The Risk Management of COVID-19:
Lessons from Financial Economics and Financial Risk Management

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Abstract

The United States had one of the worst outcomes in the management of COVID-19 risk, with a death rate in the 94th percentile of all countries. Setting aside the obvious politicized nature of COVID-19 public health recommendations and mandates, we argue that best practices in financial risk management provide parallels that could have served as valuable guidance. We demonstrate here that considerable signals were missed that would have required very little effort and would have been consistent with sound risk management. We also identify examples of misleading information such as that COVID-19 was particularly hard on the elderly. The data actually show that it had a much greater marginal impact on those not elderly. We show here that financial economists and risk managers have a strong knowledge base of how to process vast quantities of data to distinguish signals from noise and have much to teach the public health establishment.

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The COVID-19 pandemic was one of the most significant events in human history. In early October 2023, the World Health Organization reported there had been more than 770 million confirmed cases, which is about 1 in every 10.3 people, with approximately seven million deaths. In spite of limitations and questions about the accuracy of these figures but in light of the fact that almost surely millions of more cases were uncounted due to asymptomatic conditions, COVID-19 was unquestionably one of the most significant risks to humans in that roughly three-year period.

Health crises such as COVID-19 are certainly sources of substantial risk to individuals. But, they bear many similarities to financial risk, particularly that of credit risk. It would not be unreasonable to believe that say one out of every 10 loans experiences some financial distress, nor would it be unreasonable to believe that the death rate of approximately 1 in about 1,100 humans might correspond to the default rate on loans. For example, over a three-year period, the death rate of about 0.09% is close to the three-year default rate of a AA-rate bond.[1]

Since the Financial Crisis of 2008, risk managers have established a substantial knowledge base of how to identify and manage risk. While financial risk managers continue to learn, the banking failures of 2023 were largely confined to only a few banks. There is hope that the techniques are working, but it is a virtual certainty that the practice of risk management has improved. Much of the improvements have no doubt come from financial economics, which we define as the scientific study of financial data for the purpose of establishing knowledge.

The management of the COVID-19 crisis seems to stand in stark contrast, a result that appears to have been largely driven by politics. If the Chief Financial Officer of a bank is a Republican and the Chief Risk Officer is a Democrat, it seems unlikely that their political differences would result in the firm getting into financial distress. Both would want the same result: survival of the bank and alignment of the risk taken to the risk desired. But the politics of COVID-19 seems to have driven the policies carried out and no doubt contributed to the poor outcomes, particularly in the United States. For example, the United States, which seemed to have taken on a leadership role in the global fight against COVID-19, ranked 217 out of 231 countries in the death rate, putting it in about the 94th worst percentile.[2] No other G20 country had worse outcomes than the U.S. And the reason cannot lie in population density. The U. S. ranked 180

[1]https://www.livewiremarkets.com/wires/quantifying-the-risk-of-bonds-with-s-p-credit-ratings
[2]https://www.worldometers.info/coronavirus/. Data observed in early October 2023.

out of 217 countries by the United Nations.[3] Clearly U.S. public health policy made serious mistakes that were not duplicated in most other countries.

In this paper we argue that COVID-19 risk management and hence, the risk management of future pandemics, can learn a great deal from financial economics and risk management. We illustrate this point with examples of how best practices in financial risk management could have carried over into COVID-19 risk management. It would seem that lessons could be learned.

I. The Invaluable but Overlooked Information from the Vaccine Trials

On November 16, 2020, it was announced that Moderna, a Massachusetts-based pharmaceutical firm, had obtained promising results on a COVID-19 vaccine which it called mRNA-1273 SARS-CoV-2.[4] These preliminary findings were based on a sample of 13,934 people who took the vaccine and a control group of 13,883 who took a placebo. Of the vaccinated subjects, only five contracted COVID-19 over a median observation period of seven weeks, while 90 of the unvaccinated group contracted COVID-19. This reduction from 90 to 5 is the reported effectiveness rate of more than 94%. These figures were through November 7 2020. A final analysis ending November 24, 2020 was the basis for Moderna's Emergency Use Authorization (EUA) request filed with the FDA in late November of 2020 (Moderna, November 30, 2020). In the EUA application, Moderna reported that in the final analysis, 11 of the vaccinated individuals contracted COVID-19, while 185 of the unvaccinated contracted COVID-19. This reduction is 94.1%, as was reported in the application. The FDA approved the EUA a few weeks later (United States Food and Drug Administration, December 18, 2020). The results of the Moderna study were rapidly published in *The New England Journal of Medicine* (Baden et al, February 4, 2021).

On November 18, 2020, Pfizer announced that it had also developed a COVID-19 vaccine, which it called BNT162b2 mRNA Covid-19.[5] Two days later, Pfizer filed an application with the FDA for an EUA (Pfizer, November 20, 2020). This application was approved about a month later (United States Food and Drug Administration, (December 11, 2020)). The Pfizer study was published in *The New England Journal of Medicine* (Polack et al, December, 2020).

The Pfizer study administered the vaccine to 18,198 subjects and a placebo to 18,325. Eight people who received the vaccine contracted COVID-19, while 162 who received the placebo contracted COVID-19. The subjects were followed over a median of 8.7 weeks. The reduction from 162 to 8 is the effectiveness of 95.1%.

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[3]See https://statisticstimes.com/demographics/countries-by-population-density.php
[4]Moderna partnered with the National Institute of Allergy and Infectious Diseases of the National Institutes of Health.
[5]Pfizer partnered with BionTech.

The subjects in both studies were followed up in March of 2021, and these subsequent and cumulative results were published in *The New England Journal of Medicine* in November, 2021 (El Sahly et al, November 4, 2021 and Thomas et al, November 4, 2021) in back-to-back articles.

The company Moderna was created in 2010 partly for the purpose of developing a new type of vaccine, called messenger, or mRNA. Traditional vaccines inject weakened or dead microbes that place remnants of a disease into the body in the hope that the body's immune system will respond by attacking the microbes. mRNA vaccines contain genetic information that teach the body how to make a protein that is associated with the virus. The body acts as if it has the disease when it does not. The foundational knowledge and preliminary tests of mRNA vaccines go back about 30 years, but the COVID-19 vaccines were the first mRNA vaccines to hit the market.[6]

We now take a look at the results o those studies with an eye toward discerning information that would have been very useful in identifying and managing the risk.

A. Statistical Analysis of the Drug Trials

Like financial market activity and research, these studies contain a treasure trove of data, covering not only vaccine efficacy but also information on age and demographics of the sample. Moreover, they provide detailed data on adverse events. But there is additional and extremely valuable information that can be gleaned from the results of these studies that was never reported. Best practices in risk management call for a comprehensive analysis of all available data, which was simply not done in the rush to get a vaccine on the market.[7] It will become clear, however, that analyzing and promulgating this information would not have delayed the vaccines. It might, however, have raised questions about the reliability of the vaccines.

There are two primary objectives of a vaccine. One is to prevent the contraction of a disease and the other is to lessen the severity if the disease is contracted. These are the first-level benefits. Success in either can, of course, lead to conserving medical resources by shortening treatment periods, reducing the need for more aggressive and costly therapies and intensive care services, and, of course, saving lives.

Press releases and news media reports stated that the results were based on samples of around 30,000 people and achieved more than 90% effectiveness.[8] These two points are technically correct, but one is misleading. It is a virtual given that anyone but an expert would interpret a test using 30,000

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[6]It is almost surely not coincidental that Moderna's ticker symbol iS MRNA. It is of note that Moderna's stock went from $67.47 at the end of October 2020 to $127.03 at the end of November, an increase of 88.3%.

[7]The federal government made no pretenses about the urgency of a vaccine by partnering with private industry in a program it named Operation Warp Speed.

[8]For example, Palca (NPR) (November 16,2020) and Johnson (Washington Post) (November 16, 2020).

subjects to be a large sample and would infer confidence in the results. Thus, the general public believed that the drug was more than 94% effective on 30,000 people, but that statement is not true.

It is speculative to conjecture what the media and the average person believe 94% confidence really means. Some people may believe that in 94% of scientific studies, the vaccine prevented the disease. Perhaps some believe that of every 100 people who take the vaccine, 94 will not catch COVID-19. This is not even close to what it means, as we shall show. In fact, almost 99% of the people who did not take the vaccine did not catch COVID-19 in this trial. In short, it means that 94% fewer people caught COVID-19 by taking the vaccine, but as we shall see, very few people caught COVID-19 even when not taking the vaccine.

Drug efficacy is determined only from the subjects who contracted the disease. The 94% figure came only from the 185 in the placebo group and the 11 in the vaccine group that contracted COVID-19. No information whatsoever was learned about the efficacy of the drug from the subjects in both groups who did not catch Covid. Some knowledge was learned of side effects, but the efficacy was gleaned only from the 196 subjects who caught Covid from both groups. The results are indeed highly statistically significant in a binomial test of the proportions as we show here. We have the following inputs to the binomial test:

X_T = events (cases of COVID-19) in treatment groups (=11)

X_C = events (cases of COVID-19) in control group (=185)

N_T = number of subjects in treatment group (=13,934)

N_C = Number of subjects in control group (=13,883)

The binomial proportions of the two samples are

$$p_T = \frac{11}{13{,}934} = 0.0008$$
$$p_C = \frac{185}{13{,}883} = 0.0133$$

The combined frequency of events is

$$p = \frac{11+185}{13{,}934+13{,}883} = 0.0070$$

The standard error is

The *z*-statistic is, therefore,

$$z = \frac{0.0008 - 0.0125}{0.0010} = -12.50.$$

The *p*-value for a z-statistic of -12.50 is less than 0.00%. Clearly the sample with the vaccine performed much better than the control group. It passes the statistical test at an extremely high level of confidence.

As noted, with only 196 subjects who caught COVID-19, however, health authorities concluded that the vaccine was effective. The results are statistically significant but still may not elicit a high level of practical confidence if one has the full picture. For example, let us consider how few people would be needed to obtain statistical significance. Let us assume only one person in the vaccine group caught COVID-19. How many would it take in the control group to achieve a *p*-level of less than 1%, which is generally accepted as the gold standard. The answer is eight. Thus, if only 9 people caught COVID-19, one in the vaccine group and eight in the control group, the vaccine could still have been declared highly effective. The efficacy would have been 77.8%. Yet, this conclusion would have come from only nine subjects, though it is a virtual given that the efficacy would have been reported with the information of more than 27,000 subjects in the study. As one can easily see, if there were only 100 people in the study, the efficacy would be the same if there were 1,000,000 people in the study. But the media and the average person would almost surely have felt more confidence and been more likely to take the drug, if there were a large number of people in the study, even though few of them caught the disease.

How low could the effectiveness be to produce a statistically significant result? Assume again that 11 people in the vaccine group caught COVID-19. How many could have caught Covid in the control group to produce a *p*-value of less than 1%? The answer is 25. The binomial test of the proportions would have concluded with more than 99% confidence that the vaccine produced a statistically significantly lower probability of catching COVID-19 than did the placebo. Interestingly, the efficacy would have been (25 – 11)/25 = 0.56, or 56% efficacy, a figure that is likely to have not engendered much confidence. These numbers show the difficulty of using statistical analysis of drug effectiveness.

One of the problems that manifests here is the difference in absolute versus relative risk. In spite of the massive number of reported COVID-19 cases, in the Moderna drug trials only 1.33% of the subjects caught COVID-19. The absolute risk is quite low. This misperception of confusing absolute with relative risk is very common in medical research. See, e.g., Monaghan et al (2021) and Jiroutek and Turner (2019).

A more accurate announcement would have been that "in a study of almost 200 people, the drug proved to be more than 94% effective." Of course, such an announcement is unlikely to have instilled much confidence.

B. Questionable Controls in the Trial Procedure

Further concerns arise in that the subjects were not studied for an equal period of time. Moderna reported a median observation period of nine weeks after the second dose, which was based on a cutoff date of November 21, 2020. *The New England Journal of Medicine* article quotes this number as 63 days with a range of 0 to 97 days. As any risk management expert knows, risk is a function of the exposure period. No study of defaults would measure a default rate by mixing loans or bonds that have widely different exposure periods and aggregate to form a single default rate. For example, the incidence of default in a sample of loans over one year would be expected to be considerably less than the incidence over five years. Likewise, no financial economist would estimate the risk of a stock by mixing daily and weekly performance from non-overlapping periods. An economist would not compare the unemployment rate over a quarter with the unemployment rate over a month or add them and divide by two to get an average over four months. Thus, there was potentially a huge difference in exposure times of the subjects.

It is certainly a given that all subjects cannot be administered the vaccine or placebo at the same point in time. But the studies cut off on a given date and use all of the data accrued to that date. This would never make sense in economics or finance, and it seems to make little sense in medicine. Within each group the subjects should have the same exposure. If, say, a cancer drug were being tested, it would make no sense to follow some subjects for five years and some for 10. Inasmuch as COVID-19 can be contracted in an instant, modest differences in exposure periods can make the sample unreliable.

Moreover, the reporting of the median and not the average makes one suspicious that the distribution is highly skewed. After all, the median is 63, the maximum is 97, and the minimum is zero. If that is the case, the normal parametric tests, as are used in these studies, may not be appropriate.

It would not have been difficult to follow everyone for a common period of time. Information that occurs outside the observation period is simply ignored. This is not wasting information – it is doing the experiment the right way.[9] Of course, it is well-known that there was considerable pressure to get a vaccine out as fast as possible, so perhaps some corners were cut.

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[9]Consider the following analogous study. Suppose one wishes to determine the accident rate for a sample of commuters who take the same route every day. Some commuters are followed for one week, some for two weeks, some for five weeks, some for eight weeks, and some for 10 weeks. The median is five weeks, but there is considerably more than five weeks of exposure in the sample.

We shall proceed, however, by using the median reported length of time the subjects are followed as though it applies to all subjects. That is the best one can do. The investigators have the granular data, however, and could easily repeat the exercises shown here and obtain more trustworthy results.

This problem is so common in medical research that Clark et al (2002) have even written about it, noting that "unequal follow-up in the treatment groups can bias the analysis of results." Similarly, Srivastava et al(2021) use simulation to also note that there could be substantial bias in the conclusions.

C. Does the Vaccine Reduce the Severity of the Disease?

Anecdotal evidence suggests that people believe that a vaccine might not prevent one from contracting the disease but if contracted, the disease will be milder. Proving this point is quite challenging if the disease has low absolute risk. Ironically, the more effective is the vaccine, the harder it is to examine the question of whether the vaccine makes a case milder. The only means of determining if a case is milder is to observe symptoms while a patient has the disease. If the vaccine is 100% effective and no people catch the disease, there are no symptoms to observe.

The Moderna study provides insufficient evidence to study the severity of symptoms. Table 18 of the EUA application shows that there were no severe cases of the 11 from the vaccine group who caught COVID-19 and 30 severe cases of the 185 who caught COVID-19 from the placebo group. These results may seem impressive for the vaccine, but no severe cases out of a small sample of 11 is insufficient to prove anything. Moreover, the number of severe cases from the placebo group is only 16.2%. Had just two people in the vaccine group caught a severe case of COVID-19, the severity rate would have been higher than in the placebo group. This, of course, is an indication of insufficiently large samples. So, based on the Moderna trials, there was no scientific basis for concluding that its vaccine made COVID-19cases milder. In its EUA, Moderna, however, did make this claim (p. 55).

> *The known benefits among recipients of the proposed vaccine relative to placebo are:*
>
> *• Reduction in the risk of confirmed COVID-19 occurring at least 14 days after the second dose of vaccine*
>
> *• Reduction in the risk of confirmed severe COVID-19 occurring at least 14 days after the second dose of vaccine*

Does Moderna have a basis for this claim? In a binomial test, we find that 0 of 11 is statistically different from 30 of 185 with a *p*-value of 0.073. The typical standard is no more than 5%. So, it is marginally close but not clear-cut.

If it is tempting to dismiss this criticism, then consider the following facts from the Pfizer trials. There were eight cases of COVID-19 in the vaccine group and 162 in the placebo group, which is 95.2% effectiveness. From Table 12 of the EUA application, one subject of the eight (12.5%) in the vaccine group experienced a severe case of COVID-19, and nine (5.5%) of the placebo group experienced a severe case. Do we conclude that the Pfizer drug, while quite effective in preventing COVID-19, nonetheless resulted in a greater likelihood of a severe case, if the patient caught COVID-19? No, we cannot draw such conclusions. The sample sizes are simply too small to make any statement about the ability of the drug to prevent severe cases. A binomial test is significant only at 0.21.

To their credit Pfizer made no such claim, using some subtle language (p. 49):

The known benefits among recipients of the proposed vaccine relative to placebo are:

- *Reduction in the risk of confirmed COVID-19 occurring at least 7 days after Dose*
- *Reduction in the risk of confirmed COVID-19 after Dose 1 and before Dose 2*
- *Reduction in the risk of confirmed severe COVID-19 any time after Dose 1*

The third statement is key. The vaccine group had one case, which occurred after Dose 2. For the placebo group there were four cases after Dose 1 but before Dose 2. Pfizer's claim that one is significantly less than four is apparently the basis for the third statement above. Fortunately there is no statement about the vaccine reducing severe COVID-19 after Dose 2. But since the period between dose 1 and dose 2 is extremely short, there seems to be little useful information on the effect of the vaccine on severity.

In the following section we develop several valuable risk measures that were missed by the public health experts. This is important because lessons learned from COVID-19 risk management mistakes can be corrected for future epidemics.

II. Covid-19 Risk Measures that the Experts Failed to Compute

To illustrate, we shall use the Moderna study as reported in its EUA application and as appears in *The New England Journal of Medicine* article. The basic data are presented in Table 1. Of course, we have referred to these numbers previously.

Table 1

Results of the Moderna mRNA-1273 SARS CoV-2 Trials

Conducted in Fall, 2020

	Contracted Covid-19 (*C*)	Did Not Contract Covid-19 (*NC*)	Total
Vaccinated Group (*V*)	*11*	13,923	*13,934*
Non-vaccinated/Placebo Group (*NV*)	*185*	13,698	*13,883*
Total	196	27,621	27,817

Source: Modern, EUA Application, Table 17

The italicized numbers are the only ones required for immediate purposes. The remaining cells can be filled in with simple arithmetic. We also need to know the average time followed, which, as noted above, was nine weeks if one accepts the median for the average.

A. Probability of Contracting COVID-19

Risk managers pay considerable attention to the probability of an adverse event. For example, the probability of default on a loan is a critical metric in the risk manager's information set. Hence, effective risk management of Covid would suggest that we would want to know the probability a person would catch Covid. Yet, this number was not reported in these studies or elsewhere, and if anyone did generate the number, it was not made public.

We have two samples, the vaccinated group and the control group, so we should calculate these probabilities separately, treating them as conditional probabilities and applying a Bayesian approach of updating probabilities when new information is received. Using the notation $P(.)$ for probability, C for the event of contracting Covid over the observation period, NC for the event of not contracting Covid over the observation period, V for being vaccinated, and NV for being not vaccinated, we obtain two key conditional probabilities,

$$P(C|V)=\frac{11}{13{,}934}=0.079\%$$
$$P(C|NV)=\frac{185}{13{,}883}=1.333\%.$$

We might also wish to do a more precise and formal Bayesian analysis. First, we need the unconditional probability of contracting Covid, which is

$$P(C)=\frac{196}{27{,}817}=0.70\%.$$

Thus, a person chosen randomly from the entire population where approximately half are vaccinated has a 0.70% chance of catching COVID-19 in nine weeks. If we know the person is vaccinated, however, this probability changes to 0.079%. If we know the person is not vaccinated, the probability changes to 1.333%. Thus, Bayesian updating further highlights the efficacy of the vaccine, at least at that point in time, over a limited observation period, and based on the Moderna trials.

In order to make comparisons of how these numbers change over time, let us standardize these probabilities to a one-month probability. Because they were obtained over a 9-week period, we divide by 9 to convert to a weekly rate. Then we multiply by 52 to obtain an annual rate and divide by 12 to convert to a monthly rate,

$$P(C|V)=\left(\left(\frac{11}{13{,}934}\right)/9\right)\left(\frac{52}{12}\right)=0.038\%$$
$$P(C|NV)=\left(\left(\frac{185}{13{,}883}\right)/9\right)\left(\frac{52}{12}\right)=0.642\%.$$

This transformation has done nothing to diminish the impressive performance of the vaccine over these first nine weeks, but it will make it possible to compare it with tests that follow subjects over other time intervals.

We can also express the probability of contracting COVID-19 in what might be a more intuitive manner for some people. We simply invert the one-month probabilities to determine how many people it would take for one case of COVID-19 to occur in a month.

$$V:\frac{1}{0{,}00038}=2{,}630.90$$
$$NV:\frac{1}{0{,}00642}=155.86$$

Thus, these trials predict that one in every 2,631 vaccinated people would catch Covid in one month, while one in every 156 unvaccinated people would catch COVID-19 in one month. The numbers are static of course, pointing to the need to follow these people as well as create additional samples of people who can be followed over time to generate more data points. But it would seem that this measure would have been a more important metric than the one that was widely used – the cumulative number of cases of Covid – which tells nothing about the actual risk.

B. Number of Vaccinations Required to Avoid One Case, One Hospitalization, and One Death

It is easy to calculate how many people must take the vaccine to avoid one case. In medical research, this concept is known as *NNT*, the number-needed-to treat. The variable definitions are X_T, X_C, the number of subjects in the treatment and control groups respectively that contracted the disease, and N_T is the number of subjects in the treatment group. Then

$$NNT = \frac{N_T}{\max(0, X_C - X_T)}.$$

That is, if $X_C > X_T$, we treated N_T subjects and produced a reduction in the disease of $X_C - X_T$. If $X_C \leq X_T$, the control group had an equal or fewer number of people who contracted the disease, and, thus, the number needed to treat is undefined.

To make comparisons possible between vaccines and across time, however, it is best to standardize this result to a one-month period. Thus, we need the expected number of cases in one month for the vaccinated and unvaccinated groups,

$$\begin{matrix} V: 0.00038(13,934) = 5.30 \\ NV: 0.642(13,883) = 89.07 \end{matrix}.$$

We take the difference in these two expected values and divide into the number who took the vaccine,

$$NNT = \frac{13,934}{89.07 - 5.30} = 166.32.$$

Thus, about 166 people must take the drug to avoid one case in one month. This should be a disconcerting number. Consider 166 people using any product that is designed to help them, but 99.4% achieve no benefit. Of course, this is largely a function of the fact that there were few cases of COVID-19 in the full sample. The product itself did not necessarily fail. It simply was not needed by about 99% of the subjects.

Such a metric might be a very useful number for officials and the public to judge whether the vaccine was worth it. If a financial risk manager that took a significant action against a risk that was relatively small and, thus, the action did not help or was not needed about 99% of the time, the action would be questioned.

Given reliable exogenous data, one could next estimate how many vaccinations are necessary to eliminate one hospitalization and one death.[10] On October 2, 2021, the CDC estimated that there had been 146.6 million cases, with 7.5 million requiring hospitalization, and 921,000 leading to death (Centers for Disease Control, October 2, 2021). The percentage of cases resulting in hospitalization is thus, 7.5/146.6 = 0.0512, or 5.12%. The death rate per case is 0.921/146.5 = 0.0063, or 0.63%.[11] Now we can estimate the number of vaccinations required to avoid one hospitalization and one death.

We can follow the above procedure and multiply each expectation by the hospitalization or death rate to get the expected number of hospitalizations and deaths in one month. A short-cut to getting the overall answer is simply to divide by the number of vaccinations to avoid a case by the hospitalization and death rates,

$$H: \frac{166.32}{0.0512} = 3,251.0$$
$$D: \frac{166.32}{0.0063} = 26,474.1 .$$

Thus, based on the Moderna trials and CDC statistics, it would have taken over 3,200 vaccinations to avoid one hospitalization and more than 26,000 to save a life.[12] These results do not automatically mean that the vaccine should not be used, but they should have been part of a debate.

The *NNT* is a measure that has been widely reported in the literature as important for medical researchers.[13] Yet, even in this day and age, it is not always reported. Take, for example, the Hung and Kuan (2022) meta-analysis of the ability of the COVID-19 vaccines to reduce severe cases of COVID-19. The authors review seven studies with a total of over 1.3 million people taking several COVID-19 vaccines. There were a total of 689,967 people that took the vaccines and 676,673 that took a placebo. Of the vaccinated group 56 had severe cases of COVID-19, wile in the control group 236 had severe cases of COVID-19. The reduction from 236 to 56 is 180. This is a reduction of more than 76% and seems quite

[10]One could theoretically do that with the trial subjects, but with only 196 people catching Covid, the number of hospitalizations (3) and deaths (1) are too small to derive any inferences.

[11]The CDC figures unquestionably understate the number of cases, as they report only recorded cases. It has been noted by experts that many people catch COVID-19 and never feel any symptoms or do not seek medical advice, and, hence, are not recorded. But they are very important in the big picture of whether the vaccines are needed. One way the CDC could have determined the true incidence of COVID-19 would have been for it to have obtained a large sample of people, such as those in the drug trials, and gotten the subjects to agree to be regularly tested, whether symptomatic or not.

[12]These numbers are higher if we consider that the CDC cannot identify all cases.

[13]For a meta-analysis, see Mendes et al (2017) and Hildebrandt (2009).

impressive. On that basis, the authors stated that "The analysis showed that all types of vaccines can effectively prevent severe disease."

But if one considers that it took almost 700,000 people to eliminate 180 cases of severe Covid, the performance is not that impressive, with a success rate of 1-in-689,967/180 = 3,833.2.

C. How Long to Infect Half the Population?

Here we calculate how many years it would take to infect half of the population. This number is 1 minus the probability of infection raised to the n^{th} power, set equal to 0.5. First calculate the number of months. We then divide by 12 to express the result in years. We shall refer to this measure as the half-life of each group. The number of months for each group is the solution n below:

$$V = (1-0.00038)^n = 0.5$$
$$NV = (1-0.00642)^n = 0.5.$$

The solutions are

$$V: n = \left(\frac{\ln(0.5)}{\ln(1-0.00038)}\right)/12 = 151.94$$
$$NV: n = \left(\frac{\ln(0.5)}{\ln(1-0.00642)}\right)/12 = 8.97.$$

To understand this measure, consider the result for the non-vaccinated group. The one-month probability of infection, conditional on being vaccinated, is 0.038%. This means that after one month, 1 – 0.00038 = 0.9996, or 99.6% is still COVID-19-free. Then 99.96% of that group will be COVID-19-free after two months. Carry this on for 8.97 years, and 50% of the population will be infected. For the vaccinated group, the half-life would be over 150 years, but of course, this conclusion presumes the vaccine would remain as effective as it did over the short test period.

These numbers may seem low, as anecdotal evidence suggests that perhaps the half-life will be reached a lot sooner. but these measures are precisely what is inferred from the data on which the government made a decision to approve, promote, and in some cases, require vaccination. If the data make unrealistic predictions, then the data may not be very reliable. And if the data are not reliable, why were the vaccines approved on the basis of the data? Data integrity is of the utmost importance in research and policymaking.

These measures are consistent with the nine-week efficacy of the Moderna vaccine. But they present a different perspective. For example, knowing that 166 people must take the vaccine to avoid one

case is important. The COVID-19 vaccine is a very profitable drug, and Moderna made about $12 billion in profit from the drug in 2021 (Brady (2022). Virtually all of that profit came from the pockets of taxpayers, who received very little in return.

III. Other Data Points from the Randomized Clinical Trials

Moderna and Pfizer both reported results from their initial studies in late 2020. In late 2021, both had articles in *The New England Journal of Medicine* reporting on their studies as they carried forward through part of March, 2021. Both reported outstanding results. We, thus, have two studies by Moderna and two by Pfizer, covering an initial period and a cumulative period. Summary results are presented in Table 2. The results over the longer period show excellent performance of the vaccine, but they are cumulative. Including the early results, which were quite good, provides a misleading picture of the performance of the vaccines, and we shall take a look at how to remove this bias.

Table 2

Results of the Four Pfizer and Moderna Trials

Cutoff Date	Company	Median Weeks Followed	# of Subjects Vaccinated	# of Subjects Placebo	Cases of Covid-19 Vaccinated	Cases of Covid-19 Placebo	Efficacy
11/14/2020	Pfizer	8.67	18,198	18,325	8	162	95.06%
11/21/2020	Moderna	9.00	13,934	13,883	11	185	94.05%
3/13/2021	Prizer	26.00	20,998	21,096	77	850	90.94%
3/26/2021	Moderna	27.38	14,287	14,164	55	744	92.61%

As the table shows, Pfizer's efficacy fell to 90.94%, and Moderna's fell to 92.61%. Since these results are cumulative, they include the early period of about two months. This suggests a deterioration of performance during the last 18 or so weeks. We shall take a look at the second period results by backing out the first period results. For now, however, consider Table 3, which shows the key calculated risk measures for both the initial period and the second (cumulative) period for Pfizer and Moderna.

Table 3

Initial and Final Results from the Four Pfizer and Moderna Trials

Cutoff Date	Company	Monthly $P(C\|V)$	$P(C\|NV)$	Case	Vaccinations to save one Hospitalization	Death	Vaccinated Half-Life
11/14/2020	Pfizer	0.233%	0.442%	236	4,616	37,593	262.76
11/21/2020	Moderna	0.339%	0.642%	166	3,249	26,456	151.94
3/13/2021	Prizer	0.367%	0.672%	163	3,184	25,926	94.48
3/26/2021	Moderna	0.444%	0.831%	131	2,560	20,843	94.79

With both vaccines, each group showed an increase in the probability of catching Covid. For the vaccinated, Pfizer's went up from 0,233% to 0.367%. Moderna's went up from 0.339% to 0.444%. For the non-vaccinated, Pfizer's went up from 0.442% to 0.672%, and Moderna's went up from 0.642% to 0.831%. The other major statistics are there, but a fuller understanding of all of the measures will be gained by observing the second period separately. The first period is around nine weeks. The cumulative period is around six months. We can determine what happened in the second period by subtracting the cumulative cases from the totals from the first period totals. We can also get the median exposure for the second period by subtracting the median exposure in the first period from the median exposure for the full period. We assume that the number of subjects in the second period is the same as the number reported for the cumulative period. The basic data for the first and second periods are shown in Table 4.

Table 4

Results from the Pfizer and Modern Trials – First and Second Periods

Cutoff Date	Company	Median Weeks Followed	# of Subjects Vaccinated	Placebo	Cases of Covid Vaccinated	Placebo	Efficacy
11/14/2020	Pfizer	8.67	18,198	18,325	8	162	95.06%
11/21/2020	Moderna	9.00	13,934	13,883	11	185	94.05%
3/13/2021	Prizer	17.33	20,998	21,096	69	688	89.97%
3/26/2021	Moderna	18.38	14,287	14,164	44	559	92.13%

For Pfizer, the effectiveness rate dropped from 95.06% to 89.97%. For Moderna, effectiveness dropped from 94.05% to 92.13%. This should immediately make us suspicious of the vaccines' long-term efficacy.

We can also see that the probability of catching COVID-19 rose substantially in the second period over the first. This information is presented in Table 5.

Table 5

Probability of Catching COVID-19 **in First and Second Periods**

Monthly		First Period		Second Period	
Date	Company	$P(C\|V)$	$P(C\|NV)$	$P(C\|V)$	$P(C\|NV)$
11/14/2020	Pfizer	0.022%	0.442%	0.082%	0.815%
11/21/2020	Moderna	0.038%	0.642%	0.073%	0.930%

For Pfizer, the probability for the vaccinated group rose by a factor of 3.72, while for the unvaccinated group it rose by a factor of 1.84. For Moderna, the probability for the vaccinated rose by a factor of 1.92, while for the unvaccinated, it rose by a factor of 1.45. Clearly the additional roughly four months of study showed decreasing effectiveness of the vaccine. This information was known in March of 2023. But because the cumulative totals were presented, the vaccines were deemed to have been very effective. They certainly still had some effectiveness, but it was clearly declining.

IV. Further Questions and Missed Metrics

A. A Pandemic of the Unvaccinated

It was noticed that a rise in cases and hospitalizations during the summer of 2021 led CDC director Rochelle Walensky to declare it a "pandemic of the unvaccinated." (See. E.g., Sullivan (2021) and Andone and Holcomb (2021)). The evidence pointed to the fact that the overwhelming majority of COVID-19 patients in hospitals were not vaccinated. The states experiencing the strongest surge of cases were those that had the highest percentage of unvaccinated people.

That indeed the growth in cases was fueled by unvaccinated people seems to be an inarguable fact, but it is an excellent example of how a factual statement, like a high vaccine efficacy, can actually mislead.

Suppose the unvaccinated individuals came from a segment of the population that are generally unhealthy and do not take care of themselves, which can include not being fearful of the virus and not taking reasonable precautions. It seems almost surely the case from other diseases that vaccinations are a positive proactive step in improving one's health. then it could easily be the case that this pandemic of the

unvaccinated is actually a pandemic of unhealthy individuals who do not take care of themselves or take modest precautions.

Finance and in particular researchers in finance always test alternative interpretations of results, often in the form of robustness tests. It would have been easy for hospitals and public health officials to get the data and determine if it really was a pandemic of the unvaccinated. Hospitals have considerable information on their patients. Measuring a patient's general health and characteristics in personal health management would not have been difficult. If it truly were a pandemic of the unvaccinated, then the patients who were causing the surge would have to have average to good health and taking reasonable steps, except for the Covid vaccine, to take care of themselves. If this were not the case and they were unhealthy to begin with and not taking care of themselves, then it was a pandemic of patients at high risk in the first place who simply did not choose to be vaccinated, in which case the health authorities have equated effect with cause. Of course, this is a common statistical faux pas.

Moreover, it might even be reasonable to wonder if patients who were unvaccinated were most likely to be sent to a hospital or put on a ventilator, or put in intensive care because their provider considered this a higher risk factor, though it might not have been.

Risk managers and financial researchers eliminate other explanations for results before drawing a conclusion. Public health authorities should do so as well. In this case, it was clear that an initial glance at the data suggested the conclusion that public health authorities wanted to convey, an example of confirmation bias.

B. Are the Elderly at the Greatest Risk?

Early in the pandemic it was noted that the elderly are at particularly high risk. This may have caused people not considered elderly to get a false sense of comfort. This might seem to be a plausible statement, but it would seem to beg the obvious question of whether it is an abnormality. It would seem that almost every disease is hard on the elderly. Some simple data analysis can provide valuable insights.

Table 6 shows the percentage of deaths of the three major age groups considered elderly compared to the younger group, below age 65. The Covid death data come from Statista as of June, 2023. The non-Covid deaths are CDC data from 2018, well prior to COVID-19, so clearly not influenced by COVID-19.

Table 6

Composition of all Deaths Caused by COVID-19 **versus Other Factors**

By Age Group

Age Group	COVID-19	Other Causes
Below 65	24.4%	25.0%
65 to 74	22.4%	22.1%
75 to 84	26.1%	23.1%
85+	27.1%	29.7%

Notice how similar the percentages are with or without the COVID-19 effect. Interestingly, the 85+ group accounted for a slightly smaller percentage of COVID-19 deahts than of deaths from other causes. These results suggest that COVID-19 was no more of a threat to the elderly than existing threats.

A similar conclusion is drawn from a different perspective in Table 7. These figures represent deaths per 100,000 people and, hence, account for differences in the number of people in each groupe.

Table 7

Age-Adjusted Death Rates, 2018 & 2021

Age	2018	2021	Pct. Chg.
1-4	24.0	25.0	4.2%
5-14	13.3	14.3	7.5%
15-24	70.2	88.9	26.6%
25-34	128.9	180.8	40.3%
35-44	194.7	287.9	47.9%
45-54	395.9	531.0	34.1%
55-64	886.7	1,117.1	26.0%
65-74	1,783.3	2,151.3	20.6%
75-84	4,386.1	5,119.4	16.7%
85 and older	13,450.7	15,743.3	17.0%

Once again, it is apparent that COVID-19 caused a greater increase in the death rate in much younger people, particularly in the 25-44 range. Other groups that experienced greater increases than those 85 and older were the ranges of 15-24, 45-54, 55-64, and 65-74. Of course, we are effectively examining relative risk. If we considered all of the additional deaths from COVID-19 over 2018 as due toCOVID-19, even the elderly are not at terribly great risk. For example, for those 85 and older there

were about 2,300 more deaths per 100,000 during COVID-19 than in 2018. This is but 2.3 people out of 100, and that assumes that all of the increase is due to COVID-19.

C. Are Masks Effective?

Probably no question has led to as much controversy as this one. It is easy to use economics to see why public health authorities were such strong advocates of using masks. They had been used in surgery for years and were low cost, with only modest inconvenience to the user. These negatives were weighed against the potential positives of stopping or slowing the rate of infection. Setting aside the personal freedom question of whether governments can force people to essentially dress a certain way, we should take a look at what information was known at that time about mask efficacy to see whether mask mandates were beneficial and whether the answer to that question should have been known in advance.

C.1. Meta Analysis in 2015

An article in the *Journal of the Royal Society of Medicine* in 2015 (Da Zhou et al (2015)) reported on a met-analysis of the literature on surgical masks. Their conclusion states very interestingly that "… there is a lack of substantial evidence to support claims that facemasks protect either patient or surgeon from infectious contamination."

If masks are so effective, why was the evidence so inconclusive? And why did public health authorities, without a supporting body of evidence, invoke mask requirements? And why did people mostly comply? Simply believing that a barrier placed in front of the nose and mouth, which has to be sufficiently porous to admit air, would prevent infection seems naïve.

It was quickly learned that the virus was quite small, which should have raised questions about the effectiveness of masks. This does not mean that masks should have been deemed ineffective, but only that more data were needed before such a drastic measure was put in place, especially in light of the absence of prior data.

C.2. Denmark Study

An early study conducted in Denmark in April and May of 2020 appeared in the *Annals of Internal Medicine in* (Bundegaard et al (2021)) that found little effectiveness. The authors conclude that "The recommendation to wear surgical masks to supplement other public health measures did not reduce the SARS-CoV-2 infection rate among wearers by more than 50% in a community with modest infection rates, some degree of social distancing, and uncommon general mask use. The data were compatible with lesser degrees of self-protection."

C. 3. The CDC's Own Study

Even the CDC's own data in the summer of 2020 raised initial concerns. Fisher et al (2020) reported that in a sample of 152 adults (ages 18 and up) who were outpatients for COVID-19, 130 described themselves as wearing masks either always or often. This proportion of about 85% received some attention in the news and engendered a great deal of attack-and-defense arguments over what it meant. Did it mean you were more likely to catch COVID-19 if you were a mask wearer? Both sides missed the full story.

If 85% of patients catching COVID-19 were mask wearers, it does not automatically mean wearing a mask increases one's chance of catching COVID-19. Consider 100 people who caught COVID-19 with 85 being mask wearers. Then the 15 others who caught COVID-19 were non mask wearers. Suppose there were only 20 non mask wearers but hundreds of mask wearers. Then one would be more likely to catch COVID-19 if one di not wear a mask.

We can find no evidence that anyone searched for the full story. In fact, it is possible to estimate whether one were more likely to catch COVID-19 if wearing a mask than if not. This calculation requires only some additional data that were available.

Given only two simple pieces of information, it is possible to calculate the probability of COVID-19 infection for people who wear masks divided by the probability of infection for people who do not wear masks. The information required as been publicly reported. It is not possible to calculate the actual probabilities of infection for both groups unless we know the true rate of infection in society, and this information is a bit ambiguous, given that the figure for reported cases is not actually individuals. It is the number of positive tests, which includes false positives and multiple tests of the same person. This infection rate for society as a whole, however, cancels out when computing the ratio. Here we will illustrate how to do this calculation.

Define the following variables:

r = infection rate (percentage of people infected in the population at large)
m = percentage of the population at large that wear masks
S = sample of people
N = subset of S people that are infected

Assuming the sample is representative of the population at large, then by definition,

$$N=Sr.$$

That is, the N people in the sample who are infected will reflect the infection rate of the population at large, r, applied to the sample size, S. These infected people are examined to determine what percentage of this group are mask wearers. Define

u = percentage of the infected subsample who are mask wearers

Of the full sample of people, the number who wear masks is Sm. The number who do not wear masks is $S(1 - m)$. Therefore, we can obtain an estimate of the percentage of mask wearers who are infected. There are Nu mask wearers in the infected subsample and Sm mask wearers in the full sample of infected and uninfected people. Therefore, dividing the former by the latter gives us an estimate of the probability that a mask wearer will be infected. This is $P(m) = Nu/Sm$. But as defined above, $N = Sr$. So,

$$P(m) = ru/m.$$

Now we need to examine the people who are not mask wearers. The number in the full sample is $S(1 - m)$. The number who are infected is $N(1 - u)$. Therefore, the probability that a non-mask wearer becomes infected is $P(n) = N(1 - u)/S(1 - m)$. Replace the S with N/r to obtain

$$P(n) = \frac{(1-u)r}{1-m}.$$

In the absence of a reliable estimate of r, we cannot calculate these probabilities, but we can calculate the ratio (R) of the probabilities:

$$R = \frac{P(m)}{P(n)} = \frac{ru/m}{(1-u)r/(1-m)} = \frac{u(1-m)}{m(1-u)}.$$

Simple algebra reveals the ratio is more than 1 if $u > m$. This makes sense. If the subsample of infected people contains more mask wearers than the full sample of infected and uninfected people, then you are more likely to catch Covid if you are a mask wearer.

From the CDC study, we have that $u = 0.85$. During the summer of 2020, it was estimated that the percentage of Americans wearing face masks often or always was about 72% (Roper, 2020). Hence, $m = 0.72$, and

$$R = \frac{0.85(1-0,72)}{(0.72)(0.15)} = 2.20.$$

Thus, you were 2.20 times more likely to catch COVID-19 if you were a mask wearer. Opponents of masks might seize on this to declare that masks were virus magnets, but that seems unlikely

to be true. Here is where a good financial economist or risk manager would seek a more logical explanation. Perhaps it would lie in the possibility that if one wore a mask, one felt more protected and failed to take the other precautions that one ought to have taken. A false sense of security is a potentially powerful force in human behavior. And if this is the explanation, it is another example of the law of unintended consequences: force people to wear masks and they will fail to take other important precautions. Further scrutiny of the samples to determine what other measures they took might reveal more insights.

C. 4. Toto, I Don't Think We're in Kansas Anymore

The COVID-19 crisis has prompted endless debates about science, often peppered with such phrases as "follow the science" and "the science is established." Science that supports one view has often been highly promoted in the mainstream media, while science that shows the opposite has been suppressed and even censored. Some scientists have been called "flat earth theorists," while others are called "authorities." The gold standard in scholarly research is peer review, but during the COVID-19 crisis most of the COVID-19 research that was promulgated had not been peer-reviewed and even peer-reviewed studies are not guaranteed to be the 100% truth. Here is an example of a problematic non-peer reviewed study used by mask proponents to push their views forward.

In November of 2020 the CDC reported on a study (Van Dyke et al, 2020) it conducted of counties in Kansas, some of which had a statewide or locally imposed mask mandate and some of which opted out of that mandate. Its results show a 6% decrease in the spread of Covid in the 24 counties that adopted the mask mandate and a 100% increase in the 85 counties that did not.

The principal requirement of the statistical tests, and indeed most all statistical tests, is that the sample observations are independent of each other. This requirement is not met by the very nature of what is being studied – a contagious disease.

There are two groups, the mandated counties (*MC*) and the non-mandated counties (*NMC*). Within each group are sub-samples of counties, 24 in the MC group and 81 in the NMC group. Within these subsamples are the people themselves who are the ones getting COVID-19. To be statistically reliable, the subsamples and the people within those subsamples must be independent with respect to what is being measured, the incidence of COVID-19.

What this means is that the incidence of COVID-19 in a county cannot in any way affect the incidence of COVID-19 in another county. And within a county, COVID-19 contracted by a person or group of people cannot in any way affect whether other people in that county contract COVID-19. A contagious disease is inconsistent with that requirement. We will explain why this is a problem but also show how it could have been controlled.

Consider a county completely free of COVID-19. One person in that county goes to another county that has a high incidence of COVID-19 and brings it back, spreading to others of that county. Then it spreads to nearby counties. This contagion effect invalidates the statistical tests, because one random event led to an outcome that multiplied – the contagion effect.

It would be like setting up a blind taste test between Coke and Pepsi. The person tests it, guesses it is Coke and is told that it is Pepsi. As he walks away he whispers to the next person in line, "the one on the right is Pepsi." That person passes it on. And so on. Statistics can be calculated but they will not be reliable measures of the views of the subjects.

If it were a non-contagious disease and instead of masks, it were some treatment, there would not be a problem. One does not pass cancer on to someone nearby and one person's recovery based on a treatment is not affected by another's. CDC researchers are used to studying non-contagious diseases, but they also study contagious diseases. They need to recognize the difference.

Again, it does not mean the study is wrong. It just means that its reliability is low. But, there are other problems with the study.

There has been an obvious pattern in COVID-19. Outbreaks initially occurred in more urban areas. New York was hit hard very early. At that time, many largely rural areas, like West Virginia and Montana, barely got hit at all. Then COVID-19 began to decline in the hard hit areas and started burning through other areas that it had not yet reached. We have seen this happen in waves.

The CDC indicates that the *MC* were more urban and heavily populated than the *NMC*. So, what if COVID-19 had already hit the more urban areas, the *MC*, earlier, as it almost surely had done? It might well have been declining in those counties and then moving on to the more rural counties. We cannot say for certain that this happened, but it is a pattern that has happened repeatedly across the country. Statisticians call this problem "endogeneity." It means something is going on internal to a study that is causing the result that you think is coming from what you're studying. A researcher is supposed to think about this and try to control for it. Financial economists spend a great deal of effort dealing with endogeneity.

The CDC study also presents a graph that shows that the *MC* rates rose sharply after the mandate, then dipped and then began to rise again. On this basis the researchers concluded that masks were beneficial. But in the last few days of the study, the *MC* rate began to rise. What if the study were extended? That rise might continue. More on this in a moment.

The *NMC* rates rose before and after the mandate. This suggests that COVID-19 was surging, regardless of their not wearing masks. Also, *NMC* had lower rates to start with. the upward trend shows that if COVID-19 got into these counties, there could easily be a sharp percentage increase. That was

already happening. Since they were not wearing masks before and not afterwards, the mask mandate had no effect on them.

There was also no attempt to identify if outliers drove the results. Outliers are a clustering of a small number of extreme observations, and they can distort the results. A good researcher always checks for outliers, yet the word is not mentioned in the study. In fact, the graph shows three distinct outliers for the *MC* right after the mandate day that clearly shifted the graph downward. Take those out and the line would be much flatter than downward sloping.

Another weakness of the study is that the two groups were compared with themselves over unequal periods. The period measured before the mask mandate was about 31 days. The period measured after the mandate was 51 days. If there is a contagion effect, it is more likely to be picked up, the longer you observe it. It is this contagion effect that is the problem, as explained above.

Another problem is that the measure is the seven-day rolling average of infections per 100,000. This measure averages the infection rate over seven days. As you move forward a day, you drop the oldest and add the new one. The problem is that these observations are also not independent unless they are measured a week apart, so that the data do not overlap. In this study, the seven-day rolling average is measured daily. Hence, not only are the subjects being studied not independent, the measure itself is not independent.

So, how could the study have been done to address the contagion bias? COVID-19is, after all, a contagious disease so controlling for contagion would be challenging. But here is a way.

Consider two groups, mask wearers (*MW*) and non-mask wearers (*NMW*). We choose a person from one group and match that person with a person from the other group. These two people have to be similar along the lines of age, health, sex, etc. They must come from quite different geographic areas so that they cannot spread Covid to each other. The general rate of infection in the areas of each person of the pair should be the same. In other words, we are trying to make everything comparable between the two people except that one is a mask wearer, and the other is not. We would then need a relatively large sample of these pairs from geographically diverse areas. If the researchers could get samples like that, a fair comparison could be made. Considering that more than 60,000 people participated in the Moderna and Pfizer vaccine trials and provided considerable personal information, such a study seems quite reasonable.

C. 5. The Cochrane Library Study

The Cochrane Library is a U.K.-based institute that, among other activities, reviews medical research for accuracy. It emphasizes evidence-based medicine, meaning to apply rigorous methods of scientific inquiry to draw conclusions about the effectiveness of medical treatments. In 2024 it published an extensive review of over 78 randomized controlled trials of over 600,000 subjects to determine the

efficacy of masks. It concluded "The pooled results of RCTs did not show a clear reduction in respiratory viral infection with the use of medical/surgical masks."

Of course, no study is perfect, but when subjected to scientific rigor, masks do not show effectiveness. If masks worked, why would this evidence not show clearly in meta analyses? Moreover, this was known from the 2015 study and, of course, confirmed in the Cochrane study.

IV. Discussion

Risk management is the process of aligning the risk being taken with the desired risk. It is not the minimization of risk. For example, a portfolio manager can minimize risk by investing all of the funds in a simple risk-free security, such as a government treasury bill. The risk of passengers getting onto planes with weapons could likely be almost eliminated by going through the contents of all baggage and strip-searching all passengers. The risk of automobile accidents could be eliminated by banning automobiles. Of course, all these measures are unacceptable, if not downright silly. We always accept risks. It is a question of how much we wish to accept. Managing risk means that the risk we are taking is the risk we wish to accept.

Best practices in financial risk management entail the following general actions:

(1) *Identify the risk*

(2) *Specify the risk tolerance*. The risk tolerance is the amount of risk that the risk taker wishes to assume.

(3) *Measure the risk*

(4) *Compare the risk being taken (Step (3)) with the desired risk (Step (2))*

(5) *Adjust the risk taken, if necessary*. If the risk taken equals the desired risk, return to Step (3), repeating the process. If not, then take action to align the desired risk with the actual risk by either reallocating the portfolio or hedging; then return to Step (3), repeating the process.

(5) *Return to Step (3)*

The process is an ongoing one, requiring the continuous monitoring of the risk to determine if the risk being taken aligns with the desired risk and to adjust the risk where necessary. On occasion, the risk taker's tolerance should be reviewed and adjusted if they feel they should be taking more or less risk. In addition, the risk measurement methods are often adjusted through improvements. In fact, a tangential activity would involve determining if the risk measure accurately captures the risk. New research can develop better measures.

In what follows, we give an example of a financial trading firm practicing risk management. Later we show the analogy to COVID-19 risk management. The risk measure used in this example is a popular one called *Value-at-Risk* or *VaR*. It is defined as the minimum loss that over a defined time period is incurred a given percentage of the time. *VaR* is typically measured in dollars or other currency units. *VaR* is widely used when banks report risk to regulatory authorities. Regulatory *VaR* is the maximum amount that could be lost in 10 business days with 99% confidence. As an example, in March 2022 Goldman Sachs reported to the regulatory authorities that its *VaR* was $452 million. This means that over a 10-day period, it was 99% confident that the most it could lose was $452 million.[14] We walk through the process using Goldman Sachs as a hypothetical example.

(1) *Identify the risk*: a severe financial loss, though not necessarily to the point of causing bankruptcy

(2) *Specify the risk tolerance*: Assumed to be no more than a 1% chance of losing more than $500 million in ten trading days

(3) *Measure the risk*: Collect historical data, adjust for changes in portfolio composition from past to future, incorporate any other judgmental facts that might affect future risk, and then measure the *VaR*

(4) *Compare the risk taken with the desired risk*: The measured *VaR* of $452 million is compared to the risk tolerance of $500 million.

(5) *Adjust the risk taken*, *if necessary*. The risk taken is about 10% below the risk tolerance. The firm could actually slightly increase its risk, though it may consider the current position to be sufficiently close.

(6) *Return to Step (3)*

Financial risk managers are continuously measuring and monitoring the risk. There are no guarantees of perfection. But as the process of risk management has improved, particularly since the financial crisis that began in 2008, failures due to trading losses that do not involve fraud or extremely careless management have become relatively rare.[15]

Now let us take a look at how COVID-19 risk management could have applied these principles. We position ourselves from the standpoint of a policy maker with authority to either order or highly

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[14]See Goldman Sachs (2022). Regulatory *VaR* is a requirement that must be met by a bank for bank regulators. The bank itself can manage its risk with its own chosen *VaR*, which may be higher or lower, may be measured over a different number of days, and may have a different percentage tolerance. Goldman Sachs says that its risk management *VaR* is a 95%, one-day measure.

[15]It is important to note that while we use *VaR* in this example, no firm would manage risk using only *VaR*. Other measures, such as stress tests, and variants of *VaR* are commonly employed.

recommend certain actions. This could be a federal, state, or local public health official or governmental leader. The risk control objectives shown below are not recommendations. They are for illustrative purposes only.

(1) *Identify the risk*. In the case of COVID-19, this risk is that of contracting COVID-19. It could be further refined to cover hospitalization or death. For this example, we shall go with contracting COVID-19.

(2) *Specify the risk tolerance*. A reasonable objective might be to infect no more than x% of the population over a given period of time. Another objective might be that the number of cases of COVID-19 in unvaccinated people is a certain target. For this example, we shall go with the latter. At a population of about 330 million, the decision maker should specify the target probability. For example, if it is 0.5% per month, this means 1.65 million infections per month, or about 55,000 per day.

(3) *Measure the risk*. The probability of catching COVID-19 is the appropriate measure. Earlier in this article, we covered how that is done. It would require following a fixed sample of people that have diverse demographics that are representative of the entire population. Their incidence of catching COVID-19 would be indicative of the probability of catching COVID-19. Such a measure should be monitored and reported over time.

(4) *Compare the risk taken with the desired risk*. Compare the actual number catching COVID-19 to the predicted number catching COVID-19.

(5) *Adjust the risk taken, if neces*sary. If the number catching Covid substantially exceeds the expected number catching COVID-19, subject to a reasonable margin of error, more aggressive measures should be taken. If the number catching COVID-19is well below the expected number, some measures could perhaps be relaxed.

(6) *Return to Step (3)*. This is a continuous process and should be followed until the threat no longer exists.

Thus, we argue that the probability of catching COVID-19, or perhaps the 1-in-a certain number should be the risk exposure and should have been reported and used to benchmark the success or failure of the mitigation efforts that are employed. These best practices from financial risk management make sense and have worked effectively in the financial world.

V. Conclusions

Financial risk management has a set of protocols that establish best practices. These protocols require considerable accurate information extracted from financial data. Financial economics provides guidance in how to properly extract information and draw conclusions from financial data. COVID-19

risk management has many parallels with financial risk management. Terrible mistakes were made in the management of COVID-19. Setting aside politicization, information was suppressed, and measures were taken with little scientific support. The response that “We simply did not know” is hardly acceptable. If we did not know, then measures that were taken should have been applied with acknowledgment that the measures were not strongly supported and would be re-evaluated on an ongoing basis to see if they were working. Moreover, any defense of actions taken in the U. S. falls flat when one considers that the U. S. had one of the worst death rates in the world.

Public health authorities need to recognize the principles of sound risk management. The systemic risk of a pandemic bears considerable resemblance to the systemic risk that can exist in banking. The financial industry has had its problems, but it has made considerable progress in improving the risk management process. As evidenced by COVID-19, public health risk management has a much longer way to go.

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