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# CALCULATING THE COSTS AND BENEFITS OF ADVANCE PREPARATIONS FOR FUTURE PANDEMICS

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## ABSTRACT

The Covid-19 pandemic is estimated to have caused over 7 million deaths and reduced economic output by over $13 trillion to date. While vaccines were developed and deployed with unprecedented speed, pre-pandemic investments could have accelerated their widespread introduction, saving millions of lives and trillions of dollars. Combining estimates of the frequency and intensity of pandemics with estimates of mortality, economic-output, and human-capital losses from pandemics of varying severities, we calculate expected global losses from pandemics of over $800 billion annually. According to our model, spending $60 billion up front to expand production capacity for vaccines and supply-chain inputs and $5 billion every year thereafter would be sufficient to ensure production capacity to vaccinate 70% of the global population against a new virus within six months, generating an expected net present value (NPV) of over $400 billion. A proportionate advance-investment program undertaken by the United States alone would generate an expected NPV of $47 billion ($141 per capita).



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# 1 Introduction

By 2024, it is estimated that the Covid-19 pandemic will have reduced economic output by $13.8 trillion relative to pre-pandemic forecasts (International Monetary Fund 2022). Excess deaths during the pandemic are estimated at between 7 and 13 million (*Economist* 2022) while loss of future productivity and earnings from school disruption is estimated at between $10 trillion and $17 trillion (Azevedo et al. 2021). Previous pandemics also generated large losses: the 1918 flu killed 2% of the world's population and reduced GDP by 6% (Barro, Ursúa, and Weng 2020); while the Black Death killed 30% of Europe's population (Alfani 2022).

Vaccines against Covid-19 were developed, approved, and distributed at record speed, sharply reducing both the economic and social losses. Yet many countries waited years for sufficient supply resulting in millions of deaths and trillions in economic damage that could have been averted. Estimates suggest that accelerating the capacity to produce 1.5 billion courses of vaccine annually by just three months would have had a social value of $1.3 trillion (Castillo et al. 2021). This large social value eclipsed the revenue that pharmaceutical companies were earning from Covid-19 vaccines. The gap between private and social returns would likely lead companies to underinvest in the capability to produce pandemic vaccines both before and during pandemics relative to the social optimum without public policy to bolster that capability.

This paper evaluates the economic case for public investments in the vaccine production capacity infrastructure to prepare for the next viral pandemic. We follow (and extend) Marani et al. (2021) who find a generalized Pareto distribution closely describes the frequency and intensity of pandemics from 1600 to the present. They keep constant the distribution of relative pandemic intensities while allowing the arrival rate of epidemics to vary over time in response to developments such as the invention of antibiotics or increased zoonotic spillover from climate change. We combine these projections with estimates of the economic costs of pandemics of different intensities from the economic literature (Barro, Ursúa, and Weng 2020; Keogh-Brown et al. 2009; Huber, Finelli, and Stevens 2018; United Nations Development Programme 2017; International Monetary Fund 2022), the value of lives lost, and losses from school closures (Azevedo et al. 2021). In total, we estimate that the world can expect to lose over $800 billion to future pandemics annually. To account for the uncertainties in predicting pandemics, we estimate pandemic losses under a range of scenarios: under the most optimistic scenarios expected losses are at least $400 billion annually, rising to $2 trillion annually under some plausible scenarios.

With these estimates of large expected losses in hand, we proceed to estimate the return to a combination of up-front and continuing investments that reduce the damage caused by pandemics. We evaluate the benefits of this approach against a counterfactual of investing in vaccine capacity at the maximum scale and speed that can be achieved once a pandemic starts. We find expanding production capacity for vaccines and supply-chain inputs so that there is sufficient production capacity to vaccinate 70% of the global population against a new virus within six months would generate expected net benefits of over $400 billion by cutting the time to complete that vaccination campaign by more than half. According to our model, the program would require an up-front investment on the order of $60 billion and $5 billion to be spent each year thereafter. These estimates account for the risk that vaccines might fail and that vaccine hesitancy might be high.

Our analysis focuses on a global program since this would extend the benefits of accelerated and expanded capacity to the most people. However, full participation among all countries may not be achievable in equilibrium absent an international agreement. The reason is that advance investment by one country reduces its demand for in-pandemic capacity, generating positive spillovers for others, possibly leading to free riding. If countries fail to strike an international agreement, it is not an equilibrium for none of them to invest in advance. High-income countries would reap large net benefits from going it alone and investing in advance capacity. For example, we calculate that if the United States alone undertook an advance-investment program that enabled it to vaccinate 70% of its population within six months, this would generate an expected present value of $61 billion in benefits net of program costs, a gain of $47 billion ($141 per capita) over the counterfactual program. The benefits extend to middle- and low-income countries as well. For example, we calculate that an advance-investment program would provide Brazil net benefits of $57 per-capita.

While our main focus is on preparatory investments in vaccine production capacity, the logic of our arguments extends to a broader set of investments that could mitigate pandemic harm including research, development and production of a universal coronavirus vaccine, development of broad-spectrum antivirals and new antibiotics and investments that would streamline vaccine approval during pandemics (such as the rules under which human challenge trials would be appropriate).

Our paper builds on work in the scientific literature on the frequency of pandemics

including Marani et al. (2021), Carlson et al. (2021), and Bernstein et al. (2022) as well as an economics literature on the economic costs of specific past pandemics (cited above) and the expected costs of future pandemics (Fan et al. 2018; Nakamura et al. 2013, Keogh-Brown et al. 2009, Martin and Pindyck 2015, Martin and Pindyck 2017, Jaimeson and Summers 2015) although our methods capture progress in the world's ability to moderate the impact of pandemics. We expand on previous literature on the cost-effectiveness of pandemic preparedness including increased surveillance (Bernstein et al. 2022), research and development (Crank et al. 2019), vaccines including building up stockpiles (Meltzer, Cox, and Fukuda 1990; Prager, Wei, and Rose 2017; Schoenbaum 1987), and all of the above (Yamey et al. 2017). Our model of the benefits of accelerating the pace of vaccination during a pandemic and the net benefits of investing in supply capacity draws on Castillo et al. (2021), Ahuja et al. (2021), and Athey et al. (2022).

The paper is outlined as follows. Section 2 reviews and adapts analysis on the frequency and epidemics of varying intensities. After synthesizing estimates of various losses from epidemics, Section 3 derives a relationship between total losses and mortality intensity. Section 4 describes a program to accelerate widespread vaccine availability by investing in pre-pandemic preparedness. Section 5 sets out the model for evaluates the program's expected net benefits and Section 6 presents the results. Section 7 discusses whether international cooperation is needed to achieve these gains, and Section 8 concludes.

## 2 Probability of Future Pandemics

The analysis of the frequency of pandemics in history and of emerging trends by Marani et al. (2021) suggests that a pandemic of at least the magnitude of Covid-19 is a one in 138-year event. The authors document 476 significant epidemics since the year 1600, of which 271 have data on duration and deaths, forming the main basis of their estimations. Defining the intensity $i$ of an epidemic in a year to be the associated mortality expressed in terms of deaths per thousand population, The authors show that the distribution of epidemic intensity is well described by a generalized Pareto distribution having cumulative distribution function

$$\Phi_0(i) = \begin{cases} \alpha & i = [0, \mu') \\ 1 - (1-\alpha)\left[1 + \dfrac{\xi(i-\mu)}{\sigma}\right]^{-1/\xi} & i \in [\mu', \mu''] \\ 1 & i \in [\mu'', 1000], \end{cases} \quad (1)$$

where $\mu = 10^{-3}$ is the threshold below which epidemics are too small to leave a detectable record, $\alpha = 0.62$ is the probability that the epidemic is below the threshold of detectability, and $\sigma = 0.0113$ and $\xi = 1.41$ are shape parameters estimated by the authors via maximum likelihood. The complement to the cumulative distribution function, $\bar{\Phi}_0(\mathrm{i}) = 1 - \Phi_0(i)$, sometimes called the exceedance probability, has the useful interpretation as the annual probability that an epidemic with at least intensity $i$ occurs.

Marani et al. (2021) on do not provide guidance on how to extrapolate their estimates beyond the support of their data. Since we will be integrating over the distribution of pandemics of any conceivable size to compute expected pandemic losses, our approach requires such extrapolation. Our extrapolation strategy is embedded in equation (1). The support of the distribution has a natural upper bound at 1,000 deaths per thousand, since no more than the whole population can die out. It remains to specify the mass in the tail of the distribution between the highest intensity observed in their data and the natural upper bound of 1,000 deaths per thousand. Small changes in the mass of its fat tail can have a large influence on the expected value of a Pareto random variable, but extrapolation in this interval is challenging given the expanding confidence intervals there and the inevitably growing inaccuracy of the Pareto law as intensity approaches population size. We adopt a conservative approach to address this issue, capping the maximum epidemic intensity at the upper bound of the support of their data: $\mu'' = 5.7$ deaths per thousand per year for the 1918 flu.[1] We perform various sensitivity analyses for alternatives to the baseline distributions of pandemic risk. One of these doubles the upper bound on intensity to $\mu'' = 11.4$.

Starting with the basic distribution in (1), Marani et al. (2021) transform it in a way that maintains a constant distribution of relative intensities but allows the arrival rate of epidemics to vary over time. This approach allows them to exploit the long historical record to precisely estimate the distribution of relative intensities, overcoming the challenge that large pandemics are a "black swan" event, requiring a long time series to achieve a reasonable sample of them. The authors then use the frequency of recent pandemics to estimate the general arrival rate of any epidemic above a threshold size under modern conditions. Most pandemics within a given time band will be small but occur with enough frequency to provide a good estimate of an overall arrival rate, which can

[1] Our adjustment requires an atom of mass $\bar{\Phi}_0(\mu'')$ to be added at $i = \mu''$. Marani et al. (2021) leave the distribution of intensity unspecified for $i < \mu'$. The specification in equation (1) fills this gap in by adding an atom of mass $a$ at $i = 0$ and positing zero mass for $i \in (0, \mu')$.

be extrapolated to pandemics of any size under the assumption that the historical distribution of relative intensities has remained constant.

Formally, Marani et al. (2021) transform equation (1) via the metastatistical extreme value distribution (MEVD), averaging the distribution of the maximum order statistic from $n_t$ draws corresponding to the number of epidemics in year $t$. The resulting formula is

$$\Phi(i) \approx \frac{1}{w}\sum_{t=1}^{w} \Phi_0(i)^{n_t}, \tag{2}$$

where $w$ is the width of the window of years under consideration. Equation (2) has a particularly simple form if, following Marani et al. (2021), we take the window to be the most recent 20 years in their dataset, during which, according to their Supplementary Figure S1(a), there were 11 years without a detectable epidemic, six years with one, and three years with two. Substituting those data, (2) becomes

$$\Phi(i) = \frac{1}{20}[11 + 6\Phi_0(i) + 3\Phi_0(i)^2]. \tag{3}$$

The rate of epidemics over the last 20 years, which factors into $\Phi(i)$ as we have just seen, turns out to be historically low, reflecting two opposing forces operating recently.[2] Modern technology has allowed society to mitigate the death toll from pandemics. The invention of antibiotics sharply reduced the occurrence of the plague and other bacterial outbreaks. Better hospitals and medical care have also helped cut mortality. Working in the opposite direction, models of the effect of climate change on mammal movements suggest increasing zoonotic spillovers (the transmission of viruses and other parasites from animals to humans), increasing the frequency of future epidemics (Carlson et al. 2021).

The use of the most recent 20 years of data for our baseline forecast allows it to reflect the current conditions. It is challenging to forecast how the balance of the contending forces will change, however; we simply assume that the current arrival rate will continue for the foreseeable future. To account for unknown changes in the arrival rate among other uncertainties inherent in forecasting future pandemics, we analyze the sensitivity of our estimates to changes in a variety of

[2] Previous estimates of the expected economic losses from future pandemics have tended to use a longer time horizon to estimate the intensity and frequency of pandemics, which may overestimate expected losses by underweighting progress made in combatting pandemics. This helps explain why our estimates are lower than Fan et al. (2018) despite their estimates covering losses from influenza epidemics alone. We also use different methods for valuing life.

assumptions and parameters.

# 3 Social Losses in a Pandemic

## 3.1 Approach

Having estimated the arrival rate of pandemics of various intensities, we next need to pair that with estimates of the losses to society conditional on experiencing a pandemic of a given intensity to calculate expected harm from the next pandemic. The literature suggests that expected losses from epidemics are dominated by high-intensity pandemics that come along only rarely. In this section, we seek to refine existing estimates of the possibly nonlinear relationship between the intensity $i$ of an epidemic (measured by relative mortality) and associated social losses.

Some of the literature focuses on a particular category of social loss, say just deaths or just the shortfall in economic output. (Fan et al. (2018) combine value of lives lost with falls in economic output while Keogh-Brown et al. (2009) also add losses due to school closures). Here, we seek a comprehensive measure that, in addition to these two categories, includes longer-term losses from the decline in human capital associated with closures of school and training programs. Our approach will be to use the best available information from the literature to map pandemic intensity into each category of loss and then sum the categories to obtain total losses to society. Our total measure will still be conservative since it will not include difficult-to-estimate categories such as the disutility of social distancing and pain and suffering from sickness.

Conditional on an epidemic of intensity $i$ arriving in year $t$, let $ML_t(i)$ denote mortality losses from that pandemic, $OL_t(i)$ denote economic-output losses, and $LL_t(i)$ denote learning losses. Let $ML_0(i)$, $OL_0(i)$, and $LL_0(i)$ denote the analogous expressions for the base year $t = 0$. We will discuss the estimation of each loss category in turn, starting with $ML_t(i)$.

## 3.2 Mortality Losses

Mapping intensity $i$ into mortality losses $ML_t(i)$ requires two steps. First, intensity $i$, which is a proportion, needs to be converted into expected deaths in year $t$, denoted $d_t$, which is a level. Second, we need to place a monetary value on death so it can be combined with dollar losses in other categories. Marani et al. (2021) define $i$ as deaths per 1,000 population, i.e., $i = d_t/(N_t/1000)$, where $N_t$ denotes population in year $t$. Inverting, $d_t = iN_t/1000$. To convert $d_t$

into a monetary value, we use the value of a disability adjusted life year (DALY) implicit in the World Health Organization (WHO) standard for cost-effective health interventions. As reported in Marseille et al. (2015), the WHO judges a health intervention in a country to be cost effective if the required spending per DALY saved is less than three times that country's GDP per capita. Technically, DALYs lost equals the sum of years of life lost due to premature mortality (YLL) and years of health life lost due to disability (YLD). Continuing our focus on mortality rather than morbidity, we will just consider YLL as a source of lost DALYs and ignore YLD, continuing to recognize this entails that our social-loss measure will be conservative.

To convert deaths into DALYs lost requires an estimate of YLL per death. The age profile of mortality varies considerably across diseases, leading to considerable variation in YLL per death. Table 1 lists five major recent pandemics for which we can obtain good estimates from the literature for the reported variables. As the table shows, the YLL estimate for Covid-19, 16.0, is much lower than that the 50.1 for the 1918 flu, reflecting the well-known facts that deaths were skewed toward the elderly for Covid-19 but toward the young for the 1918 flu. Our calculations use the average YLL across these five diseases, 29.4. Multiplying three times the $12,263 global GDP per capita in the base year (2021) times 29.4 YLL per death yields $1.08 million in the base year. We have

$$ML_0(i) = \left(\frac{\$1.08 \text{ million} \cdot N_0}{1000}\right) i. \tag{4}$$

Mortality losses $ML_t(i)$ in year $t$ can be derived from $ML_0(i)$ under assumptions on global annual growth rates for GDP per capita and population. Assume GDP per capita grows at a constant rate $y$. Our calculations set $y = 1.6\%$, the long run global rate projected through 2060 by OECD (2022). Population growth is a more complex issue. If the current slowdown in population growth continues, the world will eventually experience population declines, though presumably these declines would slow before they lead the population to disappear. An additional complexity raised by a changing population is that it changes the nature of the optimal vaccine program. It is challenging enough to model the costs of a program targeting a fixed population let alone one that adjusts dynamically to a first growing and then shrinking population. We finesse these complexities by considering a fixed population $N_0$ for the analysis. Our results will then apply to a program optimized for current citizens, understating that installing even more capacity to accommodate larger future generations would have positive option value. Under the preceding

assumptions and parameter values,

$$ML_t(i) = (1 + y)^t ML_0(i). \tag{5}$$

### 3.3 Economic-output Losses

Turn next to the estimation of economic-output losses $OL_t(i)$ conditional on the arrival of an epidemic of intensity $i$ in the base year. We include in this category only short-run deviations in economic output from trend caused by pandemics, deliberately excluding longer-term losses such as reduction in future wages due to declines in human-capital, covered by a later calculation.

Table 1 shows the five major pandemics over the previous century for which we could find a credible estimate of economic-output losses. All but one of the estimates come from studies in the literature that use deviations for trend GDP as the main determinant of economic losses.[3,4] The last column puts all the economic-loss estimates quoted by the indicated studies on the same metric, an annual global loss in percentage terms, denoted Δ. The table also shows the estimate of intensity taken from Marani et al. (2021) in all cases except Covid-19, which is not in their data.

The five rows in Table 1 provide a sample that can be used to estimate the relationship between Δ and $i$. Figure 1 plots those variables using log scales on the axes along with a regression line estimated via ordinary least squares to be

$$\begin{matrix} \ln \Delta = & 0.74 & + & 0.46 & \ln i, \\ & (0.56) & & (0.08) & \end{matrix} \tag{6}$$

where standard errors are reported in parentheses below coefficient estimates. The regression's fit is good, with $R^2 = 0.92$.

The regression can be paired with the distribution of pandemic intensity from equation (3) to compute expected annual economic output losses from pandemics in the base year:

$$OL_0(i) = Y_0 N_0 \frac{\Delta(i)}{100}, \tag{7}$$

where $Y_t$ denotes per-capita GDP in year $t$, implying $Y_0$ is per-capita GDP in the base year. The function $\Delta(i) = 2.09 i^{0.46}$ can be derived from regression (6) by exponentiating both sides. Dividing by 100 converts the percentage into a proportion. Multiplying by $Y_0 N_0$, which equals

[3] The one exception is the estimate for Zika in United Nations Development Programme (2017).
[4] We have adjusted for the fact that some studies include the value of lives lost and others do not by taking out the value of lives lost from those that include it and adding it separately using our own valuation later in the calculation.

GDP in the base year, converts a proportional loss into a loss in levels. One can derive $OL_t(i)$ from $OL_0(i)$ by analogy to equation (5).

### 3.4 Learning Losses

The final category of losses we consider is $LL_t(i)$, learning losses from the arrival of an epidemic of intensity $i$ in year $t$. Under the assumption that school disruption moves in line with the disruption to other economic behavior, we take $LL_t(i)$ to be proportional to $OL_t(i)$. We derive the proportionality constant by examining the ratio of economic-output losses and learning losses for Covid-19 for which we have good estimates of both loss categories. We take the conservative end of the World Bank's estimated range for learning losses from Covid-19 at an aggregate $10 trillion in lifetime earnings in present value (Azevedo et al. 2021).[5] For economic-output losses from Covid-19, we take the International Monetary Fund's (2022) estimate of a $13.8 trillion shortfall relative to pre-pandemic forecasts due to the pandemic.[6] Taking the ratio of the two estimates, we have

$$LL_t(i) = \frac{10}{13.8} OL_t(i). \tag{8}$$

### 3.5 Total Losses

Let $TL_t(i) = ML_t(i) + OL_t(i) + LL_t(i)$ denote total social losses from all three categories conditional on an epidemic of intensity $i$ arriving in year $t$. For program evaluation, this conditional loss measure needs to be converted into an unconditional one reflecting the distribution of epidemic intensity estimated in Section 2 since the intensity of future pandemics is uncertain when advance investment is undertaken. We will build up to the unconditional loss measure we

[5] Azevedo et al. (2021) use the correlation between years of schooling and wages to calculate the return to an additional year of schooling and hence the cost of closed schools. If wages reflect the worker's marginal product and private returns to education reflect social returns, then future wage losses will be a good measure of future GDP losses. While Mincer (1974) equations do not measure the causal effect of education on earnings, Duflo (2001) concludes that causal estimates of the income benefits of education are close to Mincer-regression estimates where the two can be compared. In a Spence (1973) model, education can be rewarded with higher wages even if it does not increase productivity, leading private returns to exceed social returns to education. Positive spillovers from education would lead social returns to exceed private returns. We proceed by assuming that Mincer regressions give an adequate estimate of the private returns to education and that social returns weakly exceed private returns on average. If social returns to education strictly exceed private returns on average, our measure of learning losses will be conservative.

[6] We take these loss estimates for Covid-19 losses as they are reported by our sources: not annualized figures but accumulated losses over a multiyear pandemic. Since both sources use this same accounting frame, taking the ratio of them produces the proper proportionality constant.

ultimately use in a series of steps.

A straightforward measure of unconditional losses is the present value of expected losses from the stream of pandemics into the future,

$$PV(\overline{TL}) = \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^{t+1} E(TL_t(i)), \tag{9}$$

where $r$ denotes the social discount factor, which we set at $r = 4\%$ in the baseline scenario.[7,8] The factor $E(TL_t(i))$ denotes expected pandemic losses in year $t$:

$$E(TL_t(i)) = \int_0^{\infty} TL_t(i)\, d\Phi(i). \tag{10}$$

Table 2 reports a convenient rescaling of $PV(\overline{TL})$, interpreted as expected annual pandemic losses. Formally, let $AV(\overline{TL})$ denote the constant expected loss that if experienced in perpetuity would generate the present value in equation (9). One can show

$$AV(\overline{TL}) = rPV(\overline{TL}) = \frac{r}{r-y} E(TL_0(i)) \tag{11}$$

Table 2 reports the expected annual pandemic losses in total, $AV(\overline{TL})$, as well as for the component losses $AV(\overline{ML})$, $AV(\overline{OL})$, and $AV(\overline{LL})$, defined analogously to $AV(\overline{TL})$. In the baseline scenario, expected annual pandemic losses are $AV(\overline{TL}) = \$808$ billion annually. In other words, the world can expect to lose $808 billion every year to pandemics in the future. Mortality losses account for 62% of the total, followed by economic-output losses (22% of the total) and learning losses (16% of the total).

### 3.6 Sensitivity of Pandemic Loss Estimates

Subsequent rows in Table 2 analyze the sensitivity of the results to changes to parameters and changes to the assumptions behind the distribution of pandemic intensities. The first alternative scenario cuts the probability that a pandemic arrives in half, which cuts the expected loss estimates

[7] Gollier and Hammitt (2014) discuss the debate in the economic literature on the appropriate value to assume for the social discount factor $r$. Our baseline value $r = 4\%$ is well within the range of the literature and if anything is conservative given that our model incorporates growth in GDP per capita and given that pandemics involve considerable uncertainty, both of which should scale up $r$, as the authors note.

[8] The $t + 1$ exponent on the discount factor reflects the implicit assumption that surplus is realized at the end of the year.

in half. Total expected annual pandemic losses remain over $400 billion.

The next two alternative scenarios revisit the challenge of extrapolating the distribution of pandemic intensities outside of the data that Marani et al. (2021) used to estimate their power-law parameters. Mathematically, the estimated power law must break down for extreme intensities $i$ approaching 1,000 (corresponding to the whole population dying off), but it is hard to know where beyond the domain of the data this breakdown occurs. In the baseline, we adopt the conservative approach of setting the truncation point $\mu''$ on intensity at the highest intensity observed in the data ($\mu'' = 5.7$, for the 1918 flu). One alternative doubles that truncation point. Another alternative eliminates any truncation (below the die-off of the whole population, which is the natural maximum). Both alternatives assume the power law estimated by Marani et al. (2021) applies throughout their respective expanded range of intensities. Social losses are substantially higher with these relaxed caps. Doubling the truncation point increases $AV(\overline{TL})$ to $944 billion. Eliminating truncation below the die-off of the whole population increases $AV(\overline{TL})$ to over $2 trillion.[9]

Marani et al. (2021) measure an epidemic's intensity by average annual deaths, preventing them from including continuing pandemics in their data. This entails the potentially important omission of HIV from their data, which prior to Covid-19 had killed more people than any other epidemic in every one of the past 20 years. Adding HIV turns a sparse series of epidemics over the past 20 years into one with consistent arrivals. The estimated arrival rate increases so much that $AV(\overline{TL})$ increases to over $2 trillion.

The last set of scenarios analyze the sensitivity of the loss estimates to changes to average YLL per death, growth rate of GDP per capita $y$, and social discount rate $r$. Perhaps the most consequential change is that $AV(\overline{TL})$ increases to over $2.4 trillion when $r$ is reduced to 2%. Anyone who works with present values is familiar with the result that they can grow very large when the discount rate shrinks. Here, however, $AV(\overline{TL})$ is not a present value of a stream of losses but an annualized loss. The annualized loss still grows very large because future losses weigh more heavily in the annualized figure, and future losses are higher since they reflect growing GDP per capita with time.

[9] The sensitivity analyses with respect to where the intensity distribution is truncated highlight the implications of a power-law distribution's fat tails. Varying the truncation point for a normal distribution (which has thin tails) hardly matters if the truncation point is extremely high. With a power-law distribution, by contrast, varying a truncation point in an extreme range beyond the data can have a substantial effect on expected values.

Several broad observations about our baseline estimates can be drawn from the sensitivity analyses. First, they are robust. In no row does $AV(\overline{TL})$ fall below $400 billion, which is still half of a substantial baseline. Second, our baseline estimates may be quite conservative. In filling in the seemingly minor details that the previous literature left to our discretion, we erred on the side of conservatism. However, the sensitivity analyses show that allowing pandemic intensity to extend beyond pandemics observed in the past and including HIV in the data used to estimate the arrival rate of recent epidemics has more than a minor effect on estimates of expected pandemic harm. $AV(\overline{TL})$ can rise to over $2 trillion when just one of these elements is filled in with a less conservative assumption.

### 3.7 Expected Losses from Next Pandemic

Our criterion for program evaluation is more complicated than $PV(\overline{TL})$ and $AV(\overline{TL})$, so requires some discussion. The criterion involves the expected present value of social losses—not from the stream of all future pandemics—but just from the next significant epidemic. Denote this concept by $PV(\overline{TLN}^*)$, where the $N$ suffix stands for next pandemic and the star superscript indicates that to qualify for the next significant pandemic, the epidemic must exceed some threshold intensity $i^*$.

As will be seen, using $PV(\overline{TLN}^*)$ as the loss measure rather than $PV(\overline{TL})$ or $AV(\overline{TL})$ facilitates modeling the counterfactual program to which our proposed advance-investment program will be compared. We presume that this counterfactual policy would not roll out a global vaccination campaign for a minor epidemic but only one of significance. We also presume that at least some of the capacity that this program installs to mitigate harm from the next pandemic would be retained to use in pandemics after that. To absolve ourselves from having to guess how much capacity would be retained in the absence of a coordinated program to do that, we effectively cut the future off after the arrival of the next pandemic. We argue that that modeling device leads to a conservative evaluation of the benefits of our proposed advance-investment program since the proposed program generates more capacity in the next pandemic, leading to weakly more capacity available in epidemics after that.

To derive an expression for $PV(\overline{TLN}^*)$, let $\lambda_t(i^*)$ denote the hazard of a significant epidemic, i.e., the probability that an epidemic of at least intensity $i^*$ arrives in year $t$ conditional on no epidemic of at least that intensity having arrived until then since base year 0. We have

$$\lambda_t(i^*) = \Phi(i^*)^t[1 - \Phi(i^*)]. \quad (12)$$

Then

$$PV(\overline{TLN}^*) = \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^{t+1} \lambda_t(i^*) E(TL_t(i)|i \geq i^*), \quad (13)$$

The last factor is the expectation of social losses from an epidemic of at least intensity $i^*$ certainly arriving in year $t$:

$$E(TL_t(i)|i \geq i^*) = \int_{i^*}^{\infty} \frac{TL_t(i)}{1 - \Phi(i^*)} d\Phi(i). \quad (14)$$

The baseline scenario sets the threshold intensity $i^*$ for a significant pandemic to be half the intensity of Covid-19 or worse.

To compare the related loss measures, in the baseline, the expected present value of losses from the whole stream of future pandemics is $PV(\overline{TL}) = \$12.6$ trillion. The expected present value of losses from next pandemic at least half as intense as Covid-19 is $PV(\overline{TLN}^*) = \$5.2$ trillion. $PV(\overline{TLN}^*)$ is smaller than $PV(\overline{TL})$ for two reasons: it omits losses from pandemics after the next one and omits losses from pandemics less intense than $i^*$. Despite those omissions, $PV(\overline{TLN}^*)$ is more than 40% of $PV(\overline{TL})$. While pandemics of that intensity only have a 2.6% chance of occurring in any given year according to estimates from Section 2, this still means that such a pandemic can be expected within the next 38 years. By definition, such a pandemic might only be half as intense as Covid-19; but it is also possible for it to be as or more intense than Covid-19, in which case it would wreak extreme losses. Such a severe pandemic would not be expected for years, but at the baseline social discount rate of $r = 4\%$, discounting does not lead the present value of those future losses to vanish. Neither $PV(\overline{TL})$ and $PV(\overline{TLN}^*)$ average over years, so are both at least an order of magnitude larger than $AV(\overline{TL})$, which is an annual measure averaging over years.

## 4 Conceptual Discussion of Advance Investment Program

This section motivates and outlines a program of advance investment to accelerate the availability of vaccine capacity in a pandemic. The discussion in this section is conceptual; a formal model of

the program is deferred to Section 5.

### 4.1 Program Motivation and Basic Design

The estimates from the previous section suggest that significant pandemics are not so rare as to offset the enormous losses conditional on one occurring. The expected present value of social losses from the next pandemic at least half as intense as Covid-19 is $5.2 trillion in our baseline estimate and can be much higher in less conservative estimates. It is therefore important to evaluate the cost effectiveness of programs that could mitigate some of the enormous losses from the next significant pandemic.

The experience from the Covid-19 pandemic highlights the potential benefits of investing in vaccine capacity. Vaccines were developed and deployed with unprecedented speed. The reduction in mortality bolstered countries' confidence to reopen their economies, reducing economic-output losses. Yet the enormous social losses that still mounted each month beg the question of whether there was room to further accelerate vaccinations. There was roughly a two-year lag between the date Covid-19 was detected and the production of enough vaccine to fully immunize 70% of the world's population. Most of this lag was not the time required to discover or approve effective vaccines but rather the time needed to scale up production after approval. We therefore focus most of our attention in this paper on policies to accelerate production scale up. This focus is partially motivated by our belief that investing in accelerating vaccine production is one of the most cost-effective ways to prepare for future pandemics. This focus does not sacrifice much generality because the analysis of this specific investment program readily applies to other promising pandemic preparations, discussed in the conclusion.

In their summary of work by Ahuja et al. (2020) and Castillo et al. (2021), Athey et al. (2022) explain how accelerating and expanding vaccine capacity can mitigate pandemic losses. The existence of long lags between when a facility starts to add production lines for a new vaccine and when those lines are producing at full capacity[10] provide an opportunity for accelerating the availability of capacity. Presuming that every reasonable technological avenue for shortening the time to capacity availability would be exploited in a pandemic, there remains another possibility

[10] Production lines are technologically complex, requiring months to set up. Obtaining reasonable yields requires skilled technicians to learn by doing in a specific production facility. Each facility must receive independent regulatory approval. All these factors result in long lags before a facility can start producing and additional lags before production fully spins up.

for accelerating capacity, using a strategy that Athey et al. (2022) and others call "at-risk investment." Production capacity can be expanded before regulatory approval, in parallel with clinical trials, rather than sequentially, after clinical trials have succeeded and regulatory approval gained. Ordinarily, this strategy would be socially wasteful. Vaccine programs exhibited a 70% failure rate in clinical trials over the past two decades (Lo, Siah, and Wong 2020). If the vaccine fails to be approved, any of the at-risk investment that is difficult to repurpose for other vaccines or uses is wasted. However, the benefit of speed in a pandemic may offset this high risk of wastage. Athey et al. (2022) calculate that if the capacity for Covid-19 vaccines available by April 2021 were available three months earlier, that would have had a global benefit of $3 trillion.

Not just early capacity but expanded capacity can also accelerate a vaccination program. To the extent that scarce supply is the limiting factor in vaccine distribution, and scarce capacity is the rate-limiting step in supply, doubling capacity can double the rate at which vaccine is rolled out to the population.

There are limits to how much and how quickly capacity can be installed during a pandemic. Short-run supply curves for necessary inputs can be sharply upward sloping and may hit hard constraints. Supply curves tend to be more elastic and constraints more relaxed over the longer term. Thus, there are potential returns from investing in vaccine capacity in advance of the next pandemic rather than waiting until the pandemic arrives.

Here we analyze a program that secures vaccine production capability before a new pathogen emerges. Up-front investment expands total general-purpose vaccine capacity. An annual fee is paid to reserve some of that vaccine capacity to be quickly switched to the production of a vaccine when a pandemic threat emerges. For concreteness, we will analyze a program that installs enough advance capacity that, when topped up with additional investment undertaken in a pandemic, ensures the world would have enough capacity to fully vaccinate 70% of the population in six months. We factor into our calculations the risk that not all targeted individuals may wish to be vaccinated and thus only a fraction of the benefit of that target coverage may be realized for this or other reasons. The quantitative targets matter less than the key qualitative point that the program we have in mind is ambitious, involving expansive capacity. To evaluate the benefit of this advance-investment program, we compare it—not to the absence of any vaccination—but to a counterfactual program that also runs a vaccination campaign against the next significant pandemic also employing the strategy of at-risk investing but run without the benefit of the extra

capacity coming from advance investment.

### 4.2 Gap in Commercial Versus Social Incentives

Commercial markets may not generate socially optimal investment in vaccine capacity on their own for several reasons. In the absence of a special program, commercial incentives for advance investment would presumably come from the promise of high returns from vaccine sales in the next pandemic, possibly decades in the future. However, social and political pressure to keep prices of vaccines low during a pandemic can create an enormous divergence between commercial and social returns to a vaccine. Covid-19 vaccines sold for between $6 and $40, much less than the $5,800 social value of a course of annual capacity in early 2021 as estimated by Castillo et al. (2021). Few incentives were provided for speed. Even a dose price much higher than $40, if it is fixed independent of delivery date, provides little incentive to supply those doses sooner rather than later. But getting a vaccine earlier can mitigate enormous social harm. Thus, we will analyze in effect a procurement program using government or donor-organization resources to procure more capacity in advance and reserve some for pandemic preparedness.

### 4.3 Coordinated International Program

Our analysis will focus on the sum of the costs and benefits if all countries took advance preparedness action. Below we discuss how positive spillovers from advance investment may lead to less-than-optimal investment particularly for smaller countries suggesting some benefits from coordination. However, if no other countries are making advanced investments, individual countries actually have stronger incentives to undertake advance investment unilaterally than what our computations show the average country has in the coordinated global program. Thus, our analysis of a coordinated global program provides a benchmark that is useful for several exercises, setting a goal for countries to coordinate on and showing that advance investment can be incentive compatible for countries acting alone if coordination fails.

The positive spillovers from advance investment are in contrast to the often-expressed concern that investment in vaccine capacity has negative spillovers to other countries. Such concerns loom particularly large if one's mental model is that vaccine production capability is fixed, constrained by the fixed supply of key inputs. However, one lesson from Covid-19 is that additional investments were able to expand total vaccine supply in a pandemic, and there is reason

to think that additional at-risk investment would have expanded it further and help in relaxing bottlenecks which would have had positive spillovers to others (Ahuja et al. 2021). As supply is even more elastic in the long than short run, negative spillovers are even less of a concern for pre-pandemic investments proposed in this paper. Our analysis instead points to the possibility of positive spillovers: countries coming into the next pandemic with advance capacity will compete less hard for new capacity being installed, leaving more supplies for others. Once a country's dedicated capacity has served its population (in the modeled program, taking six months), that capacity can be used to serve other countries. The latter effect is a positive externality from unilateral country investment that our analysis of a coordinated global program to achieve target coverage across all countries simultaneously will not pick up. Hence, our analysis should be regarded as a lower bound on internal and external benefits from a single country's investment.

### 4.4 Did Covid-19 Already Prepare the World?

There are reasons to doubt that worldwide vaccine capacity is already at the socially efficient level as a result of investments undertaken in the Covid-19 pandemic. At its peak, the world was producing 580 million doses of mRNA Covid-19 vaccine per month. At that rate, it would take over a year and a half to produce enough vaccine to cover 70% of the world population with a full course of an mRNA vaccine. To reach this coverage in six months during the next pandemic would require an expansion of mRNA capacity. Instead, in response to the falling demand for Covid-19 vaccines, some existing mRNA capacity is reportedly being shut down (Kay, Makol, and Paton 2022). Our analysis will show that paying the owners of existing capacity an annual fee to keep their existing capacity in place and paying others to build new mRNA capacity would have a high expected return.

The world has considerably more capacity for traditional than mRNA vaccines. However, some of the traditional vaccines that are regularly administered are of sufficiently high value that health authorities might not want facilities producing these to switch to pandemic vaccines even during a pandemic (during Covid-19 very few facilities producing childhood vaccines switched to producing Covid-19 vaccines). Thus, despite the larger production capacity for traditional vaccines, reaching the desired level of reserve capacity will require new capacity to be built.

The mRNA technology is particularly useful for pandemic preparedness as it appears to be easier to scale rapidly than many other vaccine technologies. However, mRNA is still too new a

technology to know whether it can replace traditional vaccines for all diseases. There is no guarantee any single technology will provide the most effective vaccines for all viruses. Thus, the proposed program takes a portfolio approach, involving investing in capacity for several technologies to combat future pandemics.

### 4.5 Further Design Features

Contracts to ensure sufficient vaccine capacity was in place to vaccinate the world or an individual country for the next pandemic would need to guarantee that such capacity was functional and up to date. (During Covid-19 some reserve vaccine capacity failed.)[11] Given the billions of dollars at stake, appropriate monitoring systems could be devised. One way a program could be designed would be to allow—indeed encourage—contracted reserve capacity to be used for the production of other vaccines.

A program that contracts on advance capacity rather than contracting in advance on doses to be supplied in the next pandemic would generate positive spillovers to the world and better address a social planners desire for speed during a pandemic. As explained in Section 4.2, producers do not internalize the full social benefit of speed, and so may underinvest in capacity, fulfilling their supply obligations but more slowly than would be socially desirable. Contracts on doses may generate negative spillovers for other countries, pushing other countries down the queue waiting for scarce supplies. Contracts on capacity, on the other hand, can generate positive spillovers for other countries, increasing the rate at which the queue is served.

For concreteness, the program we evaluate will focus on advance vaccine capacity, but the logic applies to other advance preparations for the next pandemic. Consider advance investments in drug treatments. More research and development could lead to the discovery of new antivirals to mitigate harm in the next pandemic. Securing raw materials has been a constraint in scaling Paxlovid, an effective treatment for Covid-19, a constraint which interim supply-chain investments can relax in the next pandemic. Similar logic applies for investments increasing supply-chain resilience for other products such as personal protective equipment, testing equipment, and so forth. One reason for focusing on vaccines rather than drugs or these other products is that they

[11] Mole (2021) reports on the failure of Emergent BioSolutions to fulfill its reserve contracts to supply Johnson & Johnson vaccine because of cross-contamination problems.

are simpler to produce and easier to scale up than vaccines, so maintaining spare capacity for them is valuable, but not as valuable as for vaccines.

# 5 Model

This section formally models a program of advance investment in production capacity to accelerate vaccinations in the next pandemic.

## 5.1 Setup

Starting from base year $t = 0$, the next epidemic of at least intensity $i^*$ arrives with hazard rate $\lambda_t(i^*)$ in year $t$, where $i^*$ is the minimum intensity evoking a global vaccine response. We consider two basic options for a coordinated global vaccine program: a program of advance preparatory investment or the status quo without. Distinguish variables associated with the status-quo program with a single prime and variables associated with the advance-preparation program with two primes. Omitted primes refer to a generic program option.

Even in the status quo in the absence of advance preparations, if a significant epidemic arrives in year $t$, as we saw with the Covid-19 pandemic, the world will seek to obtain vaccines as quickly as possible. Conditional on the arrival of an epidemic, let $x'$ denote the capacity (measured in annual courses) for vaccines against that epidemic that the world can obtain without advance preparations. The model will allow more spending to buy more capacity, but disruptions to supply chains and limited input supplies will mean that no more capacity than $x'$ can be installed in the short span of an epidemic. The model takes $x'$ to be an exogenous parameter ($x' = 4.5$ billion annual courses).

## 5.2 Role of Advance Investment

Advance investment—undertaken when supply chains are more fluid and input supplies are more elastic—can generate more capacity. Indeed, we will suppose that the program specifies sufficient capacity be installed in advance to achieve an ambitious target of 70% coverage of the population within six months when combined with the maximum capacity that can be installed during an epidemic. Formally, letting $x''$ denote the ultimate capacity available with advance investment, we have $x''/2 = 0.7N_0$, where the left-hand side is multiplied by one half since $x''$ is measured in

annual courses, but the target coverage is sought in half that time (six months). Since $x' = 4.5 \text{ billion} < 15.7 \text{ billion} = 1.4N_0$, we have $x'' > x'$.

> **Remark 1.** The fact that $x'' > x'$ is the main advantage of advance investment in the model: without advance investment, the world simply cannot obtain the capacity it needs a vaccination campaign of the desired scale and speed.

Let $z''$ denote the amount of advance capacity that supports the higher capacity level $x''$ desired during a pandemic. Rather than fully endogenizing $z''$, we will take a more reduced-form approach, specifying an exogenous parameter $\theta$ measuring how much of the maximum possible investment $x'$ that the world could undertake during the pandemic the world saves itself from having to undertake then to attain the target 70% coverage in six months. When $\theta = 0$, the world leaves itself the task of installing the entirety of $x'$ during the pandemic. When $\theta > 0$, it leaves itself a smaller in-pandemic investment. Either way, the world achieves the target coverage with advance investment. But if $\theta > 0$, more of this investment is undertaken earlier, when the cost of capacity installation is lower, as the later model of costs will make clear.

> **Remark 2.** The second advantage of advance investment, which emerges from the model when $\theta > 0$, is that it can save on some of the cost of capacity installation.

Formally, we have $x'' = x' + (1 - \theta)z''$. In the absence of advance investment, by definition, $z' = 0$.

### 5.3 Vaccine Technology Platforms

Vaccines use a variety of technology platforms including inactivated viruses, viral vectors, protein subunits, virus-like particles, and messenger RNA (mRNA). Whether any platform can produce a successful vaccine, and if so, which can be developed most quickly or generate the greatest efficacy, will likely vary from disease to disease and involve a considerable element of luck. The mRNA platform technology has some features that deserve special mention. It is a new technology, its first use in an approved vaccine coming with the Moderna and Pfizer vaccines in the Covid-19 pandemic. It may ultimately be easier to scale since it circumvents the need to grow viruses in the

facility. Repurposing an mRNA vaccine production line from one disease to another may be a simple programming exercise. Since the production process for mRNA vaccines is so different from other platforms, it is likely to be difficult to quickly repurpose mRNA production lines to produce other vaccines and vice versa. Production lines for the other, traditional platforms are more likely to be fungible between each other.[12]

For purposes of the model, we will collect the various vaccine technology platforms into two: $v \in \{m, o\}$, where $v = m$ denotes the mRNA platform and $v = o$ denotes other, traditional platforms. Each platform could contain many subtechnologies, and each subtechnology could contain several vaccine candidates. The model reflects the presence of multiple candidates within platform by allowing some repurposing of capacity dedicated to unsuccessful candidates for production of successful candidates within that same platform. Let $z_m$ and $x_m$ denote advance and ultimate global capacity installed for mRNA vaccines and $z_o$ and $x_o$ denote those capacities installed for other vaccines. Although the ratios could be endogenized, to simplify modeling we fix the ratio of existing and future vaccine capacity so that 1/3 is devoted to mRNA vaccines and the rest to traditional vaccines.

Let $p$ denote the probability of that some vaccine is successfully approved as safe and effective for use against disease arising that year. Let $p_m$ denote the probability that only mRNA vaccines succeed, $p_o$ denote the probability that only vaccines using another platform are successful, and $p_b$ denote the probability that both vaccines using mRNA and those using other platforms are successful. Conditional on some vaccine succeeding, these are exhaustive and mutually exclusive events, implying $p_m + p_o + p_b = p$.

Reflecting the advantages of the at-risk investment strategy, allocating capacity to various vaccine candidates even before approval to reduce the lag in scaling up capacity for successful vaccines, we make the extreme assumption that all capacity is installed at risk for one vaccine candidate or another, and this is true for both capacity installed in advance of an epidemic and capacity installed after its arrival. Conditional on some mRNA vaccine succeeding, assume a fraction $f_m$ of the facilities were dedicated to successful mRNA candidates and can begin producing right away after approval date $\tau_A$. A fraction $g_m$ are dedicated to unsuccessful mRNA candidates but can be repurposed to produce successful mRNA candidates after a delay of $\tau_m$. The

[12] The discussion has omitted the DNA technology, as it has yet to yield an approved vaccine. For modeling purposes, one could consider it as being combined into the mRNA technology category.

remaining fraction $1 - f_m - g_m$ of capacity cannot be repurposed and is therefore useless during the pandemic. Vaccines using other platforms are modeled similarly, with a fraction $f_o$ of capacity being immediately available upon approval at date $\tau_A$, fraction $g_o$ being available with a delay $\tau_o$, and the remaining fraction useless. Note that capacity is not fungible between mRNA vaccines and other vaccines during the short epidemic span.

Let $\tau \in [0, T]$ index continuous time within the span of the epidemic (measured a finer scale—say days or months—than the yearly scale of epidemic arrival indexed by $t$). Production capacity totaled across all vaccines available at time $\tau$ under both platforms is

$$x(\tau) = \begin{cases} 0 & \tau \in [0, \tau_A] \\ s_m x_m f_m + s_o x_o f_o & \tau \in (\tau_A, \tau_A + \tau_m] \\ s_m x_m (f_m + g_m) + s_o x_o f_o & \tau \in (\tau_A + \tau_m, \tau_A + \tau_o] \\ s_m x_m (f_m + g_m) + s_o x_o (f_o + g_o) & \tau \in (\tau_A + \tau_o, T], \end{cases} \tag{15}$$

where $T$ is the duration of the epidemic and $s_m$ and $s_o$ are indicators for whether mRNA and other vaccines are successful, respectively. The total number of people vaccinated by time $\tau^*$ equals $\int_0^{\tau^*} x(\tau) d\tau$.

### 5.4 Vaccination Benefits

We adopt the model (with some simplifications) of the benefits of vaccination that Castillo et al. (2021) used in their analysis of the Covid-19 pandemic. Vaccination mitigates the harm from the epidemic experienced by the population at time $\tau$ by the proportion $h(\hat{x}(\tau))$, a function of the fraction $\hat{x}(\tau) = x(\tau)/P_0$ of the world population that has been vaccinated. Following Castillo et al. (2021), assume $h$ is a continuous, concave, piecewise linear function such that $h(0) = 0$ and $h(\hat{x}(\tau)) = 1$ for $\hat{x}(\tau) > 0.7$, which can be interpreted as the threshold for herd immunity, above which the epidemic is quelled and all harm relieved.[13] The supplemental appendix to Castillo et al. (2021) details why this functional form is a good approximation for vaccination benefits during the Covid-19 pandemic. The function's concavity reflects the larger benefits from initial courses administered to more vulnerable populations (such as frontline workers and the elderly in the case

[13] Based on data on the proportion of high-risk individuals and the differential burden of the disease on them versus others, Castillo et al. (2021) specify two additional kinks at 0.13 (the fraction of high-risk population) and 0.5, setting $h(0.13) = 0.395$ and $h(0.5) = 0.816$.

of Covid-19). Other diseases might have different demographic patterns, but benefits are still likely to be concave given any heterogeneity in harm across groups.

We scale the harm mitigated by vaccines by $\gamma \in [0,1]$ to allow for the possibility that some of the harm would have been mitigated by other measures such as improved treatments, better contact tracing, and so forth even without a vaccine. That $\gamma < 1$ might also reflect imperfect vaccine efficacy or unwillingness among a segment of the population to be vaccinated. Recalling the definition of $PV(\overline{TLN}^*)$ as the expected present value of total social losses from the next pandemic evoking a vaccine response, the expected present value of vaccination benefits in the next pandemic equals

$$\gamma PV(\overline{TLN}^*) \int_0^T h(\hat{x}(\tau))\, d\tau. \tag{16}$$

The pandemic's duration $T$ is endogenous, given by the implicit solution to

$$\int_0^T \hat{x}(\tau) d\tau = 0.7. \tag{17}$$

### 5.5 Vaccination Costs

Consider global expenditures on one of the vaccine technologies, $v \in \{m, o\}$. There are four categories of expenditure for this technology. First, advance investment costs $k_v$ per course, for a total sunk expenditure of $k_v z_v$. Second, this investment depreciates and needs to be replenished at rate $d$. We assume that during years without a pandemic, such capacity can be rented out to pharmaceutical firms for routine vaccine production to recapture a fraction $\phi$ of the yearly cost. The expected present value of the effective expenditures (net of rental income) from these two channels through the end of the next pandemic equals

$$(1-\phi)\left[k_v z_v + \sum_{t=0}^{\infty}\left(\frac{1}{1+r}\right)^{t+1} \Phi(i^*)^t d k_v z_v\right]. \tag{18}$$

A third category of vaccine expenditure is the cost of installing capacity during the pandemic needed to bridge the gap between the advance capacity $z_v$ and the capacity $x_v$ ultimately

used during the pandemic. Let $K_v(x_v - z_v)$ denote the investment cost, specified following Castillo et al. (2021):

$$K_v(q_v) = \begin{cases} k_v q_v & q_v \leq \beta \\ k_v q_v \left\{ \frac{1}{1+\varepsilon} \left[ \varepsilon \left( \frac{\beta}{q} \right) + \left( \frac{q}{\beta} \right)^{\varepsilon} \right] \right\} & q_v > \beta, \end{cases} \tag{19}$$

where $q_v = x_v - z_v$. According to this specification, the marginal cost of capacity installed during a pandemic is the same $k_v$ as that installed in advance for levels of capacity below a kink point $\beta$ (taken to be 100 million annual courses in the baseline); but above that kink point, $K_v$ exhibits decreasing returns to scale, which are more severe the higher is $\varepsilon > 0$.

A fourth category of vaccine expenditure is the marginal cost of production $c_V$ per course administered during a pandemic. Since a target 70% of the population is assumed to be covered by the pandemic's end under either program (albeit more slowly without advance investment), the expense from this threshold conditional on being in a pandemic is

$$c_v \left( \frac{x_v}{x} \right) 0.7 N_0. \tag{20}$$

As the last two categories are only expended conditional on a pandemic, the expected present value of these expenditures equals

$$\sum_{t=0}^{\infty} \left( \frac{1}{1+r} \right)^{t+1} \lambda (i^*)^t \left[ K_v(x_v - z_v) + c_v \left( \frac{x_v}{x} \right) 0.7 N_0 \right]. \tag{21}$$

Combining the four categories of expenditures and substituting simplified expressions for infinite series, the expected present value of effective (net of rental income) program expenditures on vaccines using technology $v$ can be written

$$(1-\phi) k_v z_v + \frac{(1-\phi) d k_v z_v}{r + 1 - \Phi(i^*)} + \frac{1 - \Phi(i^*)}{r + 1 - \Phi(i^*)} \left[ K_v(x_v - z_v) + c_v \left( \frac{x_v}{x} \right) 0.7 N_0 \right]. \tag{22}$$

Total program expenditures can be found by summing (22) over the two technologies $v \in \{m, o\}$.

This completes the specification of the model. Table 3 summarizes definitions of parameters used in the model and their baseline values.

## 6 Results for Program Evaluation

Table 4 presents the baseline results for outcomes from the program of advance investment evaluated relative to a counterfactual program. Recall that the counterfactual we consider is relatively sophisticated: it also runs a vaccination campaign in the next significant pandemic, installs the maximum capacity supply constraints allow, and puts as much of that capacity as possible to work at-risk to reduce production delays. The only difference is that the counterfactual comes into the pandemic without the extra capacity installed in advance.

In the baseline, the advance-investment program spends $60 billion up front to expand production capacity for vaccines and supply chain inputs, readying an extra 24 billion annual courses of advance capacity for the next pandemic above and beyond that needed to meet typical vaccination demands (we assume at least two doses are required for full vaccination, constituting a course). The advance program requires $5 billion to be spent each year to maintain capacity. Advance investment actually reduces expenditures that have to be made during the next pandemic by $32 billion program: less capacity is left to be installed during the pandemic, when the inelastic short-run supply entails quite high unit cost for capacity. Netting out rental income earned deploying the advance capacity for vaccines for other diseases between pandemics, the expected present value of the stream of expenditures through the next pandemic are $27 billion higher under the advance program. Compared to the counterfactual, the present value of gross benefits is $437 billion higher under advance investment. (This is the expected present value of the additional social losses mitigated just in the next pandemic, not considering pandemics after that, saving us from having to model how much capacity remains available under alternative programs.) The gross benefits come from achieving the target 70% vaccination coverage about seven months earlier. The expected present value of program benefits net of costs is $409 billion higher under advance investment than the counterfactual.

Table 5 shows the sensitivity of these results to selected assumptions and parameters. For space considerations, parameters that changed the results less than those displayed are omitted (see table notes for complete list). The net gain from advance investing relative to the counterfactual is always greater than $230 billion for any single parameter change considered, whether the probability of epidemic arrival is cut in half, the proportion of losses left to be mitigated by vaccines (so not already mitigated, say, by effective treatments) is reduced to $\gamma = 0.3$, the proportion of at-risk capacity assumed to be devoted to successful vaccines is reduced to $f_m =$

$f_o = 0.2$, YLL per death is reduced to 20, or the social discount rate is raised to $r = 0.06$. The net gain from advance investment is large in any case and thus evidently robust.

Some of the robustness exercises indicate how conservative some model assumptions are. If we allow the distribution of intensity to extend beyond the range of historically observed epidemics, expected net benefits from the advance program can be more than $1.4 trillion greater than the counterfactual. Reducing the social discount rate to $r = 0.02$, a value commonly used in the literature for program evaluation, expected net benefits from the advance program are $692 billion greater than the counterfactual.

The baseline design of the advance program spends $60 billion up front to install 24 billion annual courses of capacity. Even larger up-front investments would be worthwhile. Investing $113 billion up front to install 45 billion courses of annual capacity would increase the gain over the counterfactual program from $409 billion to $558 billion. Smaller up-front investments would have lower expected net benefits but would still be worthwhile. For example, an upfront investment of $30 billion to install 12 billion courses of annual capacity would generate net benefits of $426 billion in expected present value terms, $248 billion more than the counterfactual.

## 7 International Versus National Programs

Our analysis thus far has focused on a global program. This focus allows for convenient exposition, enabling us to report a single world number rather than a set of numbers for individual countries. A global program extends the net benefits from advance preparations, which we found to be very large, to the greatest number of individuals possible.

Because advance investment in vaccine supply by one country generates positive externalities to other countries, advance investment is likely to be suboptimal unless countries strike a cooperative agreement. Countries investing in advance reduce their demand for in-pandemic capacity, lowering the price for those who have engaged in advance investment and relaxing the constraint that at most capacity $x'$ can be installed in the short run. Technically, if all functions in the model were linear, there would be no spillovers between countries and thus no benefit from coordination. But the concavity of the benefit function and the convexity of the short-run capacity cost function leads countries' investments to be strategic substitutes.

An unmodeled benefit of a cooperative international agreement is that could provide insurance against variation in the severity of the pandemic across countries. The model does not

allow for heterogeneity in intensity across countries, so leaves no role for such insurance. To address real-world heterogeneity across countries, both in the average intensity of the pandemic there and the timing of when the waves hit it, the international program could pool advance investment but then allocate vaccines based on the current case rate or death rate in individual countries.[14] As with other forms of insurance, such a program carries a risk of moral hazard, i.e., that countries might take less stringent control measures knowing this will increase their vaccine supply. However, given the high costs of the pandemic even with vaccine access, moral hazard is unlikely to be a significant problem in this case.[15]

Participating countries in an international program would have to agree on how program expenditures should be allocated among them. It might be natural to ask participating countries to pay into the program according to GDP and receive vaccines according to population (or number of high-risk individuals). However, such a mechanism would involve substantial redistribution from richer to poorer countries. There may be a limit to how much redistribution can be supported before it is no longer incentive compatible for high-income countries to participate.[16] What that limit is may depend in part on the nature of the bargaining process, in particular whether negotiators commit to abandoning the whole agreement if pivotal countries do not participate or whether the agreement forges on without those countries. Perhaps paradoxically, countries are more likely to participate if they believe themselves to be pivotal, since declining to participate destroys the program they would otherwise free ride on. Making a country pivotal relaxes its incentive-compatibility constraint and allows the program to support more redistribution from it. If high-income countries do not believe themselves to be pivotal, it will be harder to engender the optimal level of their participation even in a program without any redistribution.

In the absence of an international agreement, if no other country engages in advance investment, individual countries would have strong unilateral incentives to be the one to do so. With few countries investing in advance, competition for capacity installed during the pandemic

[14] Even after the start of the pandemic, considerable uncertainty remains about both the relative severity and timing of waves in different parts of the world suggesting insurance even during a pandemic could be beneficial. For example, India's mortality from Covid-19 was initially low, only to be badly hit by the Delta wave.

[15]The perception that allocating vaccine based on local cases rewards bad performers might still undermine efforts to include insurance-type provisions in an international program. COVAX, a large, coordinated vaccine purchase mechanism for Covid-19 initially allocated vaccines without regard to cases, mortality rates, or even demand (proxied by utilization of previous shipments been utilized), possibly indicating the political challenges of building insurance into an international program.

[16] International discussions during the early stages of Covid-19 to develop a coordinated vaccine purchase arrangement across countries of very different income levels ran into some of these issues.

can be expected to be intense, leading to high capacity prices and capacity shortages. An individual country has an incentive to install capacity in advance to avoid this competition.

For example, if the United States undertook an advance-investment program (proportional to the size of the global program analyzed above), we find that the program would generate an expected present value of $61 billion in benefits net of program costs, a gain of $47 billion ($141 per capita) over the counterfactual program. Not just high-income countries but middle- and lower-income countries could also benefit from unilateral advance investment. For Brazil, for example, we find that advance investment would generate an expected present value of $16 billion in net benefits over program costs, a gain of $12 billion ($57 per capita) over the counterfactual.[17]

Investing countries could generate some revenue for themselves and social value for others by signing bilateral agreements with non-investing countries to use their facilities to produce vaccines for non-investing countries while the pandemic is severe there but not domestically. The investing country would retain priority over courses if the pandemic rises there but could benefit other countries meanwhile.

## 8 Conclusion

Pandemics are not so rare as to offset the enormous losses conditional on one occurring. Combining data on the probability distribution of epidemics of different severity and estimates of the relationship between epidemic severity (measured in deaths) and mortality, economic-output, and education losses from epidemics, we estimated that the world should expect pandemic losses to average over $800 billion every year going forward. Investments that reduce the cost of the next pandemic, even if they are relatively ambitious and expensive, can generate very high expected returns.

Investing now in building the capacity to rapidly vaccinate a large percentage of the population against a new virus could dramatically reduce the cost of future pandemics. This is true even if one factors in a risk that vaccines will not work against the next virus, that there will be a high degree of vaccine hesitancy, and that an effective antiviral will reduce the benefit of a vaccine. Specifically, we show that $60 billion in upfront investment and $5 billion in annual expenditure

[17] Since our analysis of individual-country programs holds mortality losses per capita constant at the global average, the difference in benefits between the United States and Brazil is mainly driven by the greater economic-output losses suffered in the country with higher GDP per capita and are only partially offset by longer school closures observed in MICs and LICs.

would be sufficient to fund capacity to produce 24 billion vaccine courses per year and thus vaccinate 70% of the world's population in six months in a pandemic. Under reasonable assumptions even larger capacity would have a high social return.

Instead of more being built, capacity for mRNA vaccines built up during the Covid-19 pandemic is in the process of being converted to other uses.

While this paper has focused on the benefits of maintaining vaccine supply capacity, the expected large losses from future pandemics imply that other investments that reduce their costs are also likely to generate high returns. Perhaps most closely related to this paper is the discussion about the benefits of developing and stockpiling a universal coronavirus vaccine that would protect against a wide variety of coronaviruses including ones that are yet to emerge. A new World Bank fund (Financial Intermediary Fund for Pandemic Prevention) plans to invest in, among other things, increased surveillance for the emergence of new pathogens. Research and development into new mRNA vaccines would likely improve the efficacy of this still relatively new technology and understand which type of viruses it is best suited to combatting. Berry et al. (2020) have suggested that putting in place a framework for when human challenge trials could accelerate testing of new vaccines and save millions of lives in a future pandemic. Finally, while much of the analysis in this paper are specific to reducing the cost of future viral pandemics, multidrug resistant bacteria remain a threat. Development of new antibiotics to be kept in reserve for use only in combination therapy for multidrug resistant strains would reduce the probability of a highly damaging bacterial pandemic. Scaling up antibiotics tends to be easier, cheaper, and faster than scaling up vaccines, hence our focus on vaccines. A similar logic applies to the development of broad-spectrum antivirals. Given the large expected losses from future pandemics, investments in the development of broad-spectrum antivirals are likely to be highly cost effective even if there were no certainty they would work against the next pandemic. Further work on the speed of scale up would be needed to calculate optimal stockpiles or investment in production facilities.

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**Table 1** Mortality and Economic Losses from Selected Pandemics Over Last Century

| | Deaths | | | Economic losses | |
|---|---|---|---|---|---|
| Epidemic (date) | Total deaths over pandemic (source) | Mortality intensity (annual deaths per thousand people) | YLL per death (source) | Economic loss over pandemic | Annual economic loss (% global GDP) |
| 1918 flu (1918–20) | 32.0 mil. (Marani et al. 2021) | $5.7 \times 10^{1}$ | 50.1 (Petersen et al. 2020) | 6% global GDP (Barro, Ursúa, and Weng 2020) | 2.0 |
| SARS (2002–03) | 1,000 (Marani et al. 2021) | $1.2 \times 10^{-4}$ | 27.3 (Jia et al. 2009) | 0.1% global GDP (Keogh-Brown and Smith 2008) | $2.5 \times 10^{-2}$ |
| Ebola (2014) | 11,325 (Marani et al. 2021) | $3.9 \times 10^{-4}$ | 38.6 (Helleringer and Noymer 2015) | 0.06% global GDP (Huber, Finelli, and Stevens 2018) | $8.3 \times 10^{-2}$ |
| Zika (2015–17) | 1,000 (Marani et al. 2021) | $4.5 \times 10^{-5}$ | 15.0 Puntasecca, King, and LeBeaud 2021) | 0.05% Latin American and Caribbean GDP annually (UN Development Programme 2017) | $1.7 \times 10^{-2}$ |
| Covid-19 (2020-22) | 21.3 mil. (*Economist* 2022) | $3.2 \times 10^{-1}$ | 16.0 (Pifarré i Arolas et al. 2021) | 14.4% global GDP (IMF 2022) | 3.6 |

Notes: For SARS and Zika, estimated deaths set to 1,000, the lower bound on observation threshold from Marani et al. (2021) power-law distribution. Years of lost life per death directly reported by indicated source for 1918 flu and Covid-19. For other diseases, entry computed by authors using average age at death reported by indicated source times life expectancy at that age from WHO (2022) for the relevant region and year of outbreak occurrence. YLL denotes years of lost life.

**Table 2** Expected Annual Global Pandemic Losses

| | Expected annual pandemic losses (billion dollars) | | | |
|---|---|---|---|---|
| Scenario | Mortality $AV(\overline{ML})$) | Economic output $AV(\overline{OL})$ | Learning $AV(\overline{LL})$ | Total $AV(\overline{TL})$ |
| Baseline | 505 | 176 | 127 | 808 |
| Half probability of pandemic arrival | 252 | 88 | 64 | 404 |
| Truncating intensity distribution | | | | |
| • Double upper truncation | 633 | 180 | 130 | 944 |
| • Remove upper truncation | 1812 | 193 | 140 | 2144 |
| Add HIV to epidemic frequency data | 1327 | 450 | 326 | 2103 |
| YLL per death | | | | |
| • Reduce to 20 | 344 | 176 | 127 | 646 |
| • Increase to 40 | 687 | 176 | 127 | 990 |
| GDP per capita growth rate | | | | |
| • Reduce to $y = 1.4\%$ | 466 | 162 | 117 | 746 |
| • Increase to $y = 1.8\%$ | 551 | 192 | 139 | 881 |
| Social discount factor | | | | |
| • Reduce to $r = 2\%$ | 1515 | 527 | 382 | 2423 |
| • Increase to $r = 6\%$ | 413 | 144 | 104 | 661 |

Notes: Entries are expected annual global pandemic losses in each category and in total following equation (11) in billions of 2019 dollars. The baseline scenario in the first row of results assumes a distribution of pandemic intensity given by equation (3); truncates pandemic intensity at the level of the 1918 flu; uses the arrival rate calculated using the Marani et al. (2021) data, which excludes HIV; and sets the YLL per death at 29.4, social discount factor at $r = 4\%$, and GDP per capita growth rate at $y = 1.6\%$. Other scenarios change only the indicated feature from the baseline.

**Table 3** Model Parameters

| Notation | Definition | Baseline value | Range for sensitivity analysis |
|---|---|---|---|
| $y$ | GDP per capita growth rate | 1.6% | 1.4%–1.8% |
| $d$ | Depreciation rate | 8% | 6%–10% |
| $r$ | Social discount rate | 4% | 2%–6% |
| $\phi$ | Fraction advance investment recoverable via rental | 0.7 | 0.5–0.9 |
| $\theta$ | Reduction of pandemic-time investments | 0.25 | 0–0.5 |
| $k_m$ | Unit cost of mRNA capacity in advance | $1.50 per annual course | $0.75–$3.00 |
| $k_o$ | Unit cost of traditional capacity in advance | $3.00 per annual course | $1.50–$6.00 |
| $c_m$ | Marginal cost of producing mRNA vaccines | $6.00 per course | $3.00–$12.00 |
| $c_o$ | Marginal cost of producing other vaccines | $3.00 per course | $1.50–$6.00 |
| $\varepsilon$ | Decreasing returns to capacity installed during pandemic | 1 | 0.75–1.25 |
| $p_b$ | Probability both technologies successful | 0.5 | 0.3–0.7 |
| $p_m$, $p_o$ | Probability technology alone successful | 0.15 | 0.1–0.2 |
| $f_m$, $f_o$ | Fraction of at-risk capacity successful | 0.3 | 0.2–0.4 |
| $g_m$, $g_o$ | Fraction of unsuccessful at-risk capacity repurposable | 0.4 | 0.2–0.6 |
| $\tau_m$ | Time to repurpose mRNA candidate | 2 months | 1–3 months |
| $\tau_o$ | Time to repurpose traditional candidate | 6 months | 3–9 months |
| $\gamma$ | Fraction of remaining harm mitigated by vaccine | 0.5 | 0.3–0.7 |

**Table 4** Baseline Results for Program Outcomes

| | Costs and benefits of program to undertake vaccination campaign in next significant pandemic (billion $) | | |
|---|---|---|---|
| | With advance investment | Without advance investment | Difference |
| Current value of expenditures | | | |
| • Initial advance investment | 60 | 0 | 60 |
| • Annual maintenance of advance capacity | 5 | 0 | 5 |
| • Additional expenditures in pandemic | 22 | 53 | -32 |
| Present value of program outcomes | | | |
| • Expected program costs (net of rental income) | 48 | 21 | 27 |
| • Expected gross benefits | 636 | 199 | 437 |
| • Expected net benefits | 587 | 178 | 409 |

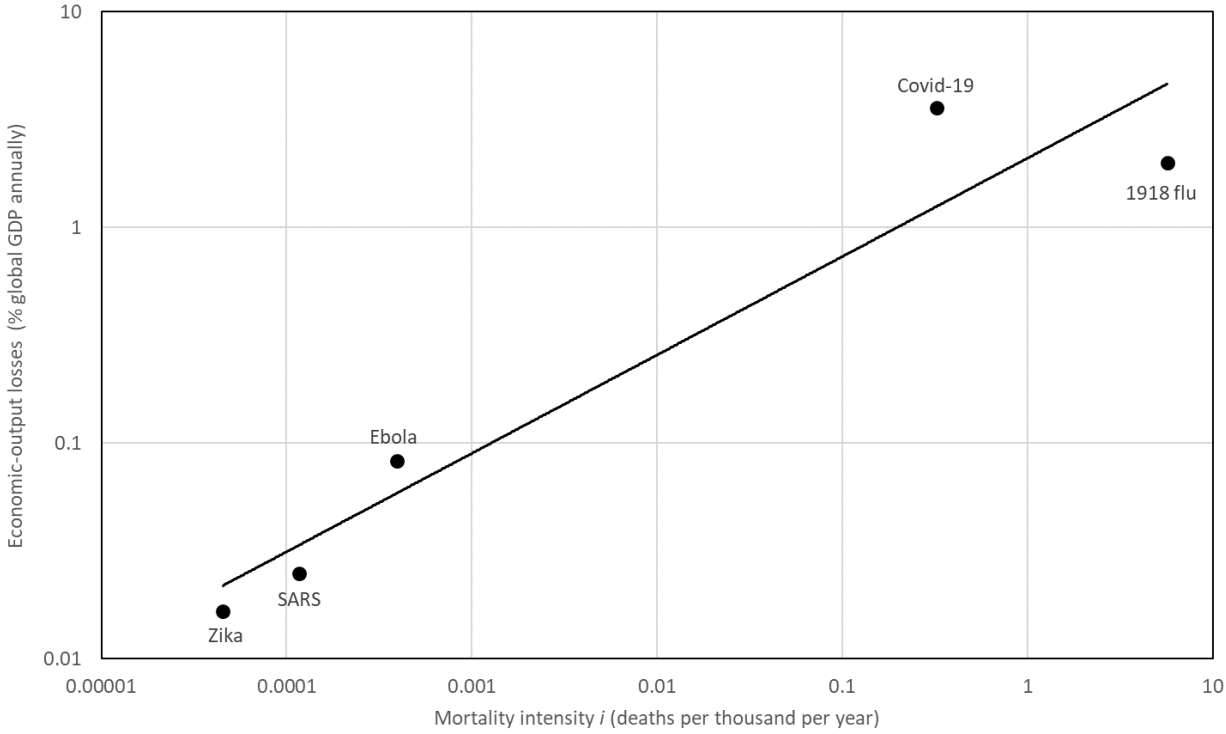
Notes: All entries are in billions of 2019 dollars rounded to the nearest billion. First set of rows report current value of expenditures in year undertaken. These are actual, not effective, expenditures, so do not net out rental income. Second set of rows report present values (from the perspective of the base year) of costs and benefits of program leading to vaccination campaign in next pandemic of at least half the intensity of Covid-19.

**Table 5** Sensitivity of Program Outcomes to Changes in Selected Parameters

| Scenario | Present value of expected net benefits of vaccination campaign in next significant pandemic (billion $) | | |
|---|---|---|---|
| | With advance investment | Without advance investment | Difference |
| Baseline | 587 | 178 | 409 |
| Half probability of pandemic arrival | 380 | 122 | 259 |
| Truncating intensity distribution | | | |
| • Double upper truncation | 739 | 225 | 513 |
| • Remove upper truncation | 2,069 | 642 | 1,427 |
| Add HIV to epidemic frequency data | 862 | 250 | 612 |
| $\gamma$ (fraction of remaining harm mitigated by vaccine) | | | |
| • Reduce to 0.3 | 333 | 98 | 235 |
| • Increase to 0.7 | 842 | 258 | 584 |
| YLL per death | | | |
| • Reduce to 20 | 426 | 127 | 299 |
| • Increase to 40 | 749 | 229 | 520 |
| $f_m, f_o$ (fraction of at-risk capacity successful) | | | |
| • Reduce to 0.2 | 475 | 129 | 346 |
| • Increase to 0.4 | 679 | 221 | 458 |
| $r$ (social discount rate) | | | |
| • Reduced to 0.02 | 992 | 300 | 692 |
| • Increased to 0.06 | 414 | 126 | 288 |

Notes: All entries are expected present values in billions of 2019 dollars. For space considerations, sensitivity analyses have been omitted for other parameters that had smaller effect on difference in program outcomes than those displayed, for example, for $f_m$ and $f_o$. Those parameters include $\varepsilon$, $y$, $d$, $\phi$, and the pairs $(g_m, g_o)$, $(k_m, k_o)$, and $(\tau_m, \tau_o)$, where the two elements of each pair are changed together. See Table 3 for the baseline values of those parameters and changes considered.

**Figure 1.** Relationship Between Epidemic Intensity Economic Losses in Historical Pandemics.




Notes: Data points from Table 1. Regression line given by equation (6). Log scales used for both axes.