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ASSESSING THE AGE SPECIFICITY OF INFECTION FATALITY RATES FOR COVID-19:
META-ANALYSIS & PUBLIC POLICY IMPLICATIONS

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Assessing the Age Specificity of Infection Fatality Rates for COVID-19: Meta-Analysis & Public Policy Implications

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ABSTRACT

This paper assesses the age specificity of the infection fatality rate (IFR) for COVID-19. Our benchmark meta-regression synthesizes the age-specific IFRs from six recent large-scale seroprevalence studies conducted in Belgium, Geneva, Indiana, New York, Spain, and Sweden. The estimated IFR is close to zero for children and younger adults but rises exponentially with age, reaching about 0.3 percent for ages 50-59, 1.3 percent for ages 60-69, 4.6 percent for ages 70-79, and 25 percent for ages 80 and above. We compare those predictions to the age-specific IFRs implied by recent seroprevalence estimates for nine other U.S. locations, three small-scale studies, and three countries (Iceland, New Zealand, and Republic of Korea) that have engaged in comprehensive tracking and tracing of COVID-19 infections. We also review seroprevalence studies of 32 other locations whose design was not well-suited for estimating age-specific IFRs. Our findings indicate that COVID-19 is not just dangerous for the elderly and infirm but also for healthy middle-aged adults, for whom the fatality rate is more than 50 times greater than the risk of dying in an automobile accident. Consequently, the overall IFR for a given location is intrinsically linked to the age-specific pattern of infections. In a scenario where the U.S. infection rate reaches 20 percent, our analysis indicates that protecting vulnerable age groups could prevent more than 200,000 deaths.

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A Supplemental Data and a Stata Code are available at <http://www.nber.org/data-appendix/w27597>

Table 1: COVID-19 Cases in New York City

	<u>Total as of July 15, 2020</u>	<u>Share of Infections</u>
NYC Residents	8 Million	NA
Estimated Infections	1.6 Million	100%
Symptomatic Cases	1.1 Million	65%
Reported Cases	220,000	12%
Hospitalization	55,000	3%
Fatalities	23,000	1%

Source: New York City Health Department (2020).

1. Introduction

As the COVID-19 pandemic has spread across the globe, some fundamental issues have remained unclear: How dangerous is COVID-19? And to whom? The answers to these questions have crucial implications in determining appropriate public health policies as well as informing prudent decision-making by individuals, families, and communities.

The standard epidemiological approach to gauging the severity of an infectious disease is to determine its *infection fatality rate* (IFR), that is, the ratio of deaths to the total number of infected individuals. The IFR is readily observable for certain viruses, such as Ebola, where nearly every case is associated with severe symptoms and the incidence of fatalities is extremely high; for such diseases, the IFR is practically identical to the *case fatality rate* (CFR), that is, the ratio of deaths to reported cases. By contrast, most people who are infected with SARS-Cov-2—the virus that causes COVID-19—are asymptomatic or experience only mild symptoms such as headache or loss of taste and may be unlikely to receive a viral test or be included in official case reports. Consequently, reported cases tend to comprise a small fraction of the total number of infections, and hence the CFR is *not* an adequate metric for the true severity of the disease.

As shown in Table 1, assessing the IFR for COVID-19 is analogous to finding a needle in a haystack, especially in a dense urban area such as New York City (NYC). The New York State Department of Health recently conducted a large-scale seroprevalence study and estimated the NYC infection rate at about 22 percent, that is, 1.6 million out of 8 million NYC residents.¹ As of mid-July, NYC had about 220,000 reported COVID-19 cases, almost exactly one-tenth of the total number of infections. About one-fourth of those reported cases were severe enough to require hospitalization, many of whom unfortunately succumbed to the disease. All told, fatalities represented about one-tenth of reported cases but only one-hundredth of all infections.

While the NYC data indicate an IFR of about 1 percent, analysis of other locations has produced a puzzlingly wide array of IFR estimates, ranging from around 0.5 percent in Geneva and Zurich to rates above 2 percent in Spain and in the Republic of Korea (henceforth “Korea”). Indeed, a

¹ See New York Department of Health (2020).

recent meta-analysis noted the high degree of heterogeneity across aggregate estimates of IFR and concluded that research on age-stratified IFR is “urgently needed to inform policymaking.”²

In this paper, we consider the hypothesis that the observed variation in IFR across locations may primarily reflect the age specificity of COVID-19 infections and fatalities. In particular, the overall IFR for a given location can be expressed as follows:

$$IFR = \sum_{a=1}^N POPSHARE_a * INFRATE_a * IFR_a$$

using data for N distinct age groups, where $POP SHARE_a$ denotes the share of age group a in the total population, $INFRATE_a$ denotes that age group’s COVID-19 infection rate, and IFR_a denotes that age group’s infection fatality rate. Demographic information about the age structure for a given location is readily available from census data. Consequently, a crucial task is to use seroprevalence data to assess age-specific infection rates and IFRs.

Rather than focusing on any single location, we proceed by conducting *meta-analysis* using data from a wide array of distinct locations, drawn from recent studies of COVID-19 prevalence in more than 50 distinct locations. We begin by highlighting key characteristics of studies that are essential for assessing age-specific IFRs, including the use of a broadly representative sample of the general population, seroprevalence methods with high positive predictive power, and tabulation of fatalities that are appropriately linked to the dates of the seroprevalence testing. Based on those criteria, we exclude 32 seroprevalence studies that are not suitable for estimating age-specific IFRs.

Using these criteria, we identify six seroprevalence studies that serve as benchmarks: Belgium, Geneva, Indiana, New York, Spain, and Sweden. Applying meta-regression methods to this set of studies, we estimate a log-linear relationship between IFR and age and obtain precise coefficients that are not significantly influenced by outliers. In particular, the estimated IFR is close to zero for children and younger adults but increases exponentially with age, reaching 0.3 percent for ages 50-59, 1.3 percent for ages 60-69, 4.6 percent for ages 70-79, and 25 percent for ages 80 and above.

Next, we compare these meta-regression predictions to the age-specific IFRs implied by recent seroprevalence studies of nine other U.S. geographical areas and to data for three countries that have engaged in comprehensive tracking and tracing of COVID-19 infections. We also compare the benchmark predictions to the results of three small-scale seroprevalence studies and to the age-specific IFRs estimated by Ferguson et al. (2020) at an early stage of the pandemic.

² See Meyerowitz-Katz and Merone (2020), p.3.

Our analysis has two key conclusions: (1) COVID-19 is not just dangerous for the elderly and infirm but also for middle-aged adults, for whom the fatality rate is roughly 50 times greater than the risk of dying in an automobile accident; and (2) age-specific policy choices and communications can dramatically decrease COVID-19 deaths. In particular, the overall IFR should *not* be viewed as an exogenously fixed parameter but as intrinsically linked to the age composition of the population and the age-specific pattern of infections.³ Consequently, individual and collective efforts that minimize infections in older adults could substantially decrease total deaths. In a scenario where the infection rate of the U.S. population reaches 20%, our analysis indicates that protecting vulnerable age groups could prevent over 200,000 deaths.

The remainder of this paper is structured as follows: Section 2 describes our methodology. Section 3 presents our meta-analysis results. Section 4 discusses the public policy implications of our analysis, including comparison to other types of fatality risks and scenario analysis of the age-specific pattern of U.S. infections and deaths. Section 5 discusses issues for further research.

2. Methodology

2.1 Overview

To perform the present meta-analysis, we collected published papers and preprints that have studied the seroprevalence and/or infection fatality rate of COVID-19. To identify these studies, we performed online searches in MedRxiv and Medline using the criterion (“infection fatality rate” or “IFR” or “seroprevalence”) and (“COVID-19” or “SARS-Cov-2”).⁴ We identified other studies listed in reports by government agencies such as the U.S. Center for Disease Control & Prevention and the U.K. Parliament Office.⁵ Finally, we confirmed the comprehensiveness of our literature search by referring to two recent meta-analysis studies that have assessed overall IFR for COVID-19 and a recent meta-analysis study comparing seroprevalence with reported cases.⁶

Before proceeding further, we restricted our meta-analysis to studies of advanced economies, based on current membership in the Organization for Economic Cooperation and Development (OECD).⁷ It should be emphasized that we applaud recent efforts to assess seroprevalence in a number of developing countries (including Brazil, Croatia, Ethiopia, and Iran), but we have excluded those studies in light of the distinct challenges associated with health care provision

³ Acemoglu, Chernozhukov, Werning, and Whinston (2020) and Chen et al. (2020) analyze optimal targeted lockdowns and reopenings in analytical frameworks with distinct age groups (e.g. young, middle-aged, and retired) using age-specific IFRs calibrated to the findings of Ferguson et al. (2020) and Verity et al. (2020), respectively. By contrast, Hall, Klenow, and Jones (2020) analyze these issues using a more stylized analytical framework in which the aggregate IFR is an exogenously fixed parameter.

⁴ These searches were conducted on July 1 and updated on July 10 and July 19.

⁵ For example, see U.K. Parliament Office (2020).

⁶ See Ioannidis (2020) and Meyerowitz-Katz and Merone (2020) for meta-analysis of the overall IFR for COVID-19 and Byambasuren et al. (2020) for a systematic comparison of seroprevalence with reported cases.

⁷ OECD countries include: Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States (<https://www.oecd.org>).

and reporting of fatalities in those locations.⁸ We also excluded studies that were focused on measuring seroprevalence in a narrow segment of the population such as health care workers or pregnant women.⁹ Appendix A lists all of the studies identified in our literature search.

2.2 Prevalence Measurement

Our meta-analysis encompasses two distinct approaches for assessing COVID-19's prevalence: (1) extensive tracking and contact-tracing using live-virus testing and (2) seroprevalence studies that test for antibodies produced in response to the virus. Testing for the live virus is done by either a quantitative reverse-transcription polymerase chain reaction (qRT-PCR) molecular test for the viral nucleic acid sequence, or an antigen test for proteins specific to the virus.¹⁰ These tests detect the virus within a few days of disease onset. While using live antigen testing is the optimal approach for determining prevalence, it requires extensive continuous testing of a population, and was only thoroughly implemented in select countries with relatively small populations, notably South Korea, Iceland, and New Zealand.

Most studies of COVID-19 prevalence have proceeded using serological analysis to determine what fraction of the population has developed either IgG or IgM antibodies to the virus. IgM antibodies develop earlier, but decrease over time, while IgG antibodies develop later and remain in high concentrations for several months. Antibodies are tested for using several methods. Enzyme-linked immunosorbent assays (ELISA) proceed by tagging antibody-antigen interactions with a reporter protein. Chemiluminescent immunoassays (CLA) work similarly by tagging the antigen-antibody interaction with a fluorescent protein. Lateral Flow Assays (LFA), also known as rapid diagnostic tests (RDT), produce a colored band upon antigen-antibody interaction.

Recognizing that SARS-Cov-2 is both novel and hazardous, public regulatory agencies have issued “emergency use authorizations” (EUA) to facilitate the rapid deployment of live virus and antibody tests based on the test characteristics reported by each manufacturer.¹¹ Subsequent studies by independent laboratories have reassessed the characteristics of these test kits, in many cases finding markedly different results than those of the manufacturer. Such differences reflect (a) the extent to which test results may be affected by seemingly trivial differences in its implementation, and (b) the extent to which seriological properties may vary across different segments of the population. For example, a significant challenge in producing accurate tests is to distinguish COVID-19 antibodies from those associated with other coronaviruses (including the common cold). Consequently, the assessment of test characteristics may vary with seemingly innocuous factors such as the season of the year in which the blood samples were collected.

⁸ See Silveira et al. (2020), Jerkovic et al. (2020), Kempen et al. (2020), and Shakiba et al. (2020) for seroprevalence analysis of locations in Brazil, Croatia, Ethiopia, and Iran, respectively. Fassihit and Gladstone (2020) highlight the shortcomings of official tabulations of COVID-19 fatalities in Iran during the early stages of the pandemic.

⁹ For example, Flannery et al. (2020) assess seroprevalence in parturient women.

¹⁰ Carter et al., 2020

¹¹ For example, see U.S. Food & Drug Administration (2020).

The reliability of seroprevalence testing depends on three key factors: (1) the seroprevalence test's sensitivity (odds the test detects the virus in an infected person); (2) the seroprevalence test's specificity (odds the test returns a negative result for a uninfected person); and (3) the true disease prevalence in the sample. In a population where the actual prevalence is relatively low, the frequency of false-positive tests is crucial for determining the reliability of the test results.

As discussed in Appendix B, the sensitivity and specificity of COVID-19 antibody tests should not be treated as fixed parameters that are known with a high degree of certainty, as would generally be the case for medical tests of other diseases that have been authorized via standard regulatory procedures. In particular, the confidence interval for each seroprevalence estimate should reflect the degree of uncertainty about its sensitivity and specificity as well as the conventional uncertainty that reflects the size of the sample used in producing that estimate.¹²

2.3 Sampling Method

Randomized Samples

To assess the prevalence of COVID-19 infections in the general population, a study should be specifically designed to utilize a random sample drawn from that population using standard survey procedures such as stratification and weighting by demographic and socioeconomic characteristics. To date, large-scale studies have followed this approach in assessing COVID-19 prevalence in Belgium, Geneva, Indiana, New York, Spain, and Sweden.¹³ For example, Spain's national seroprevalence study gathered specimens from a random sample of nearly 36,000 individuals, providing detailed results at 5-year age intervals from ages 5-9 through ages 85-89 as well as age categories for infants, small children, and elderly people ages 90 years and above.

Commercial Lab Specimens

An alternative approach is to measure seroprevalence using a "convenience sample" of blood specimens collected for some other purpose. In particular, a recent U.S. study analyzed residual sera from clinical blood samples that had been submitted to two commercial laboratories for routine testing; those samples were collected from about 16,000 patients in ten U.S. geographical locations over the period from March 23 to May 12, 2020. As noted in a companion editorial in the same medical journal, these data collection periods "*overlapped with active stay-at-home orders, when most medical appointments and elective admissions were deferred. Thus, the outpatient and inpatient populations included in the study are likely not representative of a typical pre-pandemic cohort; some of the discarded serum specimens from inpatients were likely obtained from patients hospitalized for COVID-19.*"¹⁴

That study illustrates several other limitations of convenience samples: (1) The seroprevalence results were adjusted using data provided by the commercial labs regarding patients' gender,

¹² See Manski and Molinari (2020) and Larremore et al. (2020).

¹³ See Molenberghs et al. (2020), Perez-Saez et al. (2020), Pollan et al. (2020), Menachemi et al. (2020), Rosenberg et al. (2020), and Sweden Public Health Agency (2020c,d), respectively.

¹⁴ Brown and Walensky (2020), p.82.

age group, and zip code, but could not be weighted by other demographic factors (such as race and ethnicity) or socioeconomic indicators.¹⁵ (2) The sample sizes were not tailored to ensure precise estimates in some locations with relatively low prevalence. For example, the 95% confidence intervals for all four age groups in the Minneapolis metropolitan area and in the San Francisco Bay Area included a value of zero; that is, the estimated level of seroprevalence was not statistically significant. Since IFR is computed as a ratio with prevalence in the denominator, confidence intervals for age-specific IFRs cannot be computed in these two locations. (3) The collection dates of specimens from each location reflected idiosyncratic factors rather than the timeframe over which the pandemic was contained in that location. Indeed, as discussed further below, the New York City (NYC) sample was collected in late March when the outbreak was intensifying, and the outbreak does not appear to have been fully contained in several of the other locations (Louisiana, Minneapolis, Missouri, and Philadelphia).

Blood Donors

Prior research has shown that blood donors tend to be much younger than the general population. For example, a pre-pandemic study of U.K. blood donors found a median age of 28 years for new donors and a median age of 45 years for repeat donors, with very few donors over age 65—a limitation that is particularly problematic in assessing COVID-19 IFRs for older age groups.¹⁶ The study also found that U.K. blood donors were more likely than the general population to be residents of urban areas, although that finding is likely linked to the age distribution of donors.

Those findings raise the concern that assessing seroprevalence for a sample of blood donors could overstate the true prevalence of COVID-19 if such individuals tend to be more gregarious and less risk-averse than non-donors. Indeed, such concerns were specifically flagged by the authors of a recent seroprevalence study who noted that blood donors “*might have a higher number of social interactions than other groups.*”¹⁷

These concerns can be directly investigated by comparing two distinct U.K. seroprevalence surveys: Public Health England (PHE) gauges seroprevalence using specimens from blood donors, and the U.K. Office for National Statistics (ONS) gauges seroprevalence using specimens submitted for routine testing.¹⁸ As of early June, PHE reported seroprevalence of 8.5%, whereas ONS reported a markedly lower seroprevalence of 5.4% with a 95% confidence interval of 4.3% to 6.5%; that is, the seroprevalence of PHE blood donors was markedly higher than that of the ONS sample, perhaps by as much as a factor of 2.

¹⁵ Such concerns about sample selection are underscored by the divergence between the seroprevalence estimates of the two commercial labs for specimens from the New York City area, where the adjusted prevalence for Lab A specimens was 11.5% and 5.7% for Lab B; see Havers et al. (2020), eTable 1.

¹⁶ See Lattimore et al. (2015).

¹⁷ Valenti et al. (2020), p.12.

¹⁸ See England Public Health (2020) and U.K. Office of National Statistics (2020).

Hospitals and Urgent Care Clinics

As noted above, blood specimens provided for routine testing may overstate prevalence if a substantial fraction of those samples are taken from patients who have a live virus infection. But this sample selection issue is likely to be far more severe for hospitalized patients or those seeking urgent care at an outpatient clinic.

For example, the New York Department of Health’s seroprevalence study (conducted using specimens collected at sites adjacent to supermarkets and grocery stores during the final week of April) estimated the level of prevalence in NYC at 22.7% (CI: 21.5% to 24%).¹⁹ A subsequent seroprevalence study was conducted using 28,523 specimens collected from primary care providers and urgent care facilities in NYC and surrounding suburbs from May 5 to June 5; that study found a raw prevalence of 44%. Given that all of New York was in lockdown during that period, it seems quite unlikely that true prevalence for the general population of NYC doubled during the month of May. Rather, the most plausible explanation is that a large fraction of the patients at NYC urgent care clinics during that period were seeking medical attention for COVID-like symptoms and hence inflated this estimate of COVID-19 prevalence.

Samples with Direct Recruitment of Participants

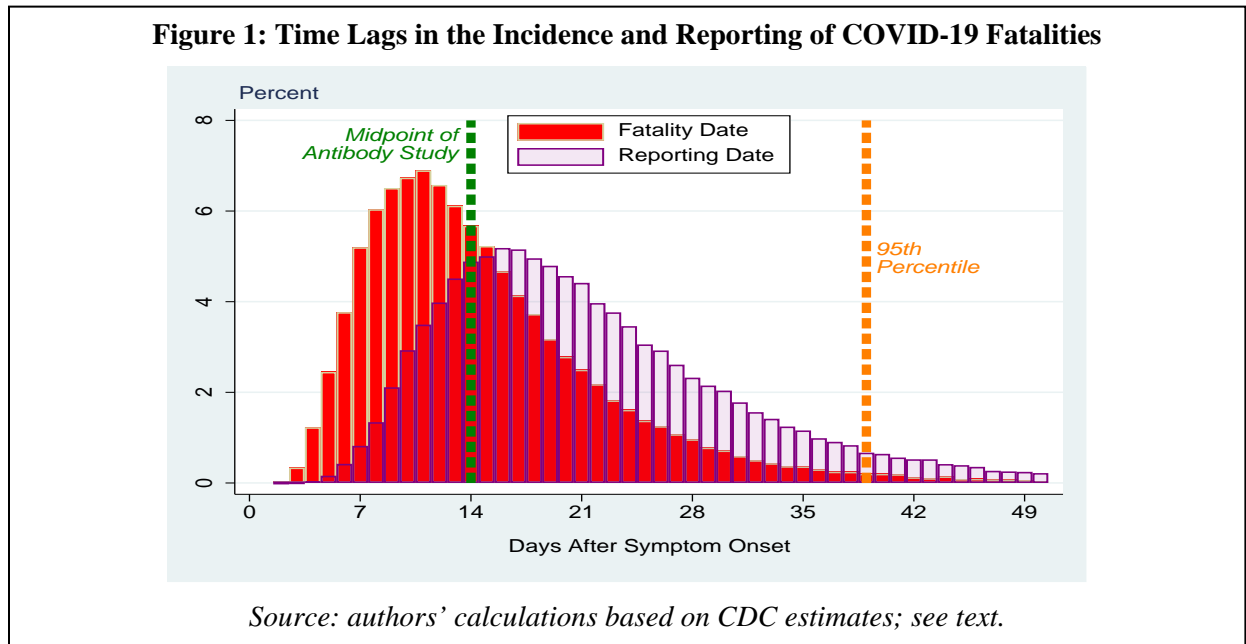
Some seroprevalence studies have involved direct recruitment of participants, raising the possibility that a substantial fraction of the sample may have volunteered for testing due to specific concerns about a previous or current COVID-19 infection and hence that the estimated prevalence could overstate the true prevalence in the general population.

This possibility can be evaluated using detailed results from a seroprevalence study conducted in Luxembourg, which specifically noted “*the need to recruit a representative sample of the Luxembourgish population over 18 years old within a short time frame in the context of the already existing confinement measures.*”²⁰ The study obtained positive IgG results for 35 out of 1,807 participants (raw prevalence 2.1%). However, 15 of those 35 individuals indicated that they had (a) previously had a positive SARS-CoV-2 test, (b) were residing in a household with someone who had a confirmed positive test, or (c) had direct contact with someone else who was a confirmed or probable case. Of course, a truly random sample would also include such cases, but these results underscore the possibility that seroprevalence could be overstated by studies involving active recruitment, especially in a location with relatively low true prevalence.

In light of these considerations, our meta-analysis excludes seroprevalence estimates from studies that relied on direct recruitment of participants as well as estimates from samples of blood donors or patients at hospitals and urgent care clinics. We also exclude studies that did not report age-specific prevalence results. See Appendix A for further details.

¹⁹ See Rosenberg et al. (2020).

²⁰ Snoeck et al. (2020), p.4.



2.4 Measurement of Fatalities

Accurately measuring total deaths, the numerator of the IFR calculation, is perhaps more difficult than assessing prevalence. The time lags from onset of symptoms to death and from death to official reporting are crucial. Symptoms typically develop within 6 days after exposure, but may develop as early as 2 days or as late as 14 days.²¹ More than 95% of symptomatic COVID patients have positive antibody (IgG) tests within 17-19 days of symptom onset.²²

The CDC estimates that the mean time interval from symptom onset to death is 15 days for ages 18-64 (interquartile range of about 9 to 24 days) and 12 days for ages 65+ (IQR of 7 to 19 days). The mean interval from date of death to the reporting of that person's death is about 7 days (interquartile range of about 2 to 19 days). Consequently, the upper bound of the 95% confidence interval between symptom onset and reporting of fatalities is about six weeks (41 days).²³

Figure 1 illustrates a scenario in which the pandemic ended two weeks prior to the date of a seroprevalence study. This figure shows the results of a stochastic simulation calibrated to reflect the CDC's estimated distribution for the time lags between symptom onset, death, and inclusion in official fatality reports. The histogram shows the frequency of deaths and reported fatalities associated with the infections that occurred on the last day prior to full containment. Consistent with the CDC confidence intervals, about 95% of cumulative fatalities are reported within roughly four weeks of the date of the seroprevalence study.

These considerations underscore the pitfalls of constructing IFRs based on the death toll at the midpoint date of a seroprevalence study, which is the approach that has been taken in most previous studies (including both of the meta-analysis studies of the overall IFR for COVID-19).

²¹ See McAloon et al. (2020).

²² See Long et al. (2020) and Sethurman et al. (2020).

²³ See U.S. Center for Disease Control & Prevention (2020e), Table 2.

Table 2: Timing of Reported Fatalities for Selected Seroprevalence Studies

Location	Cumulative Fatalities			Percent Change	
	Study Midpoint	4 Weeks Later	5 Weeks Later	Weeks 0 to 4	Weeks 4 to 5
Belgium	6,262	8,843	9,150	41	3
Geneva	255	287	291	13	1
Indiana	932	1,984	2,142	113	8
New York	20,212	28,663	29,438	42	3
Spain	26,834	27,136	28,324	1	4
Sweden	2,586	3,831	3,940	48	3
Connecticut	2,257	3,637	3,686	61	1
Louisiana	477	2,012	2,286	322	14
Minneapolis	393	964	1093	145	13
Missouri	218	562	661	158	18
Philadelphia	456	1509	1754	231	16
San Francisco Bay	265	424	449	60	6
South Florida	513	1,160	1,290	126	11
Utah	41	96	98	134	2
Western Washington	536	732	775	37	6
Castiglione d'Adda	62	62	62	0	0
Gangelt	7	9	9	29	0
Diamond Princess	8	10	11	25	10

Sources: See Appendix A.

In particular, as shown in Table 2, the cumulative fatalities at the time of a seroprevalence study can markedly understate the full death count as of four weeks later. Each of these studies was conducted in a location where the pandemic had been contained by the time that seroprevalence was measured, as evident from the fact that the fatality count leveled off over the subsequent month.

Evidently, the precise timing of the count of cumulative fatalities is relatively innocuous in locations (such as Spain and Castiglione d'Adda) where the outbreak had been contained for more than a month prior to the date of the seroprevalence study. But for the other studies

shown in Table 2, the outbreak had only recently been contained, and hence the death count continued rising markedly for several more weeks after the midpoint of the seroprevalence study.

For each of those locations, matching seroprevalence to the death count at the midpoint date of the study would significantly underestimate the true level of the IFR. For example, in the case of New York state, computing the IFR using the 4-week fatality count is nearly 1.5 times higher than using the fatality count at the midpoint date of that study (which was conducted in late April).

For Belgium and Geneva, researchers have published estimates of age-specific IFRs that reflect each location's seroprevalence results. For Spain, we construct age-specific IFRs using the seroprevalence data in conjunction with excess mortality data published by the Spanish National Institute of Statistics.²⁴ For each of the other locations listed in Table 2, we construct age-specific IFRs using the seroprevalence data in conjunction with cumulative fatalities four weeks after the midpoint date of the seroprevalence study.

We have also conducted sensitivity analysis using cumulative fatalities five weeks after the midpoint date. For most of these studies, that deviation is less than 10 percent and hence has a negligible impact on the estimates and confidence intervals of the age-specific IFRs, especially compared to the width of the confidence intervals for the seroprevalence estimates that reflect uncertainties about test characteristics as well as conventional sampling uncertainty.

However, the deviations are somewhat larger for four U.S. locations (Louisiana, Minneapolis, Missouri, and Philadelphia), presumably reflecting the extent to which the pandemic was not tightly contained over the subsequent weeks following the collection of specimen samples in those locations. Consequently, some additional caution is warranted in interpreting age-specific IFRs from each of these locations.

²⁴ See Appendix C for further details regarding the measurement of excess mortality.

Table 3: Seroprevalence Studies Conducted during Accelerating COVID-19 Outbreaks

		Cumulative Fatalities		Percent Change
		Midpoint Date	4 Weeks Later	
Los Angeles County	April 10-11	265	1,468	454%
New York City	March 23 – April 1	1,066	14,261	1,238%
Santa Clara County	April 3-4	39	113	190%
Scotland	March 21-23	72	2,273	3,057%

Sources: See Appendix A.

2.5 Exclusion of Active Outbreaks

Matching prevalence estimates with subsequent fatalities is infeasible if the seroprevalence study takes place in the midst of an accelerating outbreak. In particular, if infections and fatalities continue rising exponentially over subsequent weeks, there is *no* precise way of determining what fraction of those deaths resulted from infections before vs. after the date of the seroprevalence study.

Therefore, a crucial criterion for seroprevalence studies to be included in our meta-analysis is that the pandemic is well contained in advance of the study, as indicated by the stabilization of cumulative fatalities within the next several weeks after the midpoint date of the study.

As shown in Table 3, four studies are clearly inconsistent with that criterion: Los Angeles County (mid-April), New York City (late March), Santa Clara County (early April), and Scotland (late March).²⁵ It should be emphasized that these studies provided valuable information about seroprevalence in the midst of an active outbreak, but these seroprevalence results are not well-suited for gauging the IFR of COVID-19.²⁶

²⁵ These four studies were conducted by Sood et al. (2020), Havers et al. (2020), Bendavid et al. (2020), and Thompson et al. (2020), respectively.

²⁶ Nonetheless, all four of these studies have been used in prior meta-analyses aimed at assessing the overall IFR, using reported fatalities as of the midpoint date of each seroprevalence study.

2.6 Meta-Regression Procedure

The goal of our meta-analysis is to systematically assess previous studies of mortality and infection rates to determine how age and fatality risk are related. To perform this analysis quantitatively, we use random-effects meta-regressions, using the STATA *metareg* procedure.²⁷ Meta-regressions are a useful tool for comparing study-level summary data. Since the individual observations are not available for any study we use, comparing summary-level data is the only way to compare the studies. We use summary level data from each age group in each study, so effectively one study has multiple “groups” in our meta-regressions.²⁸

We treat each age group separately because there are likely random variations in age-specific IFR both across studies and across age groups within a study. Random-effects procedures allow for such residual heterogeneity between groups by assuming that these effects are drawn from a Gaussian distribution. The procedure provides reasonable results even if the errors are not strictly normal but may be unsatisfactory if the sample includes large outliers or the distribution of groups is not unimodal.

In analytical terms, this framework can be expressed as follows:

$$\log(IFR_{ij}) = \alpha + \beta * age_{ij} + \epsilon_{ij} + u_{ij}$$

$$\text{where } u_{ij} \sim N(0, \tau^2) \text{ and } \epsilon_{ij} \sim N(0, \sigma_{ij}^2)$$

In this specification, IFR_{ij} is the estimated IFR in study i for age group j , age_{ij} denotes the median age of that group, ϵ_{ij} denotes the source of idiosyncratic variations for that particular location and age group, and u_{ij} denotes the random effects that characterize any systematic deviations in outcomes across locations and age groups. Under the maintained assumption that each idiosyncratic term ϵ_{ij} has a normal distribution, the idiosyncratic variance is $\sigma_{ij}^2 = ((U_{ij} - L_{ij})/3.96)^2$, where U_{ij} and L_{ij} denote the upper and lower bounds of the 95% confidence interval for that study-age group. The random effects u_{ij} are assumed to be drawn from a homogeneous distribution with zero mean and variance τ^2 . The null hypothesis of $\tau^2 = 0$ characterizes the case in which there are no systematic deviations across studies or age groups. If that null hypothesis is rejected, then the estimated value of τ^2 encapsulates the magnitude of those systematic deviations.

Under our baseline specification, the infection fatality rate increases exponentially with age.²⁹ In particular, this meta-regression is specified in logarithmic terms, with the slope coefficient β

²⁷ See Harbord and Higgins (2008) and Higgins, Thompson, and Spiegelhalter (2009).

²⁸ We also replicated this analysis using fixed effects for studies and random effects for age groups within studies.

²⁹ Bonanad et al. (2020) conducted a meta-analysis study of COVID-19 case fatality rates as a function of age using aggregate data from China, Italy, New York, Spain, and the U.K. and found a very strong exponential pattern of mortality: ages 40-49: 1.1%; ages 50-59: 3%; ages 60-69: 9.5%; ages 70-79 22.8%; ages 80+: 29.6%. Similarly, Doherty et al. (2020) investigated a large sample of U.K. hospitalized COVID-19 patients and identified an exponentially increasing mortality hazard rate as a function of patient age.

encapsulating the impact of higher age on $\log(IFR)$. Consequently, the null hypothesis that IFR is unrelated to age can be evaluated by testing whether the value of β is significantly different from zero. If that null hypothesis is rejected, then the estimated values of α and β characterize the estimated relationship between $\log(IFR)$ and age. Consequently, the predicted relationship between IFR and age can be expressed as follows:

$$IFR = e^{\alpha + \beta * age_{ij}}$$

The 95% confidence interval for this prediction can be obtained using the delta method. In particular, let IFR_a denote the infection fatality rate for age a , and let σ_c denote the standard error of the meta-regression estimate of $\log(IFR_a)$. If IFR_a has a non-zero value, then the delta method indicates that its standard error equals σ_c / IFR_a , and this standard error is used to construct the confidence interval for IFR_a at each age a . Likewise, the prediction interval for $\log(IFR_a)$ is computed using a standard error of $\sigma_c + \tau$ that incorporates the systematic variation in the random effects across studies and age groups, and hence the corresponding prediction interval for IFR_a is computed using a standard error of $(\sigma_c + \tau) / IFR_a$.

As discussed above, we have identified three criteria for determining whether a given study should be included in our meta-analysis: (i) use of a sample data frame that is broadly representative of the general population; (ii) effective containment of the pandemic prior to the initiation of the prevalence survey; and (iii) reporting of prevalence estimates and confidence intervals for specific age groups as required for the estimation of age-specific IFRs. Based on those criteria, we have determined that prevalence estimates from 32 locations are not suitable for assessing the IFR of COVID-19 even though each of those studies has made significant contributions along other lines. Those studies are listed in Appendix A along with the rationale for excluding each of them from our meta-analysis.³⁰

Consequently, our meta-analysis focuses on synthesizing IFR data from 21 locations; see Appendix A for further details. These locations can be classified into four distinct groups:

- **Benchmark Studies:** Belgium, Geneva, Indiana, New York, Spain, and Sweden. Each of these locations has been the subject of a large-scale seroprevalence study using a test procedure with high positive predictive power and a sample frame that is broadly representative of the general public and that covers a wide array of age groups.³¹
- **Other U.S. Locations:** Connecticut, Louisiana, Minneapolis, Missouri, Philadelphia, San Francisco Bay Area, South Florida, Utah, and Western Washington. The seroprevalence of these nine locations were reported in a study conducted by researchers

³⁰ Sweden Public Health Agency (2020f) recently produced estimates of the infection fatality rate in Stockholm for two age groups (ages 0-69 and 70+) using a novel methodology that links live virus tests, reported cases, and mortality outcomes. Given the markedly different methodology and the breadth of the two age groups, that study is also not included in our meta-regression analysis, but it should be noted that their estimated IFR of 4.3% for ages 70+ is well aligned with the results of our meta-regression analysis.

³¹ See Molenberghs et al. (2020), Perez-Saez et al. (2020), Pollan et al. (2020), and Sweden Public Health Agency (2020c,d).

at the U.S. Center for Disease Control & Prevention, using sample specimens from two commercial laboratory companies.³² In light of potential concerns about sample data frames and incomplete containment of the pandemic at the time of specimen collection in some of these locations, we include this group of locations in our meta-analysis but not in the benchmark group.

- ***Comprehensive Tracking and Tracing Countries:*** Iceland, Korea, and New Zealand. These three countries engaged in extensive testing and tracing to halt the spread of infections. Iceland researchers also conducted a large-scale seroprevalence study, and we use the results of that study in computing age-specific IFRs for Iceland.³³ That study also indicates that reported cases in Iceland substantially understated actual prevalence; see Appendix D for details.³⁴ Thus, we make corresponding adjustments to the reported cases for Korea and New Zealand in constructing age-specific IFRs for each of those locations.
- ***Small-scale studies:*** Castiglione d’Adda, Italy; Gangelt, Germany; and the Diamond Princess cruise ship. The first two locations have had seroprevalence studies based on random samples, while data from Diamond Princess has been influential in informing subsequent studies.³⁵

In estimating this metaregression, we only use observations for age groups with a median age of 35 years or higher. COVID-19 fatality reports from numerous locations indicate that the age-specific IFR is extraordinarily close to zero for children and young adults. For example, at the end of May Belgium had a cumulative total of 9,150 deaths, with not a single fatality for ages 0 to 24 years. Similarly, the state of New York had a cumulative total of about 22,000 COVID-19 fatalities as of late May, but that death toll included less than 100 deaths of people less than 30 years old.

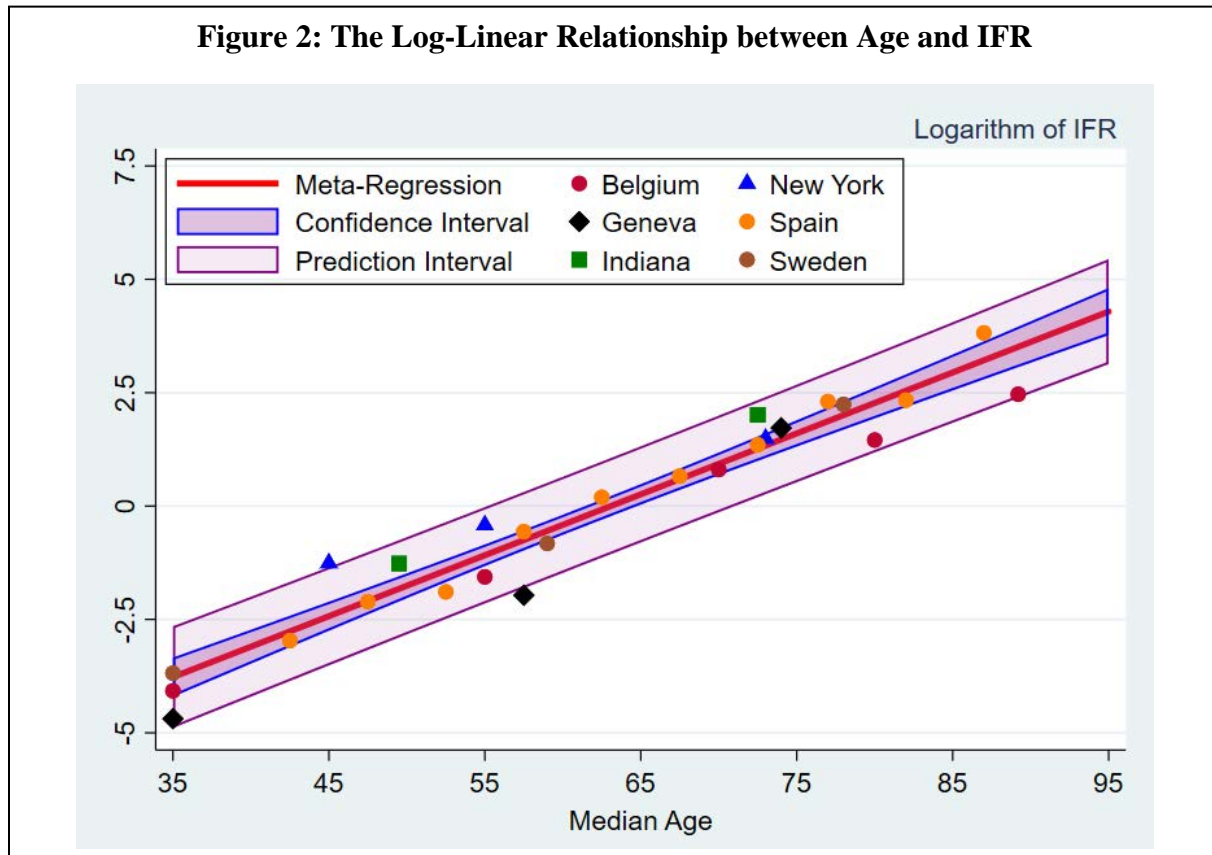
³² See Havers et al. (2020).

³³ See Gudbjartsson et al. (2020).

³⁴ See Aspelund, Droste, Stock, and Walker (2020) for statistical analysis of the deviation between reported cases and true prevalence in Iceland.

³⁵ See Pagani et al. (2020), Streeck et al. (2020), Russell et al. (2020), and Salje et al. (2020a,b).

Figure 2: The Log-Linear Relationship between Age and IFR



3. Results

3.1 Benchmark Analysis

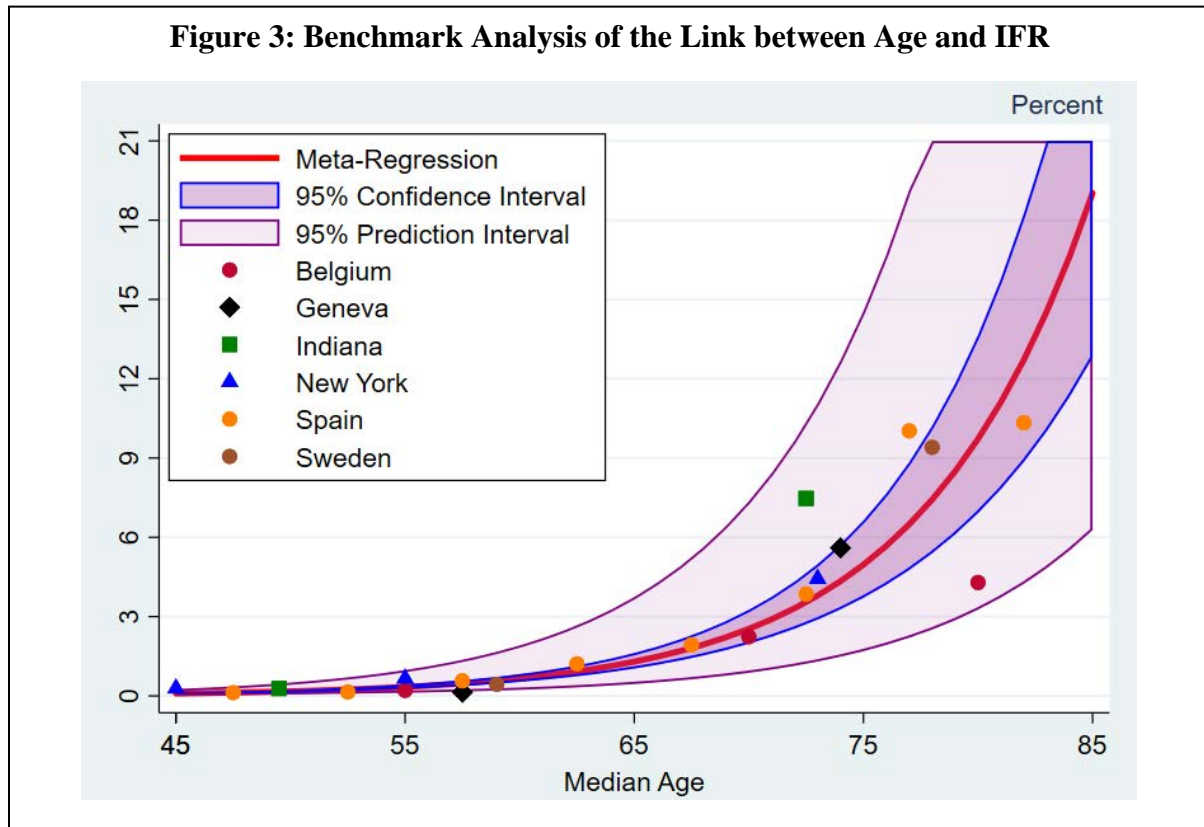
Using our benchmark sample of 26 observations from the six benchmark studies, we obtain the following meta-regression results:

$$\log(IFR_{ij}) = -8.48 + 0.134 * age$$

(0.45) (0.007)

where the standard error for each estimated coefficient is given in parentheses. These estimates are highly significant with t-statistics of -18.7 and 18.8, respectively, and p-values below 0.0005. The residual heterogeneity $\tau^2 = 0.280$ (p-value < 0.0001), confirming that the random effects are essential for capturing unexplained variations across studies and age groups. The adjusted R^2 is 94.53%.

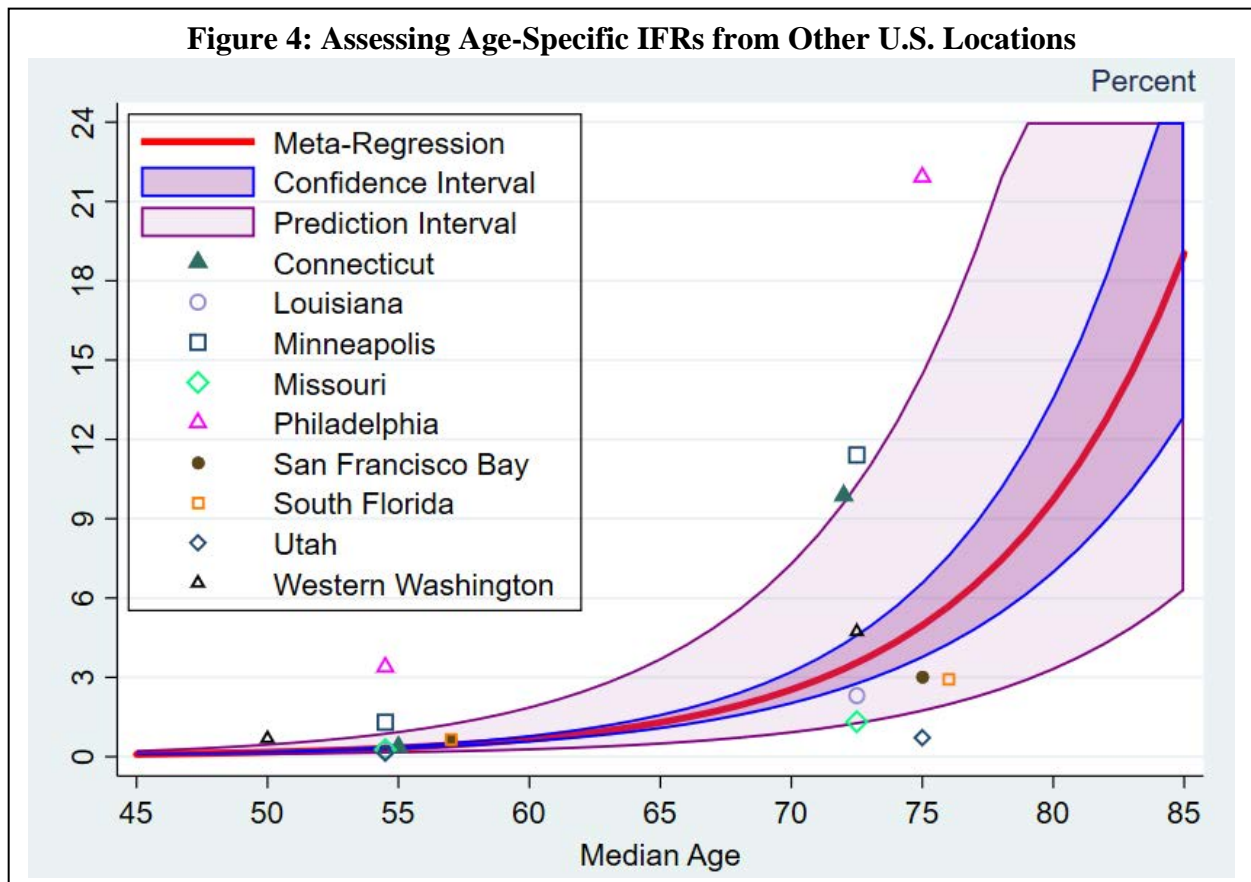
As noted above, the validity of this meta-regression rests on the condition that the data are consistent with a Gaussian distribution, i.e., there should be no clustering of observations or extreme outliers. The validity of those assumptions is evident in Figure 2. The solid red line depicts the estimated log-linear function, the dark shaded area denotes the 95% confidence interval for that estimated function, and the light shaded area denotes the 95% prediction interval that reflects the random variations across studies and age groups. The markers denote the

Figure 3: Benchmark Analysis of the Link between Age and IFR

age-specific IFRs from each study, which provide relatively balanced coverage spanning the entire age interval from 35 to 90 years. Moreover, nearly all of the observations fall within the 95 percent prediction interval; the only exceptions are an observation from the New York study (at the upper edge of the prediction interval) and an observation from the Geneva study (at the lower edge of the prediction interval)—roughly matching the incidence of moderate outliers that one would expect in a sample of 24 observations.³⁶

Figure 3 depicts the exponential relationship between age and the level of IFR in percent. Evidently, the SARS-CoV-2 virus poses a substantial mortality risk for middle-aged adults and even higher risks for elderly people: The IFR is close to zero for younger adults but rises to about 0.3 percent for ages 50-59, 1.3 percent for ages 60-69, 4.6 percent for ages 70-79, and 25 percent for ages 80 and above.

³⁶ We have also used the output of the Stata *metareg* procedure to confirm that the estimated random effects are consistent with a normal distribution.



3.2 Comparison to other U.S. Locations

We now compare the benchmark meta-regression results with the age-specific IFRs from nine other U.S. locations where seroprevalence was estimated using specimens from commercial labs. In effect, this approach is comparable to “out-of-sample” exercises that statisticians commonly use in assessing the validity of a particular model.

As shown in Figure 4, the observations from these nine locations studies mostly fit within the benchmark prediction intervals, broadly confirming the usefulness of the meta-regression in assessing age-specific IFRs beyond the locations covered by the set of benchmark studies. Moreover, the outliers in this figure are mostly above the prediction interval rather than below; that is, the unexplained variations outside the prediction interval tend to be observations with unusually high IFRs.

One observation for Connecticut lies on the upper edge of the prediction interval, and two observations for Minneapolis lie just above that prediction interval, while the middle-age observation for Philadelphia is quite far above the prediction interval. By contrast, the observations for Missouri lies at the lower edge of the prediction interval; for that location, the ratio of estimated seroprevalence to reported cases was 24:1—more than double the typical ratio

of 10:1 for other U.S. locations.³⁷ In effect, Missouri's seroprevalence might be significantly overstated, perhaps reflecting non-representative aspects of the sample data frame.

Finally, the oldest age group for Utah is well below the lower edge of the prediction interval. One plausible factor is that a large fraction of Utah residents abstain from use of alcohol, tobacco, and narcotic drugs and hence may have a lower incidence of co-morbidities compared to many other locations in the United States and elsewhere.³⁸ Consequently, this observation should not simply be dismissed as an outlier; rather, further study of that location may yield significant insights that are applicable elsewhere.

3.3 Other Comparisons

Comprehensive Tracking and Tracing Countries

The age-specific IFRs for all three countries that employed widespread testing and contact-tracing to control the virus's spread all fit well within the benchmark's 95% prediction interval. Of the three, there has only been a seroprevalence study published about one country, Iceland. The study found that Iceland's ratio of actual to reported cases was about 1.4x, enabling us to reasonably reliably compute Iceland's age-specific IFRs.³⁹

Both Iceland and New Zealand were able to fairly rapidly control the virus, and thus very few deaths occurred (10 in Iceland and 22 in New Zealand). As three of the deaths in Iceland were in healthcare workers, the death data could be greatly skewed by conflicting factors such as viral load; excluding healthcare workers alters their IFR by 30%. Since each region's death counts were so low, little can be inferred from their age-specific IFRs.

Small-Scale Studies

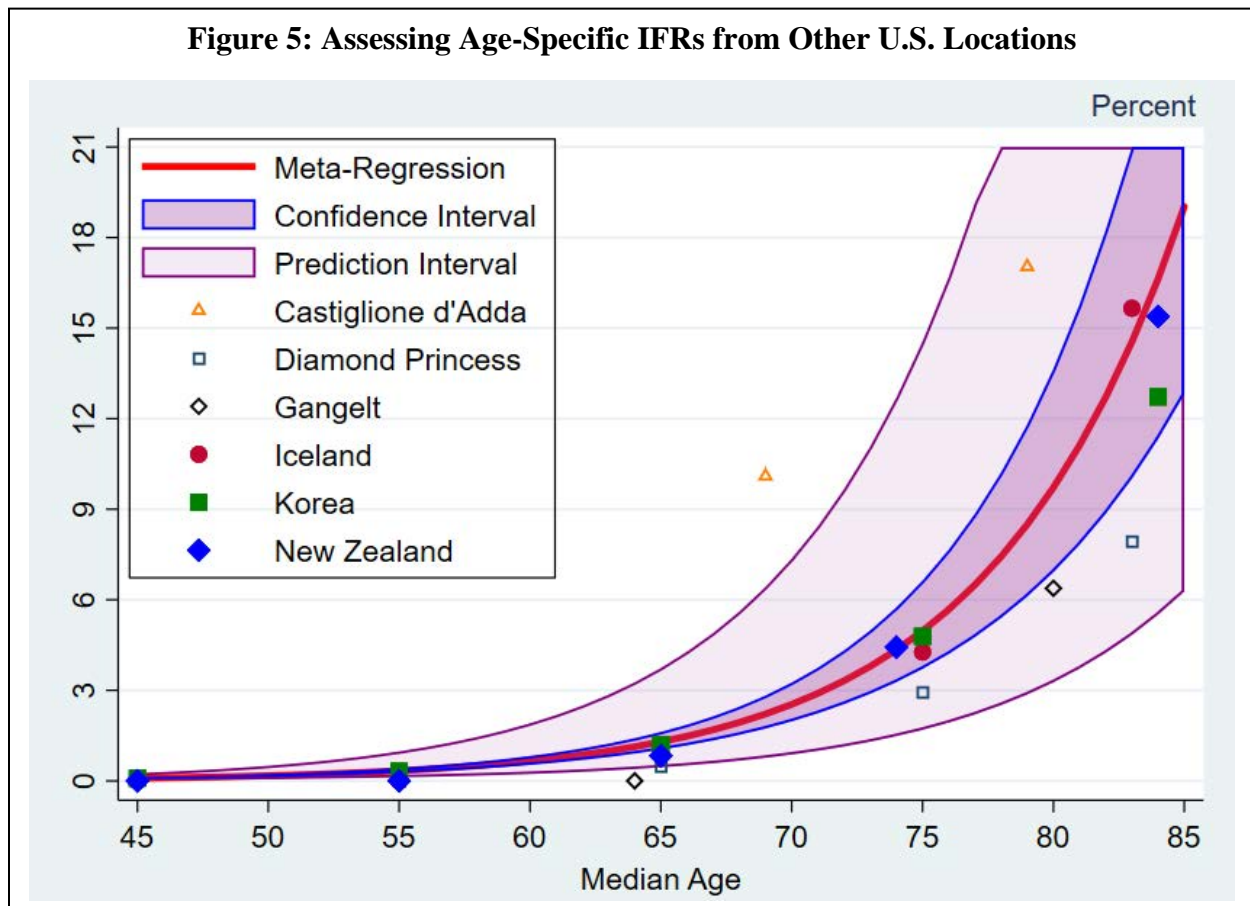
The age-specific IFRs from small-scale prevalence studies of the Diamond Princess cruise ship and the municipality of Gangelt are fully consistent with our benchmark meta-regression results once we account for the lags in the incidence and reporting of COVID-19 fatalities. As shown in Table 2 above, the number of deaths at the time of the initial infection study was only about half of the final death count a few weeks later.

These two locations also demonstrate the extent to which the results of small-scale studies can be influenced by a few observations. Our benchmark metaregression indicates an IFR of 0.3% for ages 50-59 years, i.e., one fatality out of 300 infected individuals. In Gangelt, the seroprevalence results suggest that only 150 people in that age group were infected, so it shouldn't be surprising that none of them died. Likewise, the Diamond Princess cruise ship had only 60 infected individuals in this age group, and hence a lack of fatalities among that group would also not be surprising.

³⁷ Havers, et al (2020). See Table 3.

³⁸ See United Health Foundation (2019).

³⁹ See Gudbjartsson et al. (2020).



Castiglione d'Adda's age-specific IFRs for individuals aged 65-85 are outliers above our prediction interval. This outlier status was likely due to the fact that the town was affected relatively severely and early by COVID-19 in the pandemic's first wave, and hospitals became overwhelmed, leading to rationing of medical care. It should not be surprising that the region's IFR for people aged 85 years and older falls within our benchmark estimation; at such high ages the disease is so dangerous that medical care may not influence mortality to any significant degree. The relatively high IFR for the next age cohort (65 to 85 years) could also reflect a higher incidence of co-morbidities compared to similar cohorts in other locations. Higher IFRs might also reflect dense multi-generational urban housing that resulted in increased viral load for elderly people. In sum, the extraordinarily high IFR for individuals ages 65-85 years plays a key role in explaining Castiglione d'Adda's overall IFR of about 5%.

Finally, while not included in our formal meta-analysis, it should be noted that the pathbreaking study of Ferguson et al. (2020) is broadly consistent with our findings. That study was completed at an early stage of the COVID-19 pandemic, drawing on data from expatriation flights to estimate infection rates in Wuhan and then computing age-specific IFRs based on reported fatalities in Wuhan. As in our meta-regression results, the IFR estimates in that study increase exponentially as a function of age, with rates near zero for ages 0-39 and far higher rates for older adults.

Table 4: Age-Specific Fatality Rates for COVID-19 vs. Accidental Injuries

Age Group	COVID-19 Infection Fatality Rate (%)	Automobile Accident Annualized Fatality Rate (%)	Other Accidental Injury Annualized Fatality Rate (%)
0 to 34	0.01	0.01	0.03
35 to 44	0.04	0.01	0.04
45 to 54	0.2	0.01	0.04
55 to 64	0.7	0.01	0.04
65 to 74	2.4	0.01	0.04
75 to 84	8.9	0.02	0.09
85+	36.8	0.02	0.35

Source: U.S. National Center for Health Statistics (2020)

4. Discussion

Our analysis indicates that COVID-19 poses a very low risk for children and younger adults but is hazardous for middle-aged adults and extremely dangerous for older adults. Table 4 contextualize these risks by comparing the age-specific IFRs from our meta-regression analysis to the annualized risk of a fatal auto accident or other accidental injury. For a young adult, the fatality risk of a SARS-CoV-2 infection is roughly comparable to the risks associated with engaging in other everyday activities. By contrast, an 60-year-old adult who gets infected faces a fatality risk more than 50 times higher than the annual fatality risk of driving an automobile.

Our analysis facilitates comparisons between the COVID-19 pandemic and the Spanish Flu pandemic of 1918-20. The U.S. CDC estimates that about 28 percent of the U.S. population was infected by the Spanish Flu and that the death toll was about 675,000. However, that disease was most dangerous for young adults, with an IFR of about 4 percent for people ages 20 to 40 years old but caused relatively few deaths among middle-aged and older adults—the age groups that are most vulnerable to COVID-19.

Our meta-regression analysis confirms that COVID-19 is far more deadly than seasonal flu. The U.S. CDC estimates that during winter 2018-19 influenza was associated with about 50 million infections and 34,000 fatalities, that is, an overall IFR of about 0.07 percent. By comparison, recent seroprevalence data from U.S. public health laboratories indicates that more than 20 million people (that is, 6.4 percent of the U.S. population) had been infected with SARS-CoV-2

Table 5: U.S. Scenario Analysis

Scenario	Infection Rate by Age (percent)				Deaths (thousands)	IFR (percent)
	All	0-49	50-64	65+		
Baseline	6.5	7.5	5.1	4.5	150,000	0.7
Scenario #1: <i>current pattern of age-specific prevalence</i>	20	23	16	14	465,000	0.7
Scenario #2: <i>uniform prevalence</i>	20	20	20	20	640,000	1.0
Scenario #3: <i>protection of vulnerable age groups</i>	20	26	10	6	230,000	0.4

by the last week of June.⁴⁰ Cumulative U.S. fatalities were close to 150,000 as of July 27 (four weeks after the date of the seroprevalence data, appropriately reflecting the time lags discussed in Section 2). These figures indicate that the overall IFR of COVID-19 is currently about 0.7%, in line with recent guidance from the CDC and about ten times more deadly than seasonal flu.⁴¹

Nonetheless, the current level of the overall U.S. IFR should *not* be interpreted as a fixed parameter. Rather, our meta-analysis clearly underscores the rationale for public health measures and communications aimed at reducing the aggregate IFR by mitigating the incidence of new COVID-19 infections among middle-aged and older adults.⁴²

To illustrate these considerations, Table 5 outlines three alternative scenarios for the U.S. trajectory of COVID-19 infections and fatalities. All three scenarios assume that the infection rate continues rising to a plateau of around 20% (similar to the prevalence observed in New York City as of late spring), while the age-specific IFRs reflect the U.S. national data observed to date. However, the age-specific infection rates vary markedly across the three scenarios:

- Scenario #1 assumes that age-specific prevalence will remain similar to the average pattern that has prevailed to date, as indicated by seroprevalence data from U.S. public health laboratories.

⁴⁰ See U.S. CDC (2020c). Seroprevalence estimates are reported in the U.S. CDC's Weekly COVID Surveillance Summary, based on data collected by 85 state and local public health laboratories spanning the entire country. These reports include age-specific seroprevalence but no details regarding sample selection, test characteristics, or confidence intervals and hence could not be used in our meta-regression analysis.

⁴¹ See U.S. CDC (2020e).

⁴² See Davies et al. (2020), De Salazar et al. (2020), Gleser, Gorback, and Redding (2020), Harris (2020),

- Scenario #2 assumes that the prevalence will eventually become uniform across all age groups, similar to the Spanish Flu pandemic and seasonal influenza.
- Scenario #3 assumes that public health measures and communications will restrain the incidence of new infections among middle-aged and older adults while prevalence continues rising more rapidly among children and younger adults.

To assess the implications of these three alternative assumptions, we use the age-specific IFRs from our meta-regression analysis to determine the death toll for each age group as follows:

$$Deaths_{age} = Population_{age} \times Infection Rate_{age} \times IFR_{age}$$

Scenario #1 shows that, if the current age-specific infection pattern continues until 20% of the U.S. is infected, deaths will increase by a factor of 3 to around 460,000. The outcome is far worse in Scenario #2, where the virus spreads uniformly across age groups and causes nearly 640,000 fatalities—roughly the same death toll as the Spanish Flu, though only one-third as large on a *per capita* basis. Finally, Scenario #3 is associated with a far lower proportion of older adults contracting the virus, and the total number of fatalities is held to about 230,000.

This scenario analysis underscores the possibility that the United States could plausibly end up with an overall IFR of about 1%, similar to the outcome in New York City as of late spring (as shown in Table 1). By comparison, policy measures and communications that protect vulnerable age groups could halve the overall IFR to around 0.4% and prevent over 200,000 U.S. deaths relative to the baseline in which the virus continues spreading with roughly the same age-specific prevalence that has been observed to date.

5. Directions for Further Research

While age and fatality risk are closely related, differences in the age structure of the population and age-specific infection rates surely cannot explain all deviations in IFR across regions and populations. Consequently, the role of co-morbidities and other demographic and socioeconomic factors merits further research that carefully distinguishes between infection risk and IFR.

5.1 Comorbidities

A recent U.K. study has shown that COVID-19 mortality outcomes are strongly linked to comorbidities such as chronic pulmonary disease, diabetes, and obesity.⁴³ However, that study specifically warns against drawing causal conclusions from those findings, which may reflect a higher incidence of COVID-19 rather than a higher IFR for individuals with those comorbidities. Indeed, a separate study of hospitalized U.K. COVID-19 patients found that patient age was far more important than any specific comorbidity in determining mortality risk.⁴⁴ For example, the COVID-19 fatality risk for an obese 40-year-old hospital patient was found to be moderately higher than for a non-obese individual of the same cohort but only one-tenth the fatality risk for a non-obese 75-year-old hospital patient.

The high prevalence of comorbidities among COVID-19 patients has been well documented but not compared systematically to the prevalence of such comorbidities in the general population. For example, one recent study of hospitalized COVID-19 patients in New York City (NYC) reported that 94% of those patients had at least one chronic health condition.⁴⁵ Nevertheless, that finding is not particularly surprising given the prevalence of comorbidities among middle-aged and elderly NYC residents.⁴⁶ For example, nearly 30% of older NYC adults (ages 60+) are diabetic, while 23% have cardiovascular disease (including hypertension), and 8% have chronic pulmonary diseases—practically identical to the incidence of those comorbidities in the sample of hospitalized COVID-19 patients.⁴⁷ Indeed, obesity was the *only* comorbidity that was much more prevalent among hospitalized COVID-19 patients than in the general population of older NYC adults. Nonetheless, obesity is also much more prevalent among lower-income groups who are more likely to live in high-density neighborhoods and work in high-exposure jobs, and hence such data clearly cannot be used to distinguish prevalence vs. severity of COVID-19.⁴⁸

⁴³ See Williamson et al. (2020).

⁴⁴ See Doherty et. al (2020).

⁴⁵ See Richardson et al. (2020).

⁴⁶ See Appendix Table E1.

⁴⁷ See New York State Comptroller (2015) and New York Department of Health (2020).

⁴⁸ See Appendix E for a detailed comparison of comorbidities.

5.2 Demographic and Socioeconomic Factors

Our meta-analysis has not directly considered the extent to which IFRs may vary with other demographic factors, including race and ethnicity. Fortunately, valuable insights can be garnered from other recent studies. In particular, one recent seroprevalence study of residents of two urban locations in Louisiana found no significant difference in IFRs between whites and Blacks.⁴⁹

Nonetheless, the incidence of COVID-19 mortality among people of color is extraordinarily high due to markedly different infection rates that reflect systematic racial and ethnic disparities in housing and employment. For example, a recent infection study of a San Francisco neighborhood found that 80% of positive cases were Latinx – far higher than the proportion of Latinx residents in that neighborhood.⁵⁰ That study concluded as follows: *“Risk factors for recent infection were Latinx ethnicity, inability to shelter-in-place and maintain income, frontline service work, unemployment, and household income less than \$50,000 per year.”*

Recent CDC analysis has reached similar conclusions, attributing elevated infection rates among Blacks and Hispanics to dense housing of multi-generational families, increased employment in high-contact service jobs, high incidence of chronic health conditions, and lower quality of health care.⁵¹

In summary, while the present study has investigated the effects of age on the IFR of COVID-19, further research needs to be done on how infection and fatality rates for this disease are affected by demographic and socioeconomic factors.

⁴⁹ See Feehan et al. (2020).

⁵⁰ See Chamie et al. (2020).

⁵¹ See Azar et al. (2020).

Appendix A: Comprehensive List of Seroprevalence Studies

A.1 Benchmark Studies

Location	Date	Sample Size	Test Method	Fatality Estimation Procedure
Belgium ⁵²	April 20-26	3,397	IgG ELISA	Excess mortality
Geneva ⁵³	April 6 – May 9	2,766	IgG ELISA	Bayesian framework
Indiana ⁵⁴	April 25 - 29	3,658	IgG CMA & RT-PCR	Reported Fatalities as of May 25
New York ⁵⁵	April 19-28	15,101	IgG MIA	Reported Fatalities as of May 21
Spain ⁵⁶	April 27 – May 11	35,883	IgG/IgM LFA & CMA	Excess mortality
Sweden ⁵⁷	April 27 – May 24	4,800	IgG MBA	Reported Fatalities as of June 18

Note: CMA = chemiluminescent microparticle assay; ELISA = enzyme-linked immunosorbent assay; LFA = lateral flow analysis; MBA = multiplex bead array; MIA = microsphere immunoassay; RT-PCR = reverse transcription - polymerase chain reaction. Excess mortality refers to fatalities by age in 2020 compared to corresponding months of prior calendar year(s).

⁵² See Molenberghs et al. (2020), Table 6. This study used the seroprevalence findings of Herzog et al. (2020).

⁵³ See Perez-Saez et al. (2020), Table S2. This study used the seroprevalence findings of Stringhini et al. (2020).

⁵⁴ See Menachemi et al. (2020), Table 1, total population prevalence based on seroprevalence and active infections. Population data by single year of age as of July 1, 2019 was obtained from U.S. Vital Statistics System (2020). Cumulative fatalities by age as of May 25 were obtained from Indiana State Department of Health (2020).

⁵⁵ See Rosenberg et al. (2020). Population data by single year of age as of July 1, 2019 was obtained from U.S. Vital Statistics System (2020). Some seroprevalence age brackets were adjusted (+/- 5 years) to match the age structure of the New York Department of Health (2020) COVID-19 fatality report; see the technical appendix for further detail.

⁵⁶ Age-specific IFRs were constructed using the seroprevalence findings of Pollán et al. (2020), Table S7 (both tests positive) and excess mortality data for Week 25 reported by Spain National Institute of Statistics (2020).

⁵⁷ See Sweden Public Health Authority (2020a,b,c,d,e) for information about the seroprevalence program design, antibody test standards, results for weeks 18 to 21, and COVID-19 fatalities as of week 24, respectively.

A.2 CDC Seroprevalence Locations

Location	Date	Sample Size	Cumulative Fatalities as of:
Connecticut	April 26 – May 3	1,431	May 28 ⁵⁸
Louisiana	April 1 - 8	1,184	May 6 ⁵⁹
Minneapolis, MN	April 30 – May 12	860	June 4 ⁶⁰
Missouri	April 20 – 26	1,882	May 23 ⁶¹
Philadelphia, PA	April 13 – 25	824	May 23 ⁶²
San Francisco Bay	April 23 - 27	1,224	May 25 ⁶³
South Florida	April 6 - 10	1,742	May 6 ⁶⁴
Utah	April 20 – May 3	1,132	May 25 ⁶⁵
Western Washington	March 23 – April 1	3,264	April 26 ⁶⁶

Note: See Havers et al. (2020) for seroprevalence findings of each location using IgG ELISA procedure. Population data for each study region by single year of age as of July 1, 2019 was obtained from U.S. Vital Statistics System (2020). Some seroprevalence age brackets were adjusted (+/- 5 years) to match the age structure of each state’s COVID-19 fatality report; see supplementary materials for details.

⁵⁸ See Connecticut Department of Health & Human Services (2020).

⁵⁹ See Louisiana Department of Health (2020).

⁶⁰ The Minneapolis-St. Paul-St. Cloud combined statistical area covers 20 counties in Minnesota; this CSA also covers two counties in Wisconsin that were not included in the seroprevalence study or the IFR tabulations. Cumulative fatalities in the 20-county MSA accounted for 89% of Minnesota’s cumulative COVID-19 fatalities as of June 4 and hence are assumed to have the same relative age distribution as the statewide fatality count.

⁶¹ See Utah Department of Health (2020).

⁶² The Philadelphia metropolitan statistical area covers 5 counties in Pennsylvania; this MSA also includes counties in Delaware, Maryland, and New Jersey that were not included in the seroprevalence study or the IFR tabulations. Cumulative fatalities in the 5-county MSA accounted for 61% of Pennsylvania’s cumulative COVID-19 fatalities as of May 23 and hence are assumed to have the same relative age distribution as the statewide fatality count.

⁶³ The San Francisco Bay Area covers nine counties that are members of the Association of Bay Area Governments. Cumulative fatalities in the 9-county San Francisco Bay Area are not published by age groups and hence are assumed to have the same relative age distribution as the statewide fatalities as of May 25.

⁶⁴ South Florida includes four counties that span Miami, Ft. Lauderdale, and Palm Beach. Cumulative fatalities by age for each of those four counties are tabulated by Florida Department of Health (2020).

⁶⁵ See Missouri Department of Health & Senior Services (2020).

⁶⁶ See Western Washington spans Seattle, Tacoma, and nearby counties. Cumulative fatalities are reported by Washington Department of Health (2020).

A.3 Comprehensive Tracking & Tracing of COVID-19 Infections

Location	Reporting Date	Population	Cases	Fatalities
Iceland ⁶⁷	June 14	341,250	1,734	10
New Zealand ⁶⁸	July 9	1,910,760	1,417	22
Republic of Korea ⁶⁹	July 11	51,269,183	10,086	262

A.4 Small-Scale Studies

Location	Date	Sample Size	Test Method	Fatality Estimation Procedure
Castiglione d'Adda, Italy ⁷⁰	May 18 - 25	509	IgG CLA	Excess Mortality ⁷¹ (January 1 – May 31)
Gangelt, Germany ⁷²	March 31 – April 6	919	IgG ELISA	Reported Fatalities as of May 29 ⁷³
Diamond Princess Cruise Ship ⁷⁴	February 1 – March 7	712	PCR	Reported Fatalities as of June 26 ⁷⁵

⁶⁷ See Iceland Directorate of Health (2020) for finalized data thru June 14, when Iceland had 1,796 recovered cases, 10 fatalities, and 4 individuals in isolation (none hospitalized).

⁶⁸ See New Zealand Ministry of Health (2020).

⁶⁹ See Korea Center for Disease Control (2020).

⁷⁰ See Pagani et al. (2020).

⁷¹ See Italy National Institute of Statistics (2020a,b) for Castiglione d'Adda population by age and excess mortality by age in 2020 compared to the average mortality during the same calendar dates in 2015 to 2019, respectively.

⁷² See Streeck et al. (2020).

⁷³ See Kreis Heinsberg District Administration (2020) and Stat Germania (2020) for Gangelt COVID-19 fatalities and population by age, respectively.

⁷⁴ See Mizumoto et al. (2020), Russell et al. (2020), Leffler and Hogan (2020), and Salje et al. (2020a,b).

⁷⁵ See Japan National Institute for Infectious Diseases (2020), Mizumoto et al. (2020), and Salje et al. (2020a,b).

A.5 Studies Excluded Due to Sample Selection Bias

(a) Hospitals and Urgent Care Clinics

Rationale: A substantial fraction of individuals seeking health care at a hospital or urgent care clinic may have symptoms related to an active COVID-19 infection and hence exhibit a higher prevalence of positive test results compared to a random sample of the general population.

Location	Description
Brooklyn, NY ⁷⁶	This study used samples from an outpatient clinic and yielded a much higher infection rate than other seroprevalence studies of the New York metropolitan area.
Kobe, Japan ⁷⁷	This study tested for IgG antibodies in 1,000 specimens from an outpatient clinic and found 33 positive cases. However, the study did not screen out samples from patients who were seeking treatment for COVID-related symptoms. Moreover, the study reported raw prevalence and confidence interval but did not report statistics adjusted for test characteristics. The manufacturer (ADS Biotec / Kurabo Japan) has indicated that this test has specificity of 100%, based on a sample of 14 pre-COVID specimens, but that specificity has not been evaluated by any independent study. If the true specificity is 98%, then the adjusted prevalence would not be significant. The authors concluded by noting the selection bias and recommended that “further serological studies targeting randomly selected people in Kobe City could clarify this potential limitation.”
Tokyo, Japan ⁷⁸	The authors of this study specifically cautioned against interpreting their results as representative of the general population. In particular, the sample of 1,071 participants included 175 healthcare workers, 332 individuals who had experienced a fever in the past four months, 45 individuals who had previously taken a PCR test, and 9 people living with a COVID-positive cohabitant. The study obtained a raw infection rate of 3.8%, but the rate is only 0.8% if those subgroups are excluded.
Zurich, Switzerland ⁷⁹	This study analyzed two distinct set of samples: (i) blood donors and (ii) hospital patients. Nearly all blood donors were ages 20 to 55, so that sample is not useful for assessing age-specific IFRs for older adults. The sample of hospital patients was not screened to eliminate cases directly related to COVID-19, so that sample may not be representative of the broader population. Moreover, inhabitants of the city of Zurich constituted a relatively large fraction of seropositive results compared to residents from the remainder of the canton of Zurich (which is predominantly rural). The study computes an overall IFR of 0.5%, similar to that of Geneva.

⁷⁶ See Reifer et al. (2020).

⁷⁷ See Doi et al. (2020).

⁷⁸ See Takita et al. (2020a,b).

⁷⁹ See Emmenegger et al. (2020).

(b) Studies of Blood Donors

Rationale: Prior research has shown that blood donors tend to be younger and healthier than the general population, with very few blood donors over age 60. Moreover, individuals who donate blood during a pandemic may be more gregarious and less risk-averse than non-donors. Recent U.K. seroprevalence studies indicated that English blood donors had a COVID-19 infection rate of 7.9% compared to a rate of 5.4% for a random sample of the English population.

Excluded Studies: (1) Apulia, Italy.⁸⁰ (2) Denmark.⁸¹ (3) England.⁸² (4) Milan, Italy.⁸³ (5) Netherlands.⁸⁴ (6) Scotland.⁸⁵ (7) San Francisco, CA.⁸⁶

(c) Active Recruitment of Participants

Rationale: With active recruitment, the sample may include individuals concerned about prior exposure to COVID-19 and hence a higher prevalence than the general population.

Location	Description
Luxembourg ⁸⁷	Of the 35 participants who tested positive, 19 had previously interacted with a person who was known to be infected or had a prior test for SARS-CoV-2.
Boise, Idaho ⁸⁸	This study was promoted during a “Crush the Curve” publicity campaign and required participants to sign up for a test.
Santa Clara, CA ⁷⁰	Participants were recruited via social media and needed to drive to the testing site. Stanford Medicine subsequently released a statement indicating that the study was under review due to concerns about potential biases. ⁸⁹
Frankfurt, Germany ⁹⁰	This study was conducted at a industrial worksite. Among the 5 seropositive participants, 3 had prior positive tests or direct contact with a known positive case.

(d) Other Sample Selection Issues

Location	Description
Oisie, France ⁹¹	This sample of 1,340 participants included elementary school teachers, pupils, and their families. Only two individuals in the sample were ages 65 years and above.
Saxony, Germany ⁹²	This study analyzed specimen samples from students and teachers at thirteen secondary schools in eastern Saxony and found very low seroprevalence (0.6%).

⁸⁰ See Fiorel et al. (2020).

⁸¹ See Erikstrup et al. (2020). The seroprevalence test kit used in this study was subsequently withdrawn from the market by the manufacturer due to reliability concerns; see Reuters (2020).

⁸² See England Public Health (2020).

⁸³ See Valenti et al. (2020).

⁸⁴ See Slot et al. (2020).

⁸⁵ See Thompson et al. (2020).

⁸⁶ See Ng et al. (2020).

⁸⁷ See Snoeck et al. (2020).

⁸⁸ See Bryan et al. (2020).

⁸⁹ <https://www.dailymail.co.uk/health/article-8358003/Stanford-researchers-investigation-tipping-scale-antibody-studies.html>

⁹⁰ See Fraehling et al. (2020).

⁹¹ See Fontanet et al. (2020).

⁹² See Armann et al. (2020).

A.6: Studies Excluded Due to Accelerating Outbreak⁹³

Rationale: As discussed in Section 2, if a seroprevalence study takes place in the midst of an accelerating outbreak, then there is no precise way to determine which of the subsequent fatalities resulted from new infections vs. infections prior to the date of the study.

Excluded Studies: (1) Los Angeles County.⁹⁴ (2) New York City.⁹⁵ (3) Santa Clara County.⁹⁶ (4) Scotland.⁹⁷

A.7 Studies Excluded due to Absence of Age-Specific Prevalence Data

Location	Description
British Columbia, Canada ⁹⁸	This study analyzed 885 laboratory specimens from outpatient clinics for the period May 15-27 and found only four positive cases (0.6%). This sample is not well-suited for assessing age-specific prevalence or age-specific IFRs.
Czech Republic ⁹⁹	The Czech Ministry of Health conducted a large-scale seroprevalence survey on April 23-May 1, collecting specimens from a random sample of 22,316 residents and testing for IgG antibodies using the Wantai test kit. Only 107 positive cases were identified (raw prevalence = 0.4%), and hence the test-adjusted confidence intervals include the lower bound of zero prevalence. That result is consistent with the very low number of reported cases in the Czech Republic as of early May; for example, Prague had only 1,638 reported cases for a population of 1.3 million.
Expatriate Flights ¹⁰⁰	This study performed PCR tests on 689 individuals expatriated from Wuhan, China on six international flights during January 31-February 2. There were six positive tests (raw prevalence = 0.87%), but assessment of age-specific prevalence or IFRs is not feasible given the sample size, low prevalence, and lack of case outcomes.
Japanese Evacuees ¹⁰¹	This study performed PCR tests on 565 Japanese citizens expatriated from Wuhan, China. There were eight positive tests, indicating a raw prevalence of 1.4%, but assessment of age-specific prevalence or IFRs is not feasible given the small sample, low prevalence, and lack of data on case outcomes.
Jersey (U.K.) ¹⁰²	This study collected samples from 629 households comprising 1,062 individuals and estimated seroprevalence at 4.2% (CI 2.9 to 5.5%), indicating that about 3,300 Jersey residents have been infected. Jersey has had 30 COVID-19 fatalities (as of July 15), and hence the overall IFR is about 1% (similar to that of NYC). However, the seroprevalence sample is too small to facilitate accurate assessments of age-specific IFRs; for ages 55+, there were 258 samples and 12 positive cases,

⁹³ Studies on expatriate flights and Japanese evacuees from Wuhan also occurred extremely early in the outbreak, and infection and deaths in their respective populations rose exponentially following the initial study.

⁹⁴ See Sood et al. (2020).

⁹⁵ See Havers et al. (2020).

⁹⁶ See Bendavid et al. (2020).

⁹⁷ See Thompson et al. (2020).

⁹⁸ See Skowronski et al. (2020).

⁹⁹ See Czech Ministry of Health (2020).

¹⁰⁰ See Verity et al. (2020).

¹⁰¹ See Nishiura et al. (2020).

¹⁰² See Jersey (U.K.) Health & Community Services (2020a,b).

New Orleans, LA ¹⁰³	This study analyzed a random sample of 2,640 participants and obtained a seroprevalence estimate of 6.86% and an IFR of 1.63% (CI 1.53 to 1.74%). The study reported race-specific results but not age-specific seroprevalence or IFRs.
Mount Sinai Hospital, New York City ¹⁰⁴	This study analyzed seroprevalence using specimens from four groups of patients (Cardiology, OB/GYN, Oncology, and Surgery) starting in mid-February. For the final week of the study (April 19), positive results were obtained for 47 of 243 patients; that seroprevalence estimate of 19.3% is well-aligned with the results of the New York Department of Health study. However, the sample size of this cohort is too small for assessing age-specific IFRs.
Neustadt-am-Rennsteig, Germany ¹⁰⁵	This study analyzed seroprevalence of 626 residents (71% of the population of this municipality) and estimated seroprevalence of 8.4% (52 positive cases). However, this sample size is too small for assessing age-specific IFRs.
San Francisco Mission District, CA ¹⁰⁶	This study analyzed active infections and seroprevalence of 3,953 residents in a densely populated majority Latinx neighborhood in downtown San Francisco. Positive seroprevalence in older adults was very low (22 out of 3,953) and hence too small for assessing age-specific IFRs.
San Miguel County, CO ¹⁰⁷	The San Miguel County Health Department assessed seroprevalence in March and April using samples from 5,283 participants (66% of county residents). Raw prevalence was very low (0.53%), with only 3 confirmed positive results for adults ages 60 years and above.
Slovenia ¹⁰⁸	Researchers at the University of Ljubljana assessed seroprevalence using an IgG ELISA test for a random sample of 1,318 participants on April 20 to May 3. Test-adjusted prevalence was 0.9% (CI: 0 to 2.1%), indicating that the sample may have included only 10 infected individuals; no age-specific results were reported.
United Kingdom ¹⁰⁹	The U.K. Office for National Statistics reports aggregate estimates of seroprevalence from specimens provided for routine testing using a novel IgG ELISA test conducted by research staff at the University of Oxford, but these reports do not include age-specific seroprevalence estimates.
Vo, Italy ¹¹⁰	Vo' is a municipality of 3,300 people, nearly all of whom (87%) participated in an infection survey in late February. However, there were only 54 infections among people ages 50+, so assessing age-specific IFRs is not feasible.

¹⁰³ See Feehan et al. (2020).

¹⁰⁴ See Stadlbauer et al. (2020).

¹⁰⁵ See Weis et al. (2020).

¹⁰⁶ See Chamie et al. (2020).

¹⁰⁷ See San Miguel County Department of Health & Environment (2020).

¹⁰⁸ See Vodičar et al. (2020a,b).

¹⁰⁹ See U.K. Office for National Statistics (2020).

¹¹⁰ See Lavezzo et al. (2020).

Appendix B: Positive Predictive Value of Seroprevalence Tests

A key metric of test reliability is positive predictive value (PPV), that is, the likelihood that a positive test result is a true positive. The PPV can be evaluated as follows:

$$PPV = \frac{\text{sensitivity} \times \text{prevalence}}{\text{sensitivity} \times \text{prevalence} + (1 - \text{specificity}) \times (1 - \text{prevalence})}$$

Evidently, lower prevalence can markedly diminish the reliability of seroprevalence testing. As shown in Table B1, in a seroprevalence study of Dutch blood donors using the Wantai Total Antibody ELISA, the crude prevalence rate was found to be 2.7%.¹¹¹ However, that antibody test has a PPV of 42.4%, and hence the adjusted prevalence is only 0.6 %, with a 95 percent confidence interval of 0% to 5.2%. In effect, *practically all of the positive tests obtained in this study might be false positives*. By contrast, a seroprevalence study of New York City found a much higher crude prevalence of 20.0% using a Wadsworth Pan-Ig test with a PPV of 94.8%.¹¹² Consequently, the adjusted prevalence for this study is *higher* than the crude prevalence, namely, 21.7% with a 95 percent confidence interval of 19.2% to 24.4%.

Table B1: Impact of Crude Prevalence on Positive Predictive Value

Location	Netherlands			New York City		
Crude Prevalence	2.7%			20%		
Test	<i>Wantai Total Antibody ELISA</i>			<i>Wadsworth Pan-Ig</i>		
	Mean	95% Confidence Bounds		Mean	95 % Confidence Bounds	
		Lower	Upper		Lower	Upper
Sensitivity	0.621	0.520	0.720	0.880	0.805	0.928
Specificity	0.977	0.950	1.000	0.988	0.973	0.995
PPV	0.424	0.224	1.000	0.948	0.882	0.979
NPV	0.989	0.986	0.992	0.971	0.952	0.982
Adjusted Prevalence	0.006	0.000	0.052	0.217	0.192	0.244

¹¹¹ See Slot et al. (2020)

¹¹² See Rosenberg et al. (2020).

Test sensitivity and specificity also have a high impact on PPV. As shown in Table B2, a serological study of Santa Clara County utilized a Premier Biotech LFA test and estimated prevalence at 1.5% based on a test specificity of 99.5%.¹¹³ However, a subsequent study found the specificity of that test to be only 97.2%.¹¹⁴ That revision to the test specificity reduces its PPV in the context of the Santa Clara study from 71.6% to 31.1%, and the adjusted prevalence for Santa Clara County residents is not significantly greater than zero.

Table B2: Impact of Specificity on Positive Predictive Value

Location	Santa Clara County					
Crude Prevalence	1.5%					
Test	<i>Premier Biotech LFA</i>					
Source	Bendavid et al.			Whitman et al.		
	Mean	95% Confidence Bounds		Mean	95 % Confidence Bounds	
		Lower	Upper		Lower	Upper
Sensitivity	0.828	0.760	0.884	0.828	0.760	0.884
Specificity	0.995	0.992	0.997	0.972	0.921	0.994
PPV	0.716	0.591	0.818	0.311	0.128	0.692
NPV	0.997	0.996	0.998	0.997	0.996	0.998
Adjusted Prevalence	0.012	0.009	0.014	0.000	0.000	0.010

¹¹³ See Bendavid et al. (2020).

¹¹⁴ See Whitman et al. (2020).

Appendix C: Excess Mortality

In some locations, reported deaths may not fully capture all fatalities resulting from COVID-19 infections, especially when a large fraction of such deaths occur outside of medical institutions. In the absence of accurate COVID-19 death counts, *excess mortality* can be computed by comparing the number of deaths for a given time period in 2020 to the average number of deaths over the comparable time period in prior calendar years, e.g., 2015 to 2019.

This approach has been used to conduct systematic analysis of excess mortality in European countries.¹¹⁵ Likewise, the U.S. Center for Disease Control & Prevention provides regular updates on excess mortality for U.S. geographical locations.¹¹⁶

The Belgian study used in our benchmark analysis computed age-specific IFRs using seroprevalence findings in conjunction with data on excess mortality in Belgium.

In that case, the authors noted that their measure of excess mortality over the period from March to May coincided almost exactly with Belgium’s tally of reported COVID-19 cases.¹¹⁷

Consequently, we follow a parallel approach in constructing age-specific IFRs for Spain, using the seroprevalence findings of that national study in conjunction with age-specific measures of excess mortality published by Spain National Institute for Statistics.¹¹⁸

Appendix D: Comparison of Seroprevalence vs. Reported Cases in Iceland

Age Group	Reported Cases	Estimated Infections	Confidence Interval		Ratio of Infections to Reported Cases	Confidence Interval	
			Lower	Upper		Lower	Upper
30-39	289	469	469	703	1.6	1.6	2.4
40-49	357	644	473	859	1.8	1.3	2.4
50-59	306	337	211	547	1.1	0.7	1.8
60-69	213	225	188	375	1.1	0.9	1.8
70-79	63	70	63	304	1.1	1.0	4.8
80+	25	26	13	319	1.0	0.5	12.8
All 30+	1,253	1,771	1,415	3,109	1.41	1.13	2.48

Sources: cases are reported by Iceland Directorate of Health (2020) as of June 14, when Iceland had 1,796 recovered cases, 10 fatalities, and 4 individuals in isolation (none hospitalized). Estimated infections and 95% confidence intervals are taken from the seroprevalence study of Gujbjartsson et al. (2020).

¹¹⁵ See EuroMoMo (2020).

¹¹⁶ See Rinaldi and Paradisi (2020), Modi et al. (2020), and U.S. Center for Disease Control & Prevention (2020c).

¹¹⁷ See Molenberghs et al. (2020).

¹¹⁸ See Pollán et al. (2020) and Spain National Institute of Statistics (2020).

Appendix E: Comorbidities

Table E1: Comorbidity Prevalence in New York City Hospitalized COVID-19 Patients vs. General Population

Comorbidity	NYC Hospitalized COVID Patients	NYC Population (Ages 50+)	Difference
Cancer	5.6%	6.3%	-0.7%
Cardiovascular Disease			
Hypertension	53.1%	49.2%	3.9%
Coronary artery disease	10.4%	10.5%	-0.1%
Congestive heart failure	6.5%	6.9%	-0.4%
Chronic Respiratory Disease			
Asthma	8.4%	8.6%	-0.2%
Chronic obstructive pulmonary disease	5.0%	7.7%	-2.7%
Obstructive sleep apnea	2.7%	2.8%	-0.1%
Immunosuppression			
HIV	0.8%	2.7%	-2.0%
History of solid organ transplant	1.0%	NA	NA
Kidney Disease			
Chronic	4.7%	13.1%	-8.4%
End-Stage	3.3%	0.6%	2.6%
Liver Disease			
Cirrhosis	0.3%	0.9%	-0.6%
Hepatitis B	0.1%	0.5%	-0.3%
Hepatitis C	0.1%	0.1%	0.0%
Metabolic Disease			
Obesity (BMI \geq 30)	41.7%	26.9%	14.8%
Diabetes	31.7%	27.6%	4.1%
Ever Smoked	15.6%	43.8%	-28.2%

Note: The following sources were used to gauge the prevalence of comorbidities among New York City residents ages 50 years and above. *Asthma:* U.S. Center for Disease Control & Prevention (2018). *Cancer:* New York State Cancer Registry (2016). *Cardiovascular Diseases:* New York Department of Health (2020). *Diabetes:* New York State Comptroller (2015). *HIV:* New York City Department of Health (2018). *Kidney Disease:* IPRO End-Stage Renal Disease Network of New York (2014). *Liver Disease:* Moon et al. (2019) and Must et al. (1999). *Chronic Pulmonary Disease:* New York Department of Health (2019). *Obesity:* New York City Department of Health (2019).

Table E2: Fatality Hazard Ratios for Hospitalized U.K. COVID-19 Patients

Age	Hazard Ratio	Comorbidity	Hazard Ratio
20 to 49	1	Diabetes	1.1
50 to 59	2.7	Malignant Cancer	1.1
60 to 69	5.5	Chronic Cardiac Disease	1.2
70 to 79	9.8	Chronic Pulmonary Disease	1.2
80+	13.5	Chronic Kidney Disease	1.3
		Obesity	1.3
		Liver Disease	1.5

Source: Doherty et al. (2020), Figure 5.

References

- Acemoglu, D., Chernozhukov, V., Werning, I., Whinston, M. (2020). Optimal Targeted Lockdowns in a Multi-Group SIR Model. NBER Working Paper 27102. <https://www.nber.org/papers/w27102>
- AdminStat Germania (2020). Maps, Analysis and Statistics about the Resident Population, Municipality of Gangelt – population by age. <https://ugeo.urbistat.com/AdminStat/en/de/demografia/eta/gangelt/20158575/4>
- Armann, J., Unrath, M., Kirsten, C., Luck, C., Dalpke, A., Berner, R. (2020). Anti-SARS-CoV-2 IgG antibodies in adolescent students and their teachers in Saxony, Germany (SchoolCoviDD19): very low seroprevalence and transmission rates. July 17. <https://doi.org/10.1101/2020.07.16.20155143>
- Aron, J., Muellbauer, J. (2020, May). Excess mortality: England is the European outlier in the Covid-19. Retrieved July 12, 2020, from <https://voxeu.org/article/excess-mortality-england-european-outlier-covid-19-pandemic>
- Aspelund, K., Droste, M., Stock, J., Walker, C. (2020). Identification and Estimation of Undetected COVID-19 Cases using Testing Data from Iceland. July 19. NBER Working Paper 27528. <https://www.nber.org/papers/w27528>
- Azar, K., Shen, Z., Romanelli, R., Lockhart, S., Smits, K., Robinson, S., Brown, S., Pressman, A. (2020). Disparities In Outcomes Among COVID-19 Patients In A Large Health Care System In California. *Health Affairs*. <https://doi.org/10.1377/hlthaff.2020.00598>
- Banerjee, A., Alsan, M., Breza, E., Chandrasekhar, A., Chowdhury, A., Duflo, E., Goldsmith-Pinkham, P., Olken, B. (2020). Messages on COVID-19 Prevention in India Increased Symptoms Reporting and Adherence to Preventive Behaviors Among 25 Million Recipients with Similar Effects on Non-Recipient Members of Their Communities. July. NBER Working Paper 27496. <https://www.nber.org/papers/w27496>
- Bendavid E, Mulaney B, Sood N, et al. COVID-19 Antibody Seroprevalence in Santa Clara County, California. <https://www.doi.org/10.1101/2020.04.14.20062463>
- Bonanad, C., García-Blas, S., Tarazona-Santabalbina, F., Sanchis, J., Bertomeu-González, V., Fácila, L., Ariza, A., Núñez, J., Cordero, A. (2020). The Effect of Age on Mortality of Patients with COVID-19: A metanalysis with 611,583 subjects. *Journal of the American Medical Directors Association*. May 18. <https://doi.org/10.1016/j.jamda.2020.05.045>
- Brown, T., Walensky, R. (2020). Serosurveillance and the COVID-19 Epidemic in the U.S.: Undetected, Uncertain, and Out of Control. *JAMA-Journal of the American Medical Association*. July 21. <https://jamanetwork.com/journals/jama/fullarticle/2768835>
- Bryan A, Pepper G, Wener MH, Fink SL, Morishima C, Chaudhary A, et al. (2020). Performance Characteristics of the Abbott Architect SARS-CoV-2 IgG Assay and Seroprevalence Testing in Idaho. <https://doi.org/10.1101/2020.04.27.20082362>

- Byambasuren, O., Dobler, C., Bell, K., Rojas, D., Clark, J., McLaws, M., Glasziou, P. (2020). Estimating the Seroprevalence of SARS-CoV-2 Infections: Systematic Review. <https://www.medrxiv.org/content/10.1101/2020.07.13.20153163v1>
- California Department of Public Health (2020). COVID-19 Data and Tools. <https://covid19.ca.gov/data-and-tools/>
- Carter, L. J., Garner, L. V., Smoot, J. W., Li, Y., Zhou, Q., Saveson, C. J., Sasso J. M., Gregg A.C., Soares D. J., Beskid T. R., Jervy S.R., Liu, C. (2020). Assay Techniques and Test Development for COVID-19 Diagnosis. *ACS Central Science*, 6(5), 591-605. <https://pubs.acs.org/doi/10.1021/acscentsci.0c00501>
- Chamie, G., Marquez, C., Crawford, E., Peng, J., Petersen, M., Schwab, D., Schwab, J., Martinez, J., Jones, D., Black, D., Gandhi, M., Kerkhoff, A., Jain, V., Sergi, F., Jacobo, J., ROjas, S., Tulier-Laiwa, V., Gallardo-Brown, T., Appa, A., Chiu, C., Rodgers, M., Hackett, J., CLIAhub Consortium, Kistler, A., Hao, S., Kamm, J., Dynerman, D., Batson, J., Greenhouse, B., DeRisi, J., Havlir, D. (2020). SARS-Cov-2 Community Transmission during Shelter-in-Place in San Francisco. <https://doi.org/10.1101/2020.06.15.20132233>
- Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., Yang Q., Wang J., Liu Y., Wie Y., Xia J., Yu T., Zhang X., Zhang, L. (2020). Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: A descriptive study. *The Lancet*, 395(10223), 507-513. [https://doi.org/10.1016/s0140-6736\(20\)30211-7](https://doi.org/10.1016/s0140-6736(20)30211-7)
- Chen, V., Zhou, Y., Fallahi, A., Viswanatha, A., Yang, J., Ghasemi, Y., Ohol, N., Rosenberger, J. (2020). An Optimization Framework to Study the Balance between Expected Fatalities due to COVID-19 and the Reopening of U.S. Communities. July 20. <https://doi.org/10.1101/2020.07.16.20152033>
- Chowkwanyun, M., Reed A. L. (2020). Racial Health Disparities and Covid-19—Caution and Context. *New England Journal of Medicine*. Retrieved June 30, 2020. <https://www.nejm.org/doi/full/10.1056/NEJMp2012910>
- Connecticut Department of Health & Human Services (2020). COVID-19 Cases and Deaths by Age Group. <https://data.ct.gov/Health-and-Human-Services/COVID-19-Cases-and-Deaths-by-Age-Group/ypz6-8qyf>
- Czech Ministry of Health (2020). Collective Immunity Study SARS-CoV-2: Czech Prevalence. <https://covid-imunita.uzis.cz/index.php?pg=vystupy-a-vysledky>
- Davies, N., Klepac, P., Liu, Y., Prem, K., Jit, M., CMMID COVID-19 working group, Eggo, R. (2020). Age-dependent effects in the transmission and control of COVID-19 epidemics. *Nature Medicine*. June 16. <https://www.nature.com/articles/s41591-020-0962-9>
- Day, M. (2020). Covid-19: Four-fifths of cases are asymptomatic, China figures indicate. *British Medical Journal*, M1375. <https://www.bmj.com/content/369/bmj.m1375>

- De Salazar, P., Gomez-Barroso, D., Pampaka, D., Gil, J. Penaver, B., Fernandez-Escobar, C., Lipsitch, M., Larrauri, A., Goldstein, E., Hernan, M. (2020). Lockdown measures and relative changes in the age-specific incidence of SARS-CoV-2 in Spain. July 2. <https://www.medrxiv.org/content/10.1101/2020.06.30.20143560v1>
- Doi, A., Iwata, K., Kuroda, H., Hasuike, T., Nasu, S., Kanda, A., Nagao T., Nishioka H., Tomii K., Morimoto T., Kihara, Y. (2020). Estimation of seroprevalence of novel coronavirus disease (COVID-19) using preserved serum at an outpatient setting in Kobe, Japan: A cross-sectional study. <https://www.medrxiv.org/content/10.1101/2020.04.26.20079822v2>
- Emmenegger, M., Cecco, E. D., Lamparter, D., Jacquat, R. P., Ebner, D., Schneider, M. M., Morales I.C., Schneider D., Dogancay B., Guo J., Widmer A., Domange J., Imeri M., Moos R., Zografou C., Trevisan C., Gonzalez-Guerra A., Carella A., Dubach I., Xu C., Meisl G., Kosmoliaptsis V., Malinauskas T., Burgess-Brown N., Owens R., Mongjolsapaya J., Hatch S., Screatton G., Schubert K., Huck J., Liu F., Pojer F., Lau K., Hacker D., Probst-Mueller E., Cervia C., Nilsson J., Boyman O., Saleh L., Spanaus K., Eckardstein A., Schaer D., Ban N., Tsai C., Marino J., Schertler G., Ebert N., Thiel V., Gottschalk J., Frey B., Reimann R., Hornemann S., Ring A., Knowles T., Xenarios I., Stuart D., Aguzzi A. (2020). Early plateau of SARS-CoV-2 seroprevalence identified by tripartite immunoassay in a large population. <https://www.medrxiv.org/content/10.1101/2020.05.31.20118554v2>
- Erikstrup, C., Hother, C. E., Pedersen, O. B., Mølbak, K., Skov, R. L., Holm, D. K., Saejmosé S., Nilsson A. C., Brooks P. T., Boldsen J.K., Mikkelsen C., Gybel-Brask M., Sorenson E., Dinh K. M., Mikkelsen S., Møller B. K., Haunstrup T., Haritshoj L., Jensen B. A., Hjalgrim H., Lillevang S. T., Ullum, H. (2020). Estimation of SARS-CoV-2 infection fatality rate by real-time antibody screening of blood donors. <https://www.medrxiv.org/content/10.1101/2020.04.24.20075291v1>
- EuroMoMo (2020). Excess Mortality in Europe. <https://euromomo.eu/bulletins/2020-29/>
- Fassihi, F., Gladstone, R. (2020). Confusion and Contradiction Reign in Iran's Coronavirus Reporting. *New York Times*, February 28. <https://www.nytimes.com/2020/02/28/world/middleeast/coronavirus-iran-confusion.html>
- Feehan, A., Fort, D., Garcia-Diaz, Price-Haywood, E., Velasco, C., Sapp, E., Pevey, D., Seoane, L. (2020). Point Prevalence of SARS-CoV-2 and Infection Fatality Rate in Orleans and Jefferson Parish, Louisiana, May 9-15, 2020. June 24. <https://doi.org/10.1101/2020.06.23.20138321>
- Ferguson, N, Laydon, D, Nedjati Gilani, G, Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Perez, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green, W., Hamlet, ., Hinsley, W., Okell, L., Van Elsland, S., Thompson, H., Verity, R., Volz, E., Wang, H., Wang, Y., Walker, P., Walters, Winskill, P., Whittaker, C., Donnelly, C., Riley, S., Ghani, A (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. March 16. <https://doi.org/10.25561/77482>

- Fiorel, J., Centra, M., De Carlo, A., Granato, T., Rosa, A., Sarno, M., De Feo, L., Di Stefano, M., D'Erricol, M., Lo Caputo, S., De Nittis, R., Arena, F., Corso, G., Margaglione, M., Santantonio, T. (2020). Far Away from Herd Immunity to SARS-Cov-2: results from a survey in healthy blood donors in South Eastern Italy. <https://doi.org/10.1101/2020.06.17.20133678>
- Flannery, D., Gouma, S., Dhudasia, M., Mukhopadhyay, S., Pfeifer, M., Woodford, E., Gerber, J., Arevalo, C., Bolton, M., Weirick, M., Goodwin, E., Anderson, E., Greenplate, A., Kim, J., Han, N., Pattekar, A., Dougherty, J., Kuthuru, O., Mathew, D., Baxter, A., Vella, L., Weaver, J., Verma, A., Leite, R., Morris, J., Rader, D., Elovitz, M., Wherry, E., Puopolo, K., Hensley, S. (2020). SARS-CoV-2 Seroprevalence among Parturient Women. <https://www.medrxiv.org/content/10.1101/2020.07.08.20149179v1>
- Florida Department of Health (2020). Florida COVID-19 Case Line Data. <https://open-fdoh.hub.arcgis.com/datasets/florida-covid19-case-line-data/data>.
- Fontanet, A., Tondeur, L., Madec, Y., Grant, R., Besombes, C., Jolly, N., Pellerin S.F., Ungeheuer M. N., Cailleau I., Kuhmel L., Temmam S., Huon C. Chen K. Y., Crescenzo B., Munier S., Demeret C., Grzelek L., Staropoli I., Bruel T., Gallian P., Cauchemez., Werf S., Schwartz O., Eliot M., Hoen, B. (2020). Cluster of COVID-19 in northern France: A retrospective closed cohort study. <https://www.medrxiv.org/content/10.1101/2020.04.18.20071134v1>
- Glaeser, D., Gorbach, C., Redding, S. (2020). How much does COVID-19 Increase with Mobility? Evidence from New York and Four Other U.S. Cities. July. NBER Working Paper 27519. <https://www.nber.org/papers/w27519>
- Gudbjartsson, D., Helgason, A., Jonsson, H., Magnusson, O., Melsted, P., Norddahl, G., Saemundsdottir, J., Sigurdsson, A., Sulem, P., Agustsdottir, A., Eiriksdottir, B., Fridriksdottir, R., Gardarsdottir, E., Georgsson, G., Gretarsdottir, O., Gudmundsson, K., Gunnarsdottir, T., Gylfason, A., Holm, H., Jensson, B., Jonasdottir, A., Jonsson, F., Josefsdottir, K., Kristjansson, T., Magnúsdottir, D., le Roux, L., Sigmundsdottir, G., Sveinbjornsson, G., Sveinsdottir, K., Sveinsdottir, M., Thorarensen, E., Thorbjornsson, B., Love, A., Masson, G., Jonsdottir, I., Moller, A., Gudnason, T., Kristinsson, K., Thorsteinsdottir, U., Stefansson, K. (2020). Spread of SARS-Cov-2 in the Icelandic Population. *New England Journal of Medicine*. June 11. <https://www.nejm.org/doi/full/10.1056/NEJMoa2006100>
- Grewelle, R., Leo, G. (2020). Estimating the Global Infection Fatality Rate of COVID-19. <https://www.medrxiv.org/content/10.1101/2020.05.11.20098780v1>
- Hall, R., Jones, C., Klenow, P. (2020). Trading Off Consumption and COVID-19 Deaths. June. NBER Working Paper 27340. <https://www.nber.org/papers/w27340>
- Harris, J. (2020). Data from the COVID-19 epidemic in Florida suggest that younger cohorts have been transmitting their infections to less socially mobile older adults. July 5. <https://doi.org/10.1101/2020.06.30.20143842>

- Havers, F. P., Reed, C., Lim, T. W., Montgomery, J. M., Klena, J. D., Hall, A. J., Fry A. M., Cannon D. L., Chiang C. F., Gibbons A., Krapivnya I., Morales-Betoulle M., Roguski K., Rasheed M., Freeman B., Lester S., Mills L., Carroll D., Owen S., Johnson J., Semenova, V., Blackmore, C., Blog, D., Chai, S., Dunn, A., Hand, J., Jain, S., Lindquist, S., Lynfield, R., Pritchard, S., Sokol, T., Sosa, L., Turabelidze, G., Watkins, S., Wiesman, J., Williams, R., Yendell, S., Schiffer, J., Thornburg, N. (2020). Seroprevalence of Antibodies to SARS-CoV-2 in 10 Sites in the United States, March 23-May 12, 2020. *JAMA Internal Medicine*. July 21.
<https://jamanetwork.com/journals/jama/fullarticle/10.1001/jamainternmed.2020.4130>
- Herzog, S., Bie, J. D., Abrams, S., Wouters, I., Ekinci, E., Patteet, L., Coppens, A., Spiegeleer, D., Beutels P., Van Damme P., Hens N., Theeten, H. (2020). Seroprevalence of IgG antibodies against SARS coronavirus 2 in Belgium: A prospective cross-sectional study of residual samples. <https://www.medrxiv.org/content/10.1101/2020.06.08.20125179v1>
- Higgins, J., Thompson, S., Spiegelhalter, D. (2009). A Re-Evaluation of Random-Effects Meta-Analysis. *Journal of the Royal Statistical Society A*, 172:137-159.
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2667312/>
- Iceland Directorate of Health (2020). COVID-19 in Iceland: Statistics for 28 February to 14 June 2020 - Not Updated after 14 June. <https://www.covid.is/data-old>
- Indiana State Department of Health (2020). COVID-19 Case Demographics.
<https://hub.mph.in.gov/dataset/covid-19-case-demographics>
- Ioannidis, J. (2020). The infection fatality rate of COVID-19 inferred from seroprevalence data. June 8. <https://doi:10.1101/2020.05.13.20101253>
- IPRO End-Stage Renal Disease Network of New York (2014). Annual Report.
<https://esrd.ipro.org/wp-content/uploads/2016/01/Network-2-2014-Annual-Report.pdf>
- Italy National Institute of Statistics (2020a). Resident Population by Age on January 1, 2020.
<http://demo.istat.it/pop2020/index.html>
- Italy National Institute of Statistics (2020b). Mortality Trend for January 1 to May 31 for the Years 2015-2020, with Preliminary data for 2020 using the ANPR System - L'andamento dei decessi nel periodo 1 gennaio - 31 maggio per gli anni 2015-2020, dati anticipatori per l'anno 2020 sulla base del sistema ANPR.
https://public.tableau.com/views/Mortalit_15858412215300/Mortalit
- Japan National Institute for Infectious Diseases (2020). Field Briefing: Diamond Princess COVID-19 Cases, 20 February Update. <https://www.niid.go.jp/niid/en/2019-ncov-e/9407-covid-dp-fe-01.html>
- Jerkovic, I., Ljubic, T., Basic, Z., Kruzic, I., Kunac, N., Bezic, J., Vuko A., Markotic A., Andjelinovic, S. (2020). SARS-CoV-2 antibody seroprevalence in industry workers in Split-Dalmatia and Sibenik-Knin County, Croatia.
<https://www.medrxiv.org/content/10.1101/2020.05.11.20095158v1>

- Jersey (U.K.) Health & Community Services (2020a). Coronavirus (COVID-19) Tests and Cases in Jersey. <https://www.gov.je/Health/Coronavirus/Pages/CoronavirusCases.aspx>
- Jersey (U.K.) Health & Community Services (2020b). Prevalence of Antibodies – Community Survey Round 2. June 9. <https://www.gov.je/SiteCollectionDocuments/Government%20and%20administration/R%20Prevalence%20of%20antibodies%20200609%20SJ.pdf>
- Kempen, J., Abashawl, A., Kinfemichael, H., Difabachew, M., Kempen, C., Debele, M., Menkir A., Assefa, M., Asfaw, E., Habtegabriel, L., Addisie, Y., Nilles E., Longenecker, J. (2020). SARS CoV-2 Serosurvey in Addis Adaba, Ethopia. <https://www.medrxiv.org/content/10.1101/2020.06.23.20137521v1.full.pdf>
- Khalili, M., Karamouzian, M., Nasiri, N., Javadi, S., Mirzazadeh, A., & Sharifi, H. (2020). Epidemiological Characteristics of COVID-19: A Systemic Review and Meta-Analysis. <https://www.medrxiv.org/content/10.1101/2020.04.01.20050138v1>
- Knittel C. R., Ozaltun B. (2020). What Does and Does Not Correlate with COVID-19 Death Rates. *NBER*, June 2020. <https://www.nber.org/papers/w27391>
- Kotchen T. (2010). Obesity-Related Hypertension: Epidemiology, Pathophysiology, and Clinical Management. *American Journal of Hypertension*. <https://doi.org/10.1038/ajh.2010.172>
- Kraehling, V., Kern, M., Halwe, S., Mueller, H., Rohde, C., Savini, M., Schmidt M., Wilhelm J., Becker S., Ciesek S., Gottschalk, R. (2020). Epidemiological study to detect active SARS-CoV-2 infections and seropositive persons in a selected cohort of employees in the Frankfurt am Main metropolitan area. <https://www.medrxiv.org/content/10.1101/2020.05.20.20107730v1>
- Kreis Heinsberg District Administration (2020). Coronavirus in Kreis Heinsberg Current Information. <https://www.kreis-heinsberg.de/aktuelles/aktuelles/?pid=5149>
- Korea Center for Disease Control (2020). Weekly Report on the COVID-19 Situation in the Republic of Korea as of July 11, 2020. https://www.cdc.go.kr/board/board.es?mid=a30501000000&bid=0031&list_no=367822&act=view
- Krähling, V., Kern, M., Halwe, S., Muller, H., Rohde, C., Savini, M., Schmidt, M., Wilhelm, J., Becker, S., Ciesek, S., Gottschalk, R. (2020). Epidemiological study to detect active SARS-CoV-2 infections and seropositive persons in a selected cohort of employees in the Frankfurt am Main metropolitan area. <https://doi.org/10.1101/2020.05.20.20107730>
- Larremore, D., Fosdick, B., Bubar, K., Zhang, S., Kissler, S., Metcalf, C., Buckee, C., Grad, Y. (2020). Estimating SARS-CoV-2 seroprevalence and epidemiological parameters with uncertainty from serological surveys. <https://doi.org/10.1101/2020.04.15.20067066>

- Lattimore, S., Wickenden, C., Brailsford, S. (2015). Blood donors in England and North Wales: demography and patterns of donation. *Transfusion* 55:91-99.
<https://onlinelibrary.wiley.com/doi/abs/10.1111/trf.12835>
- Lavezzo, E., Franchin, E., Ciavarella, C., Cuomo-Dannenburg, G., Barzon, L., Vecchio, C. D., Rossi L., Manganelli R., Lorigian A., Navarin N., Abate D., Sciro M., Merigliano S., Decanale E., Vanuzzo M. C., Saluzzo F., Onelia F., Pacenti M., Parisi S., Carretta G., Donato D., Flor L., Cocchio S., Masi G., Sperduti A., Cattarino L., Salvador R., Gaythorpe K. A. M, Imperial College London COVID-19 Response Team, Brazzale A. R., Toppo S., Trevisan M., Baldo V., Donnelly C. A., Ferguson N. M., Dorigatti I., Crisanti, A. (2020). Suppression of COVID-19 outbreak in the municipality of Vo, Italy
<https://www.medrxiv.org/content/10.1101/2020.04.17.20053157v1>
- Leffler, C., Hogan, M. (2020). Age-dependence of mortality from novel coronavirus disease (COVID-19) in highly exposed populations: New York transit workers and residents and Diamond Princess passengers. <https://doi.org/10.1101/2020.05.14.20094847>
- Louisiana Department of Health (2020). Louisiana Coronavirus (COVID-19) Information – Cases/Deaths by Age Group. <http://ldh.la.gov/Coronavirus/>
- Malani, A., Soman, S., Ahser, S., Novosad, P., Imbert, C., Tandel, V., Agarwal, A., Alomar, A., Sarker, A., Shah, D., Shen, D., Gruber, J., Sachdeva, S., Kaiser, D., Bettencourt, L. (2020). Adaptive Control of COVID-19 Outbreaks in India: Local, Gradual, and Trigger-Based Exit Paths from Lockdown. July. NBER Working Paper 27532.
<https://www.nber.org/papers/w27532>
- Manski, C., Molinari, F. (2020). Estimating the COVID-19 Infection Rate: Anatomy of an inference problem. *Journal of Econometrics*. April 15.
<https://www.sciencedirect.com/science/article/pii/S0304407620301676>
- McAloon, C., Collins, A., Hunt, K., Barber, A., Byrne, A., Butler, F., Casey, M., Griffin, J., Lane, E., McEvoy, D., Wall, P. (2020). The incubation period of COVID-19: A rapid systematic review and meta-analysis of observational research.
<https://www.medrxiv.org/content/10.1101/2020.04.24.20073957v1>
- McLaren J. (2020). Racial Disparity in COVID-19 Deaths: Seeking Economic Roots with Census Data. *NBER*, June 2020. <https://www.nber.org/papers/w27407>
- Menachemi, N., Yiannoutsos, C., Dixon, B., Duszynski, T., Fadel, W., Wools-Kaloustian, K., Needleman, N., Box, K., Caine, V., Norwood, C., Weaver, L., Halverson, P. (2020). Population Point Prevalence of SARS-CoV-2 Infection Based on a Statewide Random Sample—Indiana, April 25-29, 2020. *Morbidity and Mortality Weekly Report*, U.S. Center for Disease Control & Prevention. July 24.
<https://www.cdc.gov/mmwr/volumes/69/wr/mm6929e1.htm>
- Meyerowitz-Katz, G., & Merone, L. (2020). A systematic review and meta-analysis of published research data on COVID-19 infection-fatality rates. July 7.
<https://www.medrxiv.org/content/10.1101/2020.05.03.20089854v4>

- Millett G. A., Jones A. T., Benkeser D., Baral S., Mercer L., Beyrer C., Honermann B., Lankiewicz E., Mena L., Crowley J. S., Sherwood J., Sullivan P. (2020). Assessing Differential Impacts of COVID-19 on Black Communities.
<https://doi.org/10.1016/j.annepidem.2020.05.003>
- Minnesota Department of Health (2020). Situation Update for COVID-19.
<https://www.health.state.mn.us/diseases/coronavirus/situation.html#deathm1>
- Missouri Department of Health & Senior Services (2020). Missouri COVID-19 Dashboard.
<http://mophep.maps.arcgis.com/apps/MapSeries/index.html?appid=8e01a5d8d8bd4b4f85add006f9e14a9d>. Reported fatalities as of May 23 obtained using <https://archive.org>.
- Modi, C., Boehm, V., Ferraro, S., Stein, G., Seljak, U. (2020). How deadly is COVID-19? A rigorous analysis of excess mortality and age-dependent fatality rates in Italy.
<https://www.medrxiv.org/content/10.1101/2020.04.15.20067074v3>
- Moon A., Singal, A., Tapper, E. (2019). Contemporary Epidemiology of Chronic Liver Disease and Cirrhosis. *Journal of Clinical and Gastroenterology and Hepatology*.
[https://www.cghjournal.org/article/S1542-3565\(19\)30849-3/abstract](https://www.cghjournal.org/article/S1542-3565(19)30849-3/abstract)
- Moritsugu, K. (2020). How accurate are China's virus numbers? April 1.
<https://www.pbs.org/newshour/world/how-accurate-are-chinas-virus-numbers>
- Mizumoto, K., Kagaya, K., Zarebski, A., Chowell, G. (2020). Estimating the Asymptomatic Proportion of Coronavirus Disease 2019 (COVID-19) Cases on Board the Diamond Princess cruise ship, Yokohama, Japan, 2020. *Euro Surveillance*, March 12.
<https://www.eurosurveillance.org/content/10.2807/1560-7917.ES.2020.25.10.2000180>
- Molenberghs, G., Faes, C., Aerts, J., Theeten, H., Devleeschauwer, B., Sierra, N., Braeye, T., Renard, F., Herzog, S., Lysyne, P., Van der Heyden, J., Van Oyen, H., Van Damme, P., and Hens, N. (2020). “Belgian Covid-19 Mortality, Excess Deaths, Number of Deaths per Million, and Infection Fatality Rates (8 March - 9 May 2020).”
<https://doi.org/10.1101/2020.06.20.20136234>
- Moritsugu, K. (2020). How accurate are China's virus numbers? April 1.
<https://www.pbs.org/newshour/world/how-accurate-are-chinas-virus-numbers>
- Must A., Spadano J., Coakley E., Field A., Golditz, G., Dietz W. (1999). The Disease Burden Associated with Overweight and Obesity. *Journal of the American Medical Association*.
<https://jamanetwork.com/journals/jama/fullarticle/192030>
- Ng, D., Goldgof, G., Shy, B., Levine, A., Balcerek, J., Bapat, S. P., Prostko J., Rodgers M., Collier K., Pearce S., Franz S., Du L., Stone M., Pillai S., Sotomayor-Gonzalez A., Servellita V., Martin C., Granados A., Glasner D. N., Han L. H., Truong K., Qazi D., Hsu E., Gu W., Santos Y. A., Custer B., Green V., Williamson P., Hills N. K., Lu C. M., Reyes K., Hakim J., Sujishi K., Alazzeah F., Pharm L., Oon C., Miller S., Kurtz T., Hakkett J., Simmons G., Busch M. P., Chiu, C. (2020). SARS-CoV-2 seroprevalence and neutralizing activity in donor and patient blood from the San Francisco Bay Area.
<https://www.medrxiv.org/content/10.1101/2020.05.19.20107482v2>

- New York City Department of Health (2018). HIV/AIDS Annual Surveillance Report. <https://www1.nyc.gov/assets/doh/downloads/pdf/dires/hiv-surveillance-annualreport-2018.pdf>
- New York City Department of Health (2019). Health of Older Adults in New York City. <https://www1.nyc.gov/site/doh/about/press/pr2019/health-of-older-adults-in-new-york-city>
- New York City Department of Health. (2020). COVID-19 Data. Downloaded on July 16 from: <https://www1.nyc.gov/site/doh/covid/covid-19-data.page>.
- New York Department of Health (2018). Information for Action Report. https://www.health.ny.gov/statistics/prevention/injury_prevention/information_for_action/docs/2018-08_ifa_report.pdf
- New York Department of Health (2020a). COVID-19 Tracker – Fatalities by Age Group. <https://covid19tracker.health.ny.gov/views/NYS-COVID19-Tracker/NYSDOHCOVID-19Tracker-Fatalities>.
- New Zealand Ministry of Health (2020). COVID-19 Current Cases. Downloaded on July 9. <https://www.health.govt.nz/our-work/diseases-and-conditions/covid-19-novel-coronavirus/covid-19-current-situation/covid-19-current-cases#age>
- Nishiura, H., Kobayashi, T., Miyama, T., Suzuki, A., Jung, S., Hayashi, K., Kinoshita R., Yang Y., Yuan B., Akhmetzhanov A. R., Linton, N. M. (2020a). Estimation of the asymptomatic ratio of novel coronavirus infections (COVID-19). *International Journal of Infectious Diseases*, 94, 154-155. [https://www.ijidonline.com/article/S1201-9712\(20\)30139-9/pdf](https://www.ijidonline.com/article/S1201-9712(20)30139-9/pdf)
- Nishiura, H., Kobayashi, T., Yang, Y., Hayashi, K., Miyama, T., Kinoshita, R., Linton N. M., Jung S., Yuan B., Suzuki A., Akhmetzhanov, A. R. (2020b). The Rate of Underascertainment of Novel Coronavirus (2019-nCoV) Infection: Estimation Using Japanese Passengers Data on Evacuation Flights. *Journal of Clinical Medicine*, 9(2), 419. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7074297/>
- Nopsopon, T. (2020). COVID-19 Antibody in Thai Community Hospitals. <https://www.medrxiv.org/content/10.1101/2020.06.24.20139188v3>
- Pennsylvania Department of Health (2020). COVID-19 Data for Pennsylvania. <https://www.health.pa.gov/topics/disease/coronavirus/Pages/Cases.aspx>
- Perez-Saez, F. J., Lauer, S. A., Kaiser, L., Regard, S., Delaporte, E., Guessous, I., Stringhini S., Azman, A. (2020). Serology-informed estimates of SARS-COV-2 infection fatality risk in Geneva, Switzerland. <https://www.medrxiv.org/content/10.1101/2020.06.10.20127423v1>
- Pollán, M., Perez-Gomez, B., Pastor-Barriso, R., Oteo, J. Hernan, M., Perez-Olmeda, M., Sanmartin, J., Fernandez-Garcia, A., Cruz, I., Fernandez de Larrea, N., Molina, M., Rodriguez, Cabrera, F., Martin, M., Merino-Amador, P., Leon Paniagua, J., Munoz-Montalvo, J., Blanco, F., Yotti, R. (2020). Prevalence of SARS-COV-2 in Spain (ENE-COVID): A nationwide, population-based seroepidemiological study. *Lancet*. [https://doi.org/10.1016/S0140-6736\(20\)31483-5](https://doi.org/10.1016/S0140-6736(20)31483-5)

- Public Health England (2020). Sero-Surveillance of COVID-19: Week 22.
<https://www.gov.uk/government/publications/national-covid-19-surveillance-reports/sero-surveillance-of-covid-19>
- Reifer, J., Hayum, N., Heszkel, B., Klagsbald, I., Streva, V. A. (2020). SARS-CoV-2 IgG Antibody Responses in New York City.
<https://www.medrxiv.org/content/10.1101/2020.05.23.20111427v2>
- Reuters (2020). Denmark to Send Back Inaccurate Antibody Tests. May 20.
<https://www.reuters.com/article/us-health-coronavirus-denmark-kits/denmark-to-send-back-inaccurate-antibody-tests-from-chinas-livzon-idUSKBN22W2TC>
- Rinaldi, G., Paradisi, M. (2020). An empirical estimate of the infection fatality rate of COVID-19 from the first Italian outbreak.
<https://www.medrxiv.org/content/10.1101/2020.04.18.20070912v2>
- Rosenberg, E., Tesoriero, J., Rosenthal, E., Chung, R., Barranco, M., Styer, L., Parker, M., Leung, S., Morne, J., Greene, D., Holtgrave, D., Hoefler, D., Kumar, J., Udo, T., Hutton, B., Zucker, H. (2020). Cumulative incidence and diagnosis of SARS-CoV-2 infection in New York. *Annals of Epidemiology*.
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7297691/>
- Russell, T., Hellewell, J., Jarvis, C., van Zandvoort, K., Abbott, S., Ratnayake, R., CMMID COVID-19 working group, Flasche, S., Eggo, R., Edmunds, W., Kucharski, A. (2020). Estimating the Infection and Case Fatality Ratio for Coronavirus Disease (COVID-19) using Age-Adjusted Data from the Outbreak on the Diamond Princess Cruise Ship, February 2020. *Euro Surveillance*, March 26.
<https://www.eurosurveillance.org/content/10.2807/1560-7917.ES.2020.25.12.2000256>
- Salje, H., Kiem, C., Lefrancz, N., Courtejoie, N., Bosetti, P., Paireau, J., Andronico, A., Hoze, N., Richet, J., Dubost, C.-L., Le Strat, Y., Lessler, J., Levy-Bruhl, D., Fontanet, A., Opatowski, L., Boelle, P.-Y., Cauchemez, S. (2020a). Estimating the Burden of SARS-Cov-2 in France. *Science*, June 26. <https://doi.org/10.1126/science.abc3517>
- Salje, H., Kiem, C., Lefrancz, N., Courtejoie, N., Bosetti, P., Paireau, J., Andronico, A., Hoze, N., Richet, J., Dubost, C.-L., Le Strat, Y., Lessler, J., Levy-Bruhl, D., Fontanet, A., Opatowski, L., Boelle, P.-Y., Cauchemez, S. (2020b). Erratum for the Report: Estimating the Burden of SARS-Cov-2 in France. *Science*, June 26.
<https://doi.org/10.1126/science.abd4246>
- Saltzman, J. (2020). Nearly a third of 200 blood samples taken in Chelsea show exposure to coronavirus. *Boston Globe*, April 17.
<https://www.bostonglobe.com/2020/04/17/business/nearly-third-200-blood-samples-taken-chelsea-show-exposure-coronavirus/>
- San Miguel County Department of Health & Environment (2020). IgG Antibody Tests: Statistics and Demographics. <https://www.sanmiguelcountyco.gov/590/Coronavirus>

- Sethuraman, N., Jeremiah, S., Ryo, A. (2020). Interpreting Diagnostic Tests for SARS-CoV-2. *Journal of the American Medical Association*.
<https://jamanetwork.com/journals/jama/fullarticle/2765837>
- Silveira, M., Barros, A., Horta, B., Pellanda, L., Victora, G., Dellagostin, O., Struchiner C., Burattini M., Valim A., Berlezi E., Mesa J., Ikeda M. K., Mesenburg M., Mantesso M., Dall’Agnol M., Bittencourt R., Hartwig F. P., Menezes A. M., Barros F. C., Hallal P., Victora, C. G. (2020). Repeated population-based surveys of antibodies against SARS-CoV-2 in Southern Brazil.
<https://www.medrxiv.org/content/10.1101/2020.05.01.20087205v2>
- Shakiba M, Nazari S, Mehrabian F, et al. Seroprevalence of COVID-19 virus infection in Guilan province, Iran. medRxiv doi: <https://doi.org/10.1101/2020.04.26.20079244>
- Skowronski, D., Sekiriv, I., Sabaiduc, S., Zou, M., Morshed, M., Lawrence, D., Smolina, K., Ahmed, M., Galanis, E., Fraser, M., Singali, M., Naus, M., Patrick, D., Kaweski, S., Mills, C., Reyes, R., Kelly, M., Levett, P., Petric, M., Henry, B., Kraijden, M. (2020). Low SARS-CoV-2 seroprevalence based on anonymized residual sero-survey before and after first-wave measures in British Columbia, Canada, March-May 2020. July 13.
<https://www.medrxiv.org/content/10.1101/2020.07.13.20153148v1>
- Slot, E., Hogema, B. M., Reusken, C. B., Reimerink, J. H., Molier, M., Karregat, J. H., Ijlst J., Novotny V. M. J., Lier R. A. W., Zaaier, H. L. (2020). Herd immunity is not a realistic exit strategy during a COVID-19 outbreak. <https://www.researchsquare.com/article/rs-25862/v1>
- Slovenia Government Communication Office. (2020). First study carried out on herd immunity of the population in the whole territory of Slovenia. May 6. Downloaded on July 4 from: <https://www.gov.si/en/news/2020-05-06-first-study-carried-out-on-herd-immunity-of-the-population-in-the-whole-territory-of-slovenia/>
- Snoeck, C. J., Vaillant, M., Abdelrahman, T., Satagopam, V. P., Turner, J. D., Beaumont, K., Gomes C. P. C., Fritz J. V., Schroder V. E., Kaysen A., Pavelka L., Stute L., Meyers G. R., Pauly L., Hansen M., Pauly C., Aguayo G. A., Perquin M., Hanff A. M., Ghosh S., Gantenbein M., Huiart L., Ollert M., Krüger, R. (2020). Prevalence of SARS-CoV-2 infection in the Luxembourgish population: The CON-VINCE study.
<https://www.medrxiv.org/content/10.1101/2020.05.11.20092916v1>
- Sood, N., Simon, P., Ebner, P., Eichner, D., Reynolds, J., Bendavid, E., Bhattacharya, J. (2020). Seroprevalence of SARS-CoV-2–Specific Antibodies Among Adults in Los Angeles County, California, on April 10-11, 2020. *JAMA-Journal of the American Medical Association*. <https://jamanetwork.com/journals/jama/fullarticle/2766367>
- Spain National Institute of Statistics – Instituto Nacional de Estadística (2020). Estimación del Número de Defunciones Semanales durante el Brote de Covid-19: diferencia absoluto del acumulado en lo que va de año. Downloaded on July 1 from: <https://www.ine.es/jaxiT3/Tabla.htm?t=35179>.

- Stadlbauer, D., Tan, J., Jiang, K., Hernandez, M., Fabre, S., Amanat, F., Teo, C., Arunkumar, G., McMahon, M., Jhang, J., Nowak, M., Simon, V., Sordillo, E., van Bakel, H., Krammer, F. (2020). Seroconversion of a City: Longitudinal monitoring of SARS-CoV-2 seroprevalence in New York City. June 29. <https://doi.org/10.1101/2020.06.28.20142190>
- Streeck, H., Schulte, B., Kümmerer, B., Richter, E., Höller, T., Fuhrmann, C., Bartok, E., Dolscheid, R., Berger, M., Wessendorf, L., Eschbach-Bludau, M., Kellings, A., Schwaiger, A., Coenen, M., Hoffmann, P., Stoffel-Wagner, B., Nöthen, M., Eis-Hübinger, A., Exner, M., Schmithausen, R., Schmid, M., Hartmann, G. (2020). Infection fatality rate of SARS-CoV-2 infection in a German community with a super-spreading event. June 2. <https://doi.org/10.1101/2020.05.04.20090076>
- Stringhini S, Wisniak A, Piumatti G, Azman AS, Lauer SA, Baysson H, et al. Repeated seroprevalence of anti 1 -SARS-CoV-2 IgG antibodies in a population-based sample. <https://doi.org/10.1101/2020.05.02.20088898>
- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020a). Study Plan for Assessing the Spread of COVID-19 by Measuring SARS-COV-2 Seroprevalence in a Demographic Cross-Section - Studieupplägg för Folkhälsomyndighetens undersökning av seroprevalens mot SARS-CoV-2 för skattning av genomgången covid-19 i ett tvärsnitt av befolkningen. June 13. <https://www.folkhalsomyndigheten.se/contentassets/6561cbb8fcb8435788fb69f5fd1b4356/studieu-pplagg-seroprevalens-covid-19.pdf>
- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020b). Guidance for Antibody Testing - Vägledning för antikroppspåvisning. Version 3, June 30. <https://www.folkhalsomyndigheten.se/contentassets/2c3d8e40926e4bcc942aa640922bb758/vagledning-antikroppspavisning.pdf>
- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020c). Seroprevalence of Antibodies following COVID-19 Infection in Blood Samples from Outpatient Care, Interim report 1, updated on June 18 using data thru week 21 - Påvisning av antikroppar efter genomgången covid-19 i blodprov från öppenvården, delrapport 1 - uppdaterad 2020-06-18 med data för prover insamlade vecka 21. June 18. <https://www.folkhalsomyndigheten.se/publicerat-material/publikationsarkiv/p/pavisning-av-antikroppar-efter-genomgangen-covid-19-hos-blodgivare-delrapport-2/>.
- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020d). COVID-19 Report for Week 24 - COVID-19 veckorapport vecka 24. June 18. https://www.folkhalsomyndigheten.se/globalassets/statistik-uppfoljning/smittsamma-sjukdomar/veckorapporter-covid-19/2020/covid-19-veckorapport-vecka-24_final.pdf .
- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020e). COVID-19 Analytical Statistics. Excel spreadsheet downloaded on June 19 from: <https://www.folkhalsomyndigheten.se/smittskydd-beredskap/utbrott/aktuella-utbrott/covid-19/statistik-och-analyser/bekraftade-fall-i-sverige/>.

- Sweden Public Health Authority – Sveriges Folkhälsomyndighetens (2020e). The Infection Fatality Rate of COVID-19 in Stockholm – Technical Report.
<https://www.folkhalsomyndigheten.se/publicerat-material/publikationsarkiv/t/the-infection-fatality-rate-of-covid-19-in-stockholm-technical-report/>
- Takita, M., Matsumura, T., Yamamoto, K., Yamashita, E., Hosoda, K., Hamaki, T., Kusumi, E. (2020a). Challenges of community point-of-care antibody testing for COVID-19 herd-immunity in Japan. *QJM: An International Journal of Medicine*.
<https://academic.oup.com/qjmed/article/doi/10.1093/qjmed/hcaa182/5848417>
- Takita, M., Matsumura, T., Yamamoto, K., Yamashita, E., Hosoda, K., Hamaki, T., Kusumi, E. (2020b). Regional Difference in Seroprevalence of SARS-CoV-2 in Tokyo: Results from community point-of-care antibody testing.
<https://journals.sagepub.com/doi/10.1177/2150132720942695>
- Thompson, C., Grayson, N., Paton, R., Lourenço, J., Penman, B., Lee, L. N., Odon V., Mongkolsapaya J., Chinnakannan S., Dejnirattisai W., Edmans M., Fyfe A., Imlach C., Kooblall K., Lim N., Liu C., Lopez-Camacho C., McNally C. A., Ramamurthy N., Ratcliff J., Supasa P., Wang B., Mentzer A. J., Turner M., Semple C., Baillie J. K., ISARIC4C Investigators., Harvala H., Screaton G., Tempterton N., Klenerman P., Jarvis L. Gupta S., Simmonds, P. (2020). Neutralising antibodies to SARS coronavirus 2 in Scottish blood donors - a pilot study of the value of serology to determine population exposure.
<https://www.medrxiv.org/content/10.1101/2020.04.13.20060467v1>
- U.K. Office for National Statistics (2020). Coronavirus (COVID-19) Infection Survey Pilot. June 5.
<https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/bulletins/coronaviruscovid19infectionsurveypilot/>
- U.K. Parliament Office (2020). Antibody Tests for COVID-19. June 16.
<https://post.parliament.uk/analysis/antibody-tests-for-covid-19/>
- United Health Foundation (2019). America's Health Rankings: Annual Report.
<https://www.AmericasHealthRankings.org>
- U.S. Food & Drug Administration (2020). EUA Authorized Serology Test Performance. July 1.
<https://www.fda.gov/medical-devices/emergency-situations-medical-devices/eua-authorized-serology-test-performance>
- U.S. Center for Disease Control and Prevention (2018). Asthma Data by State or Territory.
https://www.cdc.gov/asthma/most_recent_data_states.htm
- U.S. Center for Disease Control and Prevention (2020a). Interim Guidelines for COVID-19 Antibody Testing. May 23. <https://www.cdc.gov/coronavirus/2019-ncov/lab/resources/antibody-tests-guidelines.html>
- U.S. Center for Disease Control and Prevention (2020b). COVID-19 in Racial and Ethnic Minority Groups. July 18. <https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html>

- U.S. Center for Disease Control and Prevention (2020c). COVID-19 Case Updates. <https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html>
- U.S. Center for Disease Control and Prevention (2020d). COVIDView Weekly Report: U.S. Virologic Surveillance - Public Health Laboratories. <https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/index.html>
- U.S. Center for Disease Control and Prevention (2020e). COVID-19 Pandemic Planning Scenarios. Updated July 10. <https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html>
- U.S. National Center for Health Statistics (2020). Underlying Cause of Death 1999-2018. <https://wonder.cdc.gov/ucd-icd10.html>
- U.S. National Vital Statistics System (2020). Bridge-Race Population Estimates – Data Files and Documentation. https://www.cdc.gov/nchs/nvss/bridged_race/data_documentation.htm
- Utah Department of Health (2020). COVID-19 Surveillance. <https://coronavirus-dashboard.utah.gov/#demographics>.
- Valenti, L., Bergna, A., Pelusi, S., Facciotti, F., Lai, A., Tarkowski, M., Berzuini A., Caprioli F., Santoro L., Baselli G., Ventura C. D., Erba E., Bosari S., Galli M., Zehender G., Prati, D. (2020). SARS-CoV-2 seroprevalence trends in healthy blood donors during the COVID-19 Milan outbreak. <https://www.medrxiv.org/content/10.1101/2020.05.11.20098442v2>
- Verity, R., Okell, L. C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N., Cuomo-Dannenburg G., Thompson H., Walker P., Fu H., Dighe A., Griffin J., Cori A., Baguelin M., Bhatia S., Boonyasiri A., Cucuniba Z. M., Fitzjohn R., Gaythorpe K. A. M., Green W., Hamlet A., Hinsley W., Laydon D., Nedjati-Gilani G., Riley S., van-Elsand S., Volz E., Wang H., Wang Y., Xi X., Donnelly C., Ghani A., Ferguson, N. (2020). Estimates of the severity of COVID-19 disease. <https://www.medrxiv.org/content/10.1101/2020.03.09.20033357v1>
- Vodičar, P., Valenčak, A., Zupan, B., Županc, T., Kurdija, S., Korva, M., Petrovec, M., Demšar, J., Knap, N., Štrumbelj, E., Vehovar, V., Poljak, M. (2020a). Report on the National Survey on the Prevalence of COVID-19 Disease in Slovenia. July 6. <https://covid19.biolab.si/>
- Vodičar, P., Valenčak, A., Zupan, B., Županc, T., Kurdija, S., Korva, M., Petrovec, M., Demšar, J., Knap, N., Štrumbelj, E., Vehovar, V., Poljak, M. (2020b). Low prevalence of active COVID-19 in Slovenia: A nationwide population study on a probability-based sample. *Clinical Microbiology and Infection*. July 10. <https://doi.org/10.1016/j.cmi.2020.07.013>
- Washington Department of Health (2020). 2019 Novel Coronavirus Outbreak (COVID-19) Cases and Deaths by Week of Illness Onset, County, and Age. https://www.doh.wa.gov/Portals/1/Documents/1600/coronavirus/data-tables/PUBLIC_CDC_Event_Date_SARS.xlsx

- Weis, S., Scherag, A., Baier, M., Kiehntopf, M., Kamradt, T., Kolanos, S., Ankert, J., Glockner, S., Makarewicz, O., Hagel, S., Bahrs, C., Kimmig, A., Proquitte, H., Guerra, J., Loffler, B., Pletz, M., CoNAN study group (2020). Seroprevalence of SARS-CoV-2 antibodies in an entirely PCR-sampled and quarantined community after a COVID-19 outbreak: The CoNAN study. July 17. <https://doi.org/10.1101/2020.07.15.20154112>
- Williamson, E., Walker A., Bhaskaran, K., Bacon, S., Bates, C., Morton, C., Curtis, H., Mehrkar, A., Evans, D., Inglesby, P., Cockburn, J., McDonald, H., MacKenna, B., Tomlinson, L., Douglas, I., Rentsch, C., Mathur, R., Wong, A., Grieve, R., Harrison, D., Forbes, H., Schultze, A., Croker, R., Parry, J., Hester, F., Harper, S., Perera, R., Evans, S., Smeeth, L., Goldacre, B. (2020). OpenSAFELY: factors associated with COVID-19 death in 17 million patients. *Nature*. July 1. <https://doi.org/10.1038/s41586-020-2521-4>
- Wu, J., Leung, K., Bushman, M., Kishore, N., Niehus, R., Salazar, P. M., Cowling B. J., Lipsitch M., Leung, G. M. (2020). Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China. *Nature Medicine*, 26(4), 506-510. <https://www.nature.com/articles/s41591-020-0822-7>
- Yancy, C. W. (2020). COVID-19 and African Americans. *Journal of the American Medical Association*, 323(19), 1891. <https://jamanetwork.com/journals/jama/fullarticle/2764789>
- Zeek, A., Briggs, A. (2020). COVID-19 study's preliminary findings show spread of virus in Indiana. May 13. <https://news.iu.edu/stories/2020/05/iupui/releases/13-preliminary-findings-impact-covid-19-indiana-coronavirus.html>