35.79 billion per week. Figure 7 plots the incremental benefit of extending the suppression policy by one additional week against the constant cost of the policy. We show only the interesting parts of the graphs for the three suppression R_0 scenarios, just around the time when the two lines cross, which represents the optimal stopping time. It can be seen that when $R_0 = 1.0$, the lines cross after 34 weeks, for $R_0 = 0.7$ after 12 weeks, and for $R_0 = 0.5$ after eight weeks.

Some may argue that VSL should not be included in the benefits calculations because it does not represent a true monetary outflow, or perhaps because a lower VSL value should be used. We, therefore, redo our calculations without taking VSL into account. These calculations lead to somewhat earlier stopping times, which are 30 weeks when $R_0 = 1.0$, 11 weeks when $R_0 = 1.0$, and seven weeks when $R_0 = 1.0$.

IV. Sensitivity to the assumptions and other caveats

The model used in this paper relies on a particular set of assumptions outlined above. Given a large number of unknowns, the findings should be caveated. Below, we discuss the sensitivity of the results to different assumptions.

The peak of the pandemic curve. We have assumed that infected people infect an equal number of others in the two weeks that they are sick. If all new infections instead happened in the first week of illness, the peak of the pandemic curve would be reached faster. For the non-intervention scenario with $R_0 = 2.4$, the peak of the curve would be reached in the beginning of June as opposed to the middle of July.

Asymptomatic population. We have assumed that 10% of the population is asymptomatic. However, this number is likely to be larger given the lack of widespread testing. We recalculate what effect the change in this assumption would have on the no-intervention scenario. If the percentage of asymptomatic population were 50% instead (as is often assumed in modeling the spread of the influenza virus), the attack rate for the no-intervention scenario will drop to only 14.69%. However, if we assumed that all these asymptomatic people could infect others, the attack rate would be 46.47%.

Effectiveness of the mitigation policy. In our model, once the suppression policy ends, it is replaced by a less restrictive mitigation policy. We assumed that mitigation can achieve a 30% decrease in spread of the disease than the no-intervention scenario, or $R_0 = 1.68$. We tried changing this assumption to a more optimistic assumption that mitigation can reduce the no-intervention R_0 by 40 percentage points, to 1.44. (We left intact the assumption that mitigation with contact tracing achieves $R_0 = 1.2$.) We more effective mitigation, the optimal duration of the suppression policy is reduced. For example, in the scenario when suppression $R_0 = 1.0$, the optimal stopping time shortens from 34 to 32 weeks when VSL is taken into account, and from 30 to 24 weeks, when it is not.

Infection fatality ratio. Given that widespread testing for COVID-19 is not available, it is very likely that the fatality ratio is significantly lower than the one we used. For example, Mizumoto et al. (2020) estimate that the IFR for COVID-19 is only between 0.04% and 0.12%, while the population-weighted IFR that we use in the paper is 0.74%. We multiply our IFR estimates in Table II across the age groups by the 0.12%/0.74% ratio to achieve the same relative risk distribution across the age groups as before but lower the population-weighted IFR to 0.12%. The results show that with the no-intervention policy, the pandemic will kill 312,094 people and will cost the economy $2.2 trillion.

Potential nonlinearities in medical costs. We have not taken into account the potential nonlinearities in clinical outcomes. If at one point the demand for medical resources begins to exceed capacity, there will be more fatalities than what we estimated, leading to higher total costs of the outbreak.

The cost of the suppression strategy to the U.S. economy. We may have underestimated the weekly cost of the suppression policy to the U.S. economy. We check that increasing our estimated cost two-fold, to $71.6 billion per week, does not dramatically affect the results. The only change from the earlier estimates on the optimal suppression duration is it is reduced from 30 to 29 weeks for the assumption $R_0 = 1.0$, and only when VSL is not taken into account.

Other costs and benefits. We briefly discuss other costs and benefits of the suppression policy which we have not quantified. One economic benefit of the suppression policy is that it will lower pollution levels due to decreased travel and production. Another benefit, no modeled here, is that if the COVID-19 survivors suffer from longer-term negative health consequences, a longer suppression duration can reduce these longer-term costs. We have also not factored in the cost of government stimulus policies. Furthermore, some corporations will default on debt and declare bankruptcies, resulting in less efficient redeployment of assets. Finally, the lower quality of education during the home schooling period may result in a marginally less productive future workforce.

V. Conclusion

When does the cure become worse than the curse? To our knowledge, this paper presents the first attempt to find the optimal duration of the suppression policy by analyzing its costs and benefits. We caveat our findings by pointing out that there are still many unknowns and some of the analysis could be further refined. Once new COVID-19 specific estimates become available, the model can be easily updated.

The analysis in this paper shows that the suppression policy is unlikely to achieve desired results if it is abandoned too soon. Another interesting finding is that the optimal duration of the policy depends on how effective it is in reducing the rate of new infections. The higher its effectiveness, the sooner the policy can be optimally ended and replaced with the less economically costly mitigation policy until the vaccine becomes available. Finally, the analysis shows that the results are not very sensitive to assigning a high value of life. This is especially important given the ongoing discussions about the value of life of the elderly population, which is the most at risk from the virus.

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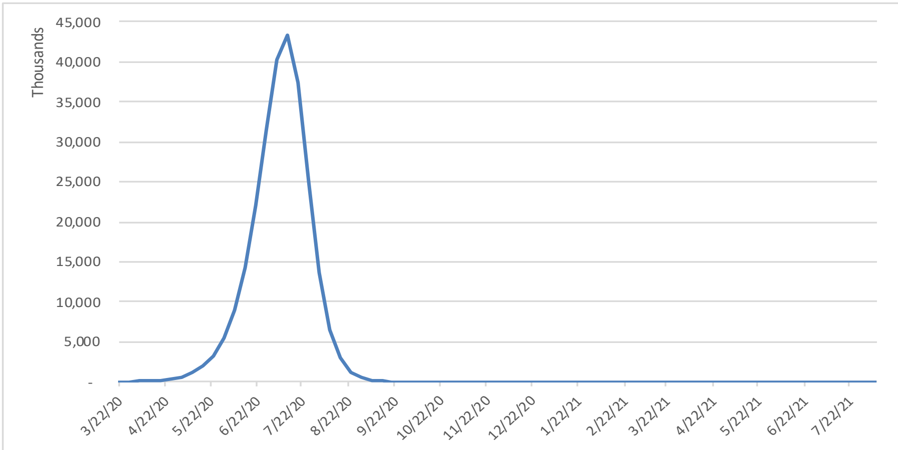
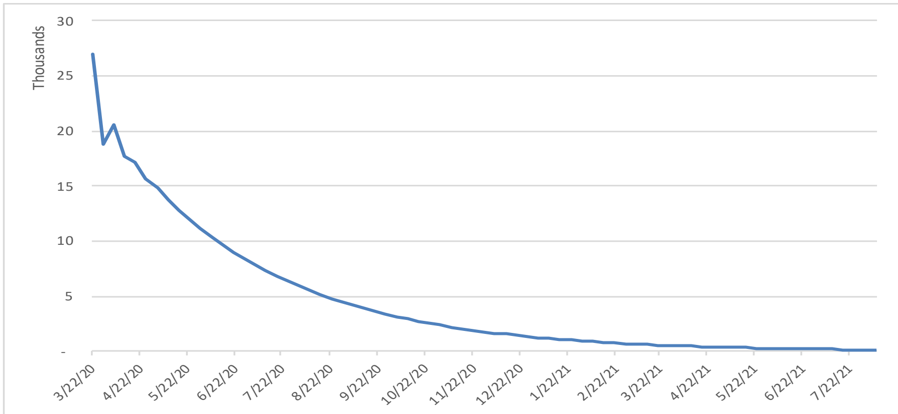
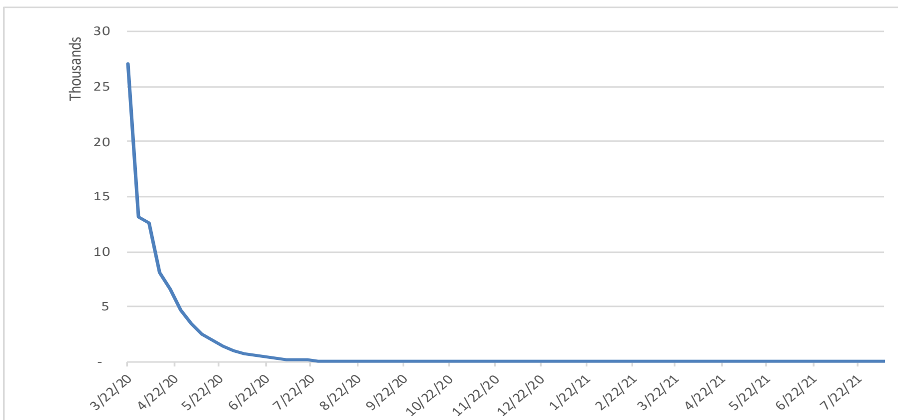


Figure 1. New symptomatic infections with no intervention. The figure plots the pandemic curve for COVID-19 if there are no interventions. It assumes that the illness period is 2 weeks, and $R_0 = 2.4$. The fraction of symptomatic individuals is .9, and asymptomatic people cannot infect others. The peak number of new infections occur in the week of 7/12/20. The attack rate is 79.5%, the total number of deaths is 1,924,577, and the cost of the outbreak is \$13.18 trillion with VSL and \$1.20 trillion without.

$R_0 = 1.0$



$R_0 = 0.7$



$R_0 = 0.5$

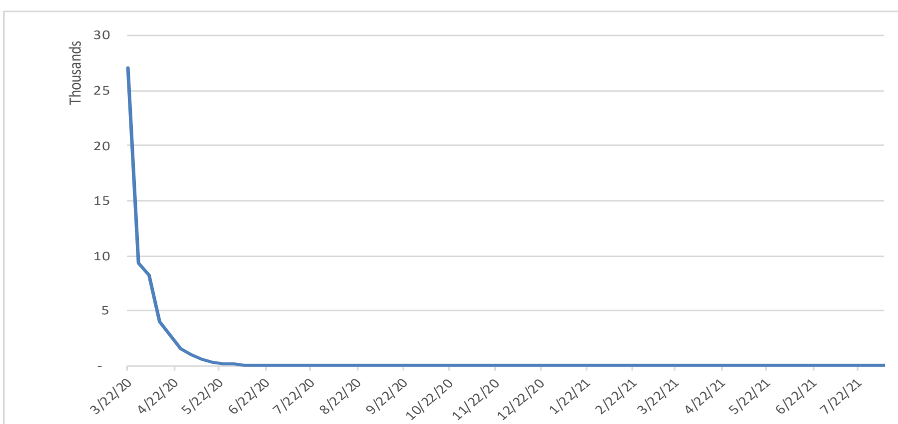


Figure 2. New symptomatic infections with suppression policy in place for 78 weeks. The figures plots the pandemic curve for COVID-19 with the suppression policy in place for 78 weeks, with R_0 as indicated above each chart. The illness period is assumed to be 2 weeks, and the fraction of symptomatic individuals 0.9, with the assumption that asymptomatic people cannot infect others. When $R_0 = 1.0$, the AR=0.10%, the total number of deaths is 2,300, the total cost of the outbreak is \$15.76 billion with VSL and \$1.43 billion without. When $R_0 = 0.7$, AR=0.03%, the number of deaths is 439, the total cost of the outbreak is \$3.01 billion with VSL and \$273 million without. When $R_0 = 0.5$, AR=0.02%, the number of deaths is 211, the total cost of the outbreak is \$1.45 billion with VSL and \$131 million without.

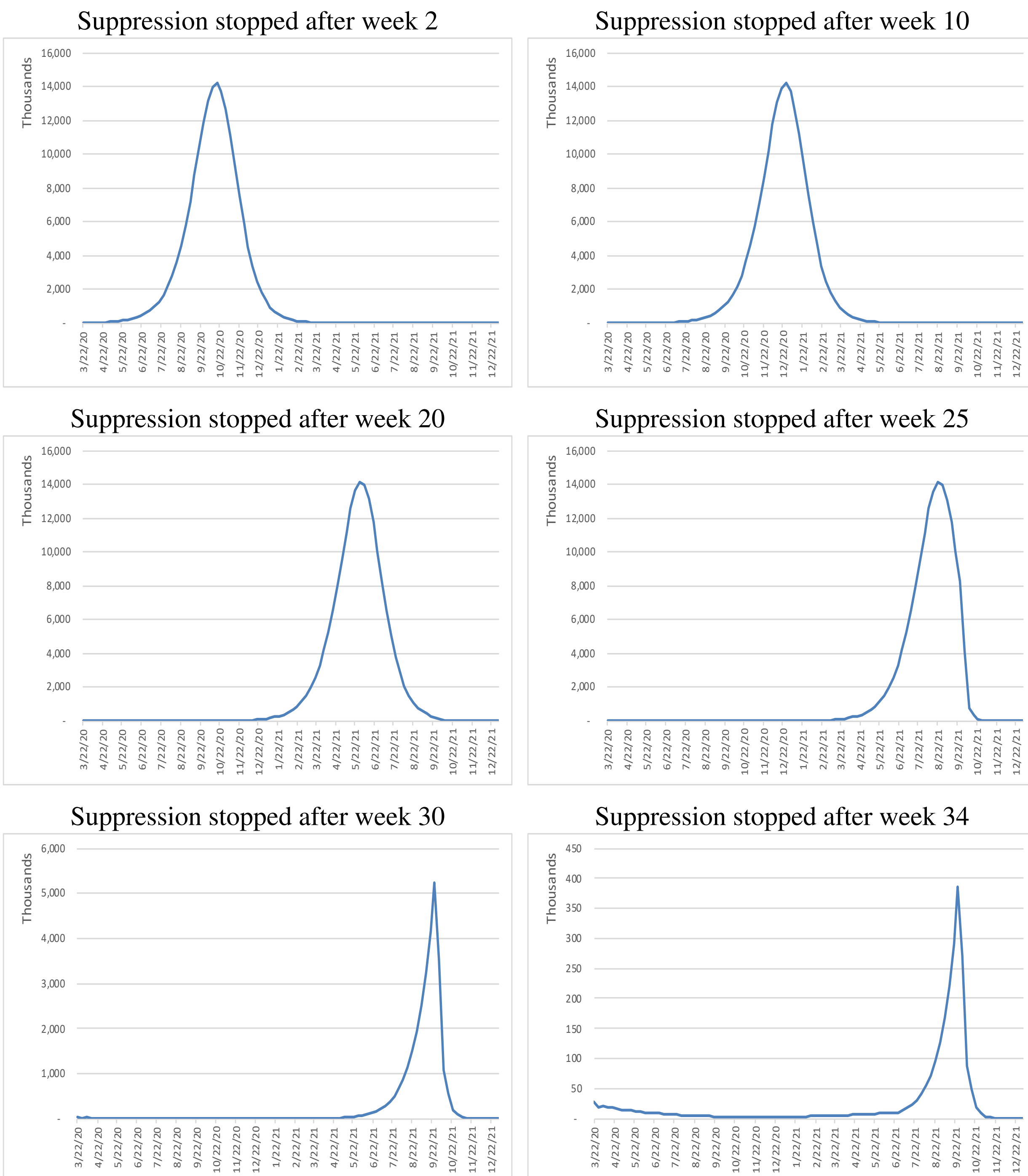


Figure 3. New symptomatic infections with suppression policy extended to the number of weeks indicated above each figure, assuming that suppression policy achieves $R_0 = 1.0$. The figures plot the COVID-19 pandemic curves when the suppression policy is kept in place as indicated above each figure, after which a mitigation policy is adopted.

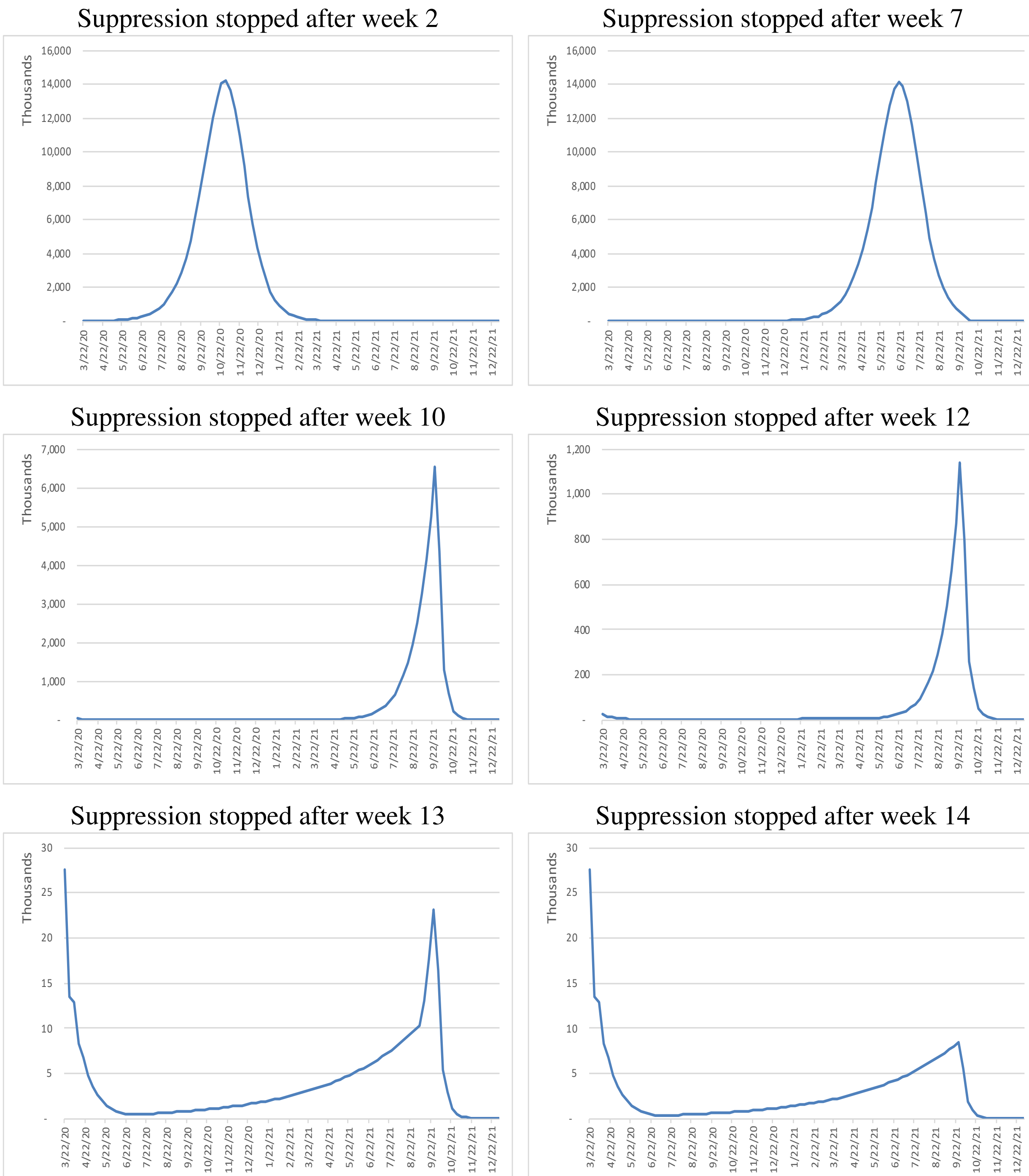


Figure 4. New symptomatic infections with suppression policy extended to the number of weeks indicated above each figure, assuming that suppression policy achieves $R_0 = 0.7$. The figures plot the COVID-19 pandemic curves when the suppression policy is kept in place as indicated above each figure, after which a mitigation policy is adopted.

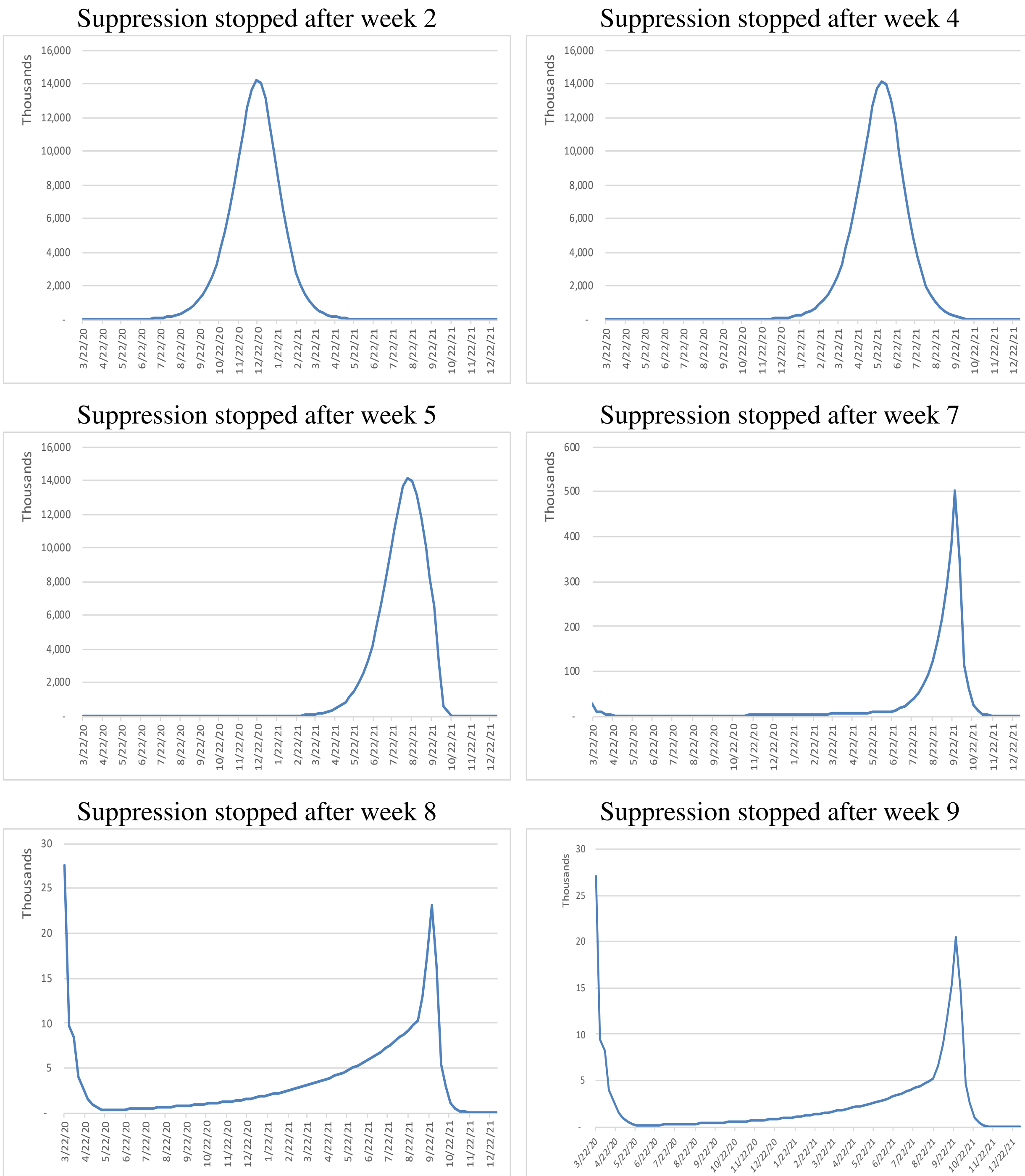
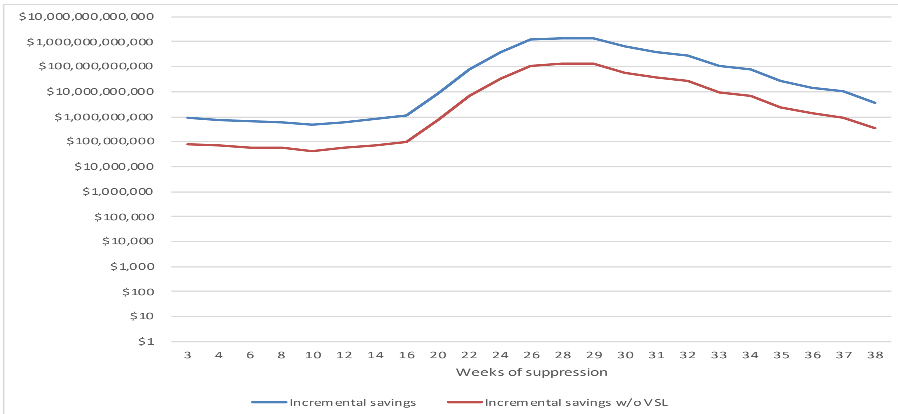
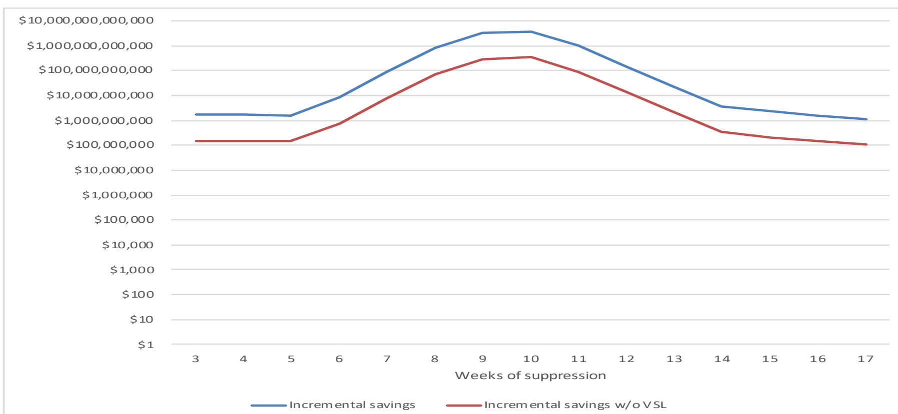


Figure 5. New symptomatic infections with suppression policy extended to the number of weeks indicated above each figure, assuming that suppression policy achieves $R_0 = 0.5$. The figures plot the COVID-19 pandemic curves when the suppression policy is kept in place as indicated above each figure, after which a mitigation policy is adopted.

$R_0 = 1.0$



$R_0 = 0.7$



$R_0 = 0.5$

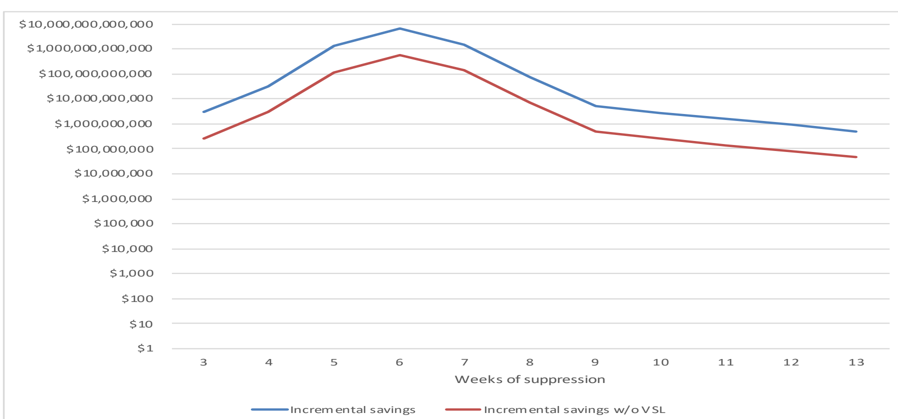
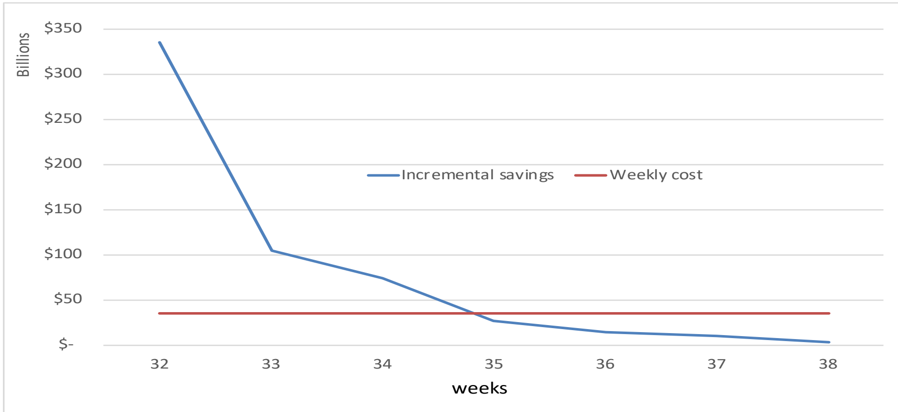
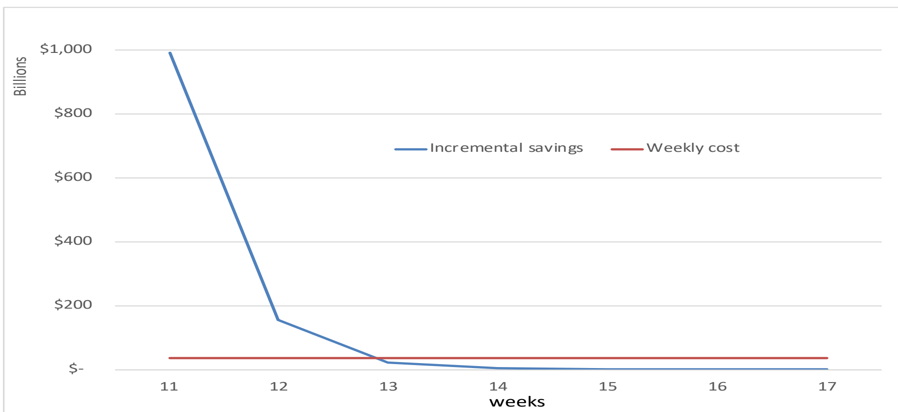


Figure 6. Incremental savings from an additional week of suppression. The figures plot incremental savings from extending the suppression policy by an additional week relative to replacing it with the mitigation policy. Both scenarios assume that the mitigation policy will be kept in place until week 78, when a vaccine becomes available. The blue line factors the value of statistical life (VSL) into the cost calculations and the red line does not. The assumptions used for the suppression policy R_0 are presented above each figure.

$R_0 = 1.0$



$R_0 = 0.7$



$R_0 = 0.5$

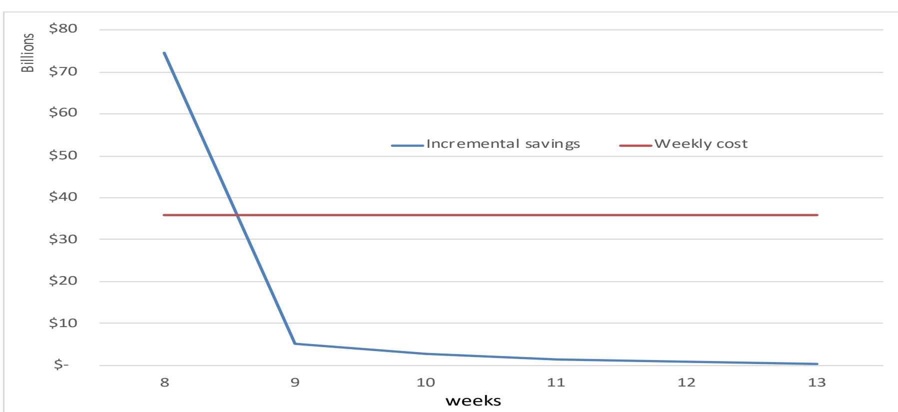


Figure 7. Incremental costs and savings of an additional week of suppression. The figures plot incremental costs and savings of an additional week of the suppression policy, conditional on the policy having been in place in the prior weeks. The constant cost of the suppression strategy equals \$35.79 billion per week. The assumptions used for the suppression policy R_0 are presented above each figure.

Table I
Assumptions about R_0

This tables presents assumptions about R_0 as a function of public health strategies and vaccine availability.

Public health strategy	R_0	Source for the assumption
No intervention	2.40	Ferguson et al. (2020)
Suppression scenarios:		
- pessimistic	1.00	Author's assumption
- middle	0.70	Author's assumption
- optimistic	0.50	Author's assumption
Mitigation without contact tracing	1.68	A 30% reduction from no-intervention R_0 in place if number of new infections $\geq 10,000$
Mitigation with contact tracing	1.20	A 50% reduction from no-intervention R_0 in place if number of new infections $< 10,000$
After vaccine becomes available	0.30	Author's assumption

Table II
Risks Associated with COVID-19 Infection by Age Group

This table presents the risks associated with COVID-19, by age group.

	Age Group							
	0-19	20-44	45-54	55-64	65-74	75-84	$\geq$85	Source for the assumptions
% of US population	25%	33%	13%	13%	9%	5%	2%	Statista
% symptomatic	80%	90%	90%	90%	90%	90%	90%	WHO (2020)
% high-risk	8%	15%	24%	33%	51%	51%	51%	CEA (2019), author
Probability of outpatient visit								
- low-risk patients	32%	32%	32%	31%	62%	62%	62%	CEA (2019), author
- high-risk patients	77%	63%	63%	63%	82%	82%	82%	CEA (2019), author
Clinical outcomes								
Conditional on infection being diagnosed								
Prob. of hospitalization	2%	18%	25%	25%	36%	45%	51%	CDC (2020) midpoint estimate
Probability of death	0%	0%	1%	2%	4%	7%	19%	CDC (2020) midpoint estimate
Unconditional, assuming only 50% of infections are diagnosed								Author's assumption
Prob. of hospitalization	1.0%	8.8%	12.4%	12.7%	18.0%	22.3%	25.4%	Estimate above × 50%
Probability of death	0.0%	0.1%	0.3%	1.0%	1.9%	3.7%	9.4%	Estimate above × 50%

Table III
Costs Associated with COVID-19 Illness by Age Group

This table summarizes per person medical costs conditional on the outcome of the COVID-19 infection, by age group. The assumptions are drawn from CEA (2019), Table 2. For the age groups that did not appear in that table, the estimates are averaged between the adjacent age groups.

	Age Group						
	0-19	20-44	45-54	55-64	65-74	75-84	$\geq$85
Case not medically attended							
Medical cost (all risk)	\$5	\$5	\$5	\$5	\$5	\$5	\$5
Lost productivity (all risk)	\$76	\$76	\$76	\$76	\$152	\$152	\$152
Outpatient visit							
Low-risk medical cost	\$161	\$212	\$233	\$254	\$410	\$410	\$410
Low-risk lost productivity	\$152	\$152	\$228	\$304	\$456	\$456	\$456
High-risk medical cost	\$1,098	\$1,227	\$1,234	\$1,240	\$806	\$806	\$806
High-risk lost productivity	\$608	\$304	\$456	\$608	\$1,063	\$1,063	\$1,063
Hospitalization							
Low-risk medical cost	\$25,408	\$32,174	\$34,960	\$37,745	\$19,379	\$19,379	\$19,379
Low-risk lost productivity	\$1,367	\$1,823	\$1,899	\$1,974	\$1,974	\$1,974	\$1,974
High-risk medical cost	\$70,938	\$80,760	\$75,334	\$69,908	\$28,346	\$28,346	\$28,346
High-risk lost productivity	\$3,493	\$3,189	\$3,417	\$3,645	\$2,734	\$2,734	\$2,734
Fatalities							
Low-risk medical cost	\$48,769	\$129,184	\$164,925	\$200,666	\$70,989	\$70,989	\$70,989
Low-risk lost productivity	\$1,367	\$1,823	\$1,899	\$1,974	\$1,974	\$1,974	\$1,974
High-risk medical cost	\$453,461	\$128,429	\$164,773	\$201,117	\$55,865	\$55,865	\$55,865
High-risk lost productivity	\$3,493	\$3,189	\$3,417	\$3,645	\$2,734	\$2,734	\$2,734
VSL (in \$, mil.)	5.76	12.34	10.05	7.75	5.29	5.29	5.29

Table IV
Baseline scenarios

This table presents the baseline outcomes of keeping the suppression policy in place only for the first two weeks and then switching to the mitigation policy at week 3 and keeping it in place until the vaccine becomes available in week 78.

Assumption for the suppression policy R_0	Attack rate	Fatalities	Total Cost ($, billions)	Total Cost w/o VSL ($, billions)
$R_0 = 1.00$	55.23%	1,337,584	$9,163.05	$0.83
$R_0 = 0.70$	55.23%	1,337,475	$9,162.30	$0.83
$R_0 = 0.50$	55.21%	1,337,203	$9,160.44	$0.83