Mortality and Longevity

Long-Term Impacts of Exposure to the COVID-19 Pandemic in a Cohort Perspective

AUGUST | 2025

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Long-Term Impacts of Exposure to the COVID-19 Pandemic in a Cohort Perspective

Remaining Life Expectancy, Scarring, and Selection

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CONTENTS

Executive Summary **4**

Section 1 Introduction **6**

Section 2 Data and Methods **8**

2.1 Data 8

2.2 Predicting Age-Specific Mortality Rates by Cohort in the Absence of the Pandemic 8

2.3 Measuring and Quantifying the Impact of the Pandemic on Cohort Mortality Trajectories 9

2.4 Estimating the Correlation between Excess Mortality in Consecutive Years 11

Section 3 Results **12**

3.1 Expected and Observed Cohort-Specific Mortality Rates 12

3.2 Mortality Trends under Four Scenarios 17

3.3 Association between Excess Mortality in 2020-2021 and 2021-2022 22

Section 4 Discussion **23**

4.1 Limitations 23

Section 5 Acknowledgments **24**

References **25**

About The Society of Actuaries Research Institute **27**

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Remaining Life Expectancy, Scarring, and Selection

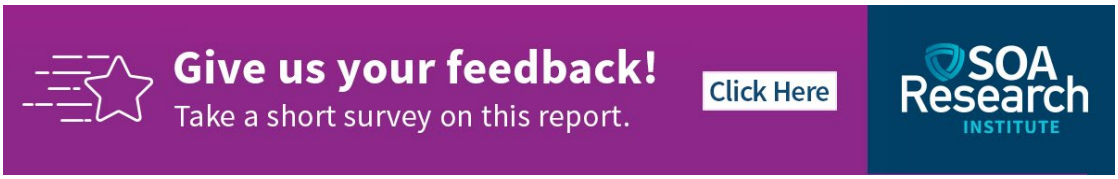
Executive Summary

This report presents findings from a project investigating the long-term impacts of the COVID-19 pandemic on mortality. The project had three objectives: 1) estimating the reduction in life expectancy experienced by birth cohorts affected by the pandemic, 2) understanding how future life expectancy will change under different mortality scenarios after the acute phase of the pandemic, and 3) investigating whether excess mortality at one age is associated with excess mortality at subsequent ages across cohorts. The study is based on cohort mortality data from the Human Mortality Database for 1985-2023. Cohort-specific excess mortality rates and ratios were computed by comparing observed death rates to deaths expected based on pre-pandemic mortality trajectories. The gap between observed and expected mortality was investigated under four different scenarios representing different paces of return to pre-pandemic trends. Finally, the correlation between cohort-specific excess mortality in 2020-2021 and 2021-2022 was assessed, revealing important insights into the presence of mortality selection, acquired immunity, and scarring effects.

The main findings of the study are summarized below:

- Every cohort included in the study displayed higher-than-expected mortality in 2020-2023 compared with expected trends based on ten years of pre-pandemic data.
- Excess cohort mortality was higher at ages affected by 2020-2021 mortality than at ages affected by 2021-2022 and shows further declines at ages affected by 2022-2023 mortality. Despite declines in excess mortality, mortality at all ages affected by the pandemic was above the expected level.
- Even if mortality were to immediately return to pre-pandemic trends, losses of life that have already occurred imply that declines in the probability of reaching age 95 for females will range from 1.4% to 11.7%, with an average decline of 4.8%. Among males, the declines will range from 1.7% to 12.3%, with an average decline of 5.2%.
- A permanent deviation of mortality from pre-pandemic trends – i.e., no return to the pre-pandemic mortality trend – would imply an average decline of 10.8% in the probability of reaching age 95 for both females and males.
- These reductions in expected longevity translate into 206,253 additional female deaths before age 95 under the best-case scenario, which grow more than two-fold to 505,208 under the worst-case scenario.
- The corresponding figures for males are 113,083 additional deaths under the best-case scenario, which more than doubles to 259,840 under the worst-case scenario.
- Comparing excess mortality rates between 2020-2021 and 2021-2022, the level of excess mortality in 2020-2021 predicts almost perfectly the level in 2021-2022, suggesting that common factors such as the prevalence of pre-existing conditions or comorbidities and socioeconomic status (correlated environments) explain variation in excess mortality across cohorts in both periods.

- Conversely, the lack of a relationship between the level of excess mortality in 2020-2021 and changes in excess mortality between 2020-2021 and 2021-2022, suggest that high excess mortality at a given age was not systematically associated with lower-than-average — as positive selection of survivors and acquired immunity would imply — or higher-than-average — as scarring would imply — excess mortality at subsequent ages. These findings are consistent either with the absence of acquired immunity, selection, and scarring effects or with effects of opposite sign (e.g. acquired immunity and scarring) offsetting each other.



Section 1 Introduction

The potential effects of past mortality conditions on future mortality can be classified by sign (positive or negative) and by whether they act through a direct (physiological) or indirect (associational) mechanism.[1] Positive effects imply that higher mortality in the past, or positive mortality shocks, are associated with higher mortality in the future. Negative effects imply the opposite relationship. Direct effects are those acting at an individual level through a physiological mechanism, e.g., infection from the hepatitis B virus, increasing the risk of dying from liver cancer.[2] Positive direct effects are usually grouped under the term "scarring," while negative direct effects are given the name of "acquired immunity" since they often result from exposure to a disease offering temporary or permanent immunity against reinfection (e.g., influenza). Indirect effects (sometimes referred to as correlated environments) are more complex to categorize as positive or negative and are more easily understood as confounders (i.e., variables which affect both past and current mortality conditions) as the term is used in the causal inference literature.[3] Poverty is a good example, likely to positively affect both past and current mortality (positive effect). However, one can also think of confounders that would have a positive impact on past mortality and a negative impact on current mortality. Another indirect mechanism, which does not fit neatly within the confounders group, is selection. Selection refers to the impact of past mortality on population composition. Usually, selection is thought to lower future mortality, with past shocks removing the frailest individuals from the population and, thus, reducing future mortality.[4] However, as for confounders, one can also imagine a positive effect of selection on mortality, e.g., war casualties. The concept of selection is also closely related to that of harvesting,[5] but the latter is usually reserved for short-term effects.

At its core, the relationship between past and future mortality can only operate directly (physiologically) through cohorts. For example, if it is hypothesized that being exposed to COVID-19 increases the risk of mortality for other causes of death (scarring), the analysis should focus on relationships between past and present mortality within cohorts over subsequent ages (cohort perspective), rather than within age groups over time (period perspective). The same argument applies for acquired immunity. Even though indirect links between past and current mortality can operate across cohorts, most should be stronger within cohorts. The presence of mortality selection, i.e., COVID-19 mortality only affecting the frailest and, thus, potentially lowering future mortality, also operates exclusively within cohorts.

Aside from the question of whether the effects of past mortality on future mortality are easier to identify within cohorts, there is a second argument for adopting this perspective. Demographers distinguish between two types of demographic measures, those based on the number of events occurring to a cohort of individuals (cohort measures) and those based on the number of events occurring to any individual in each time point (period measures). Birth cohorts (all individuals born in the same year) are the most common type of cohort, though not the only one. Cohort rates are arguably easier to model compared to period rates because the passing of time in a cohort perspective occurs in the form of aging. The relationship between age and mortality has been the subject of demographic research dating back to at least the 1600's and a variety of parsimonious but accurate mortality laws for different ages have been developed.[6–12] With the advent of more computing power, the tools available to flexibly model the age-mortality relationship have increased. New tools include semi-parametric methods based on penalized splines[13,14], closely related to Generalized Additive Models.[15]

For both theoretical and modeling reasons, assessing the long-term impact of the COVID-19 pandemic on mortality is a much simpler enterprise when examining cohort-specific mortality trajectories rather than period ones. Based on previous research on forecasting cohort mortality rates[14,16], observed age-specific mortality rates for a cohort up to age 60 gives enough information to accurately forecast future mortality for that cohort, at least to age 90, with remarkably simple models. To perform the same kind of projection on a period basis would instead be close to impossible without accepting wide margins of uncertainty.

In this report, a cohort perspective is adopted to investigate the realized and potential impact of the COVID-19 pandemic on the mortality of cohorts born between 1935 and 1949 in the United States. For each cohort, mortality at ages unaffected by the pandemic are used to fit models that relate age to mortality. The observed and projected cohort age-specific mortality rates are then compared to assess the impact of COVID-19 in 2020-2023. Finally, different scenarios for mortality beyond the acute phase of the pandemic are formulated to examine how life expectancy for each of the affected cohorts varies when moving from more optimistic to more pessimistic assumptions.

Section 2 Data and Methods

2.1 DATA

Deaths and exposures by Lexis triangle for the years 1985-2023 were obtained from the Human Mortality Database (HMD).[17] These data were used to compute age-specific mortality rates by single years of age and birth cohort. The analysis was restricted to the 1935-1949 cohorts, which reached ages 70 to 85 in 2020. This restriction provided pre-pandemic mortality data for ages 50 to 69 for each cohort, which served as the basis for constructing cohort forecasts of age-specific mortality rates in the absence of the COVID-19 pandemic.

2.2 PREDICTING AGE-SPECIFIC MORTALITY RATES BY COHORT IN THE ABSENCE OF THE PANDEMIC

Predicting age-specific mortality rates for several cohorts using a unique modeling approach is challenging. The main issue encountered is that the amount of data for older cohorts is significantly greater than for younger cohorts, since older cohorts have already gone through more years of life. In turn, this means that simpler parametric models, like Gompertz[6] or the Perks-Kannisto logit model[9,10], generally provide more realistic estimates for younger cohorts since they impose a very regular age progression. In contrast, more flexible GAM-based models provide a better fit for the mortality profile of older cohorts, because they are able to fit the observed rates at all ages and produce reasonable extrapolations for narrow age ranges. The downside of using different approaches for different cohorts is that comparing results across cohorts, particularly with respect to uncertainty, becomes harder, and inconsistencies or discontinuities may arise. To balance model fit with comparability across cohorts, the analysis employed a procedure that achieves a good fit for both younger and older cohorts by relaxing the functional-form constraints typically imposed by Gompertz or Kannisto models. At the same time, the approach ensured that only demographically plausible age progressions were permitted. The procedure combines the selection of an "optimal" model life table to represent the observed mortality of a cohort with a modeling step based on the Brass relational logit model. This procedure has its predecessor in the Brass logit life table system[18] and a similar idea is discussed in the UN Manual X.[19] The procedure has three steps. First, the data for each cohort is limited to the ten ages before the first one affected by the pandemic. For the 1949 cohort, ages 60 to 69 are used while, for the 1935 cohort, ages 75 to 84 are used. Second, the analysis refers to the West family United Nation model life table[20–23], which achieves the lowest Root Mean Squared Difference (RMSD) relative to the observed mortality rates. Formally, denoting with LT_i the i^{th} model life table:

$$LT_i = argmin_i \left(\sqrt{\frac{\sum_{x=a}^{b} (M_x^{obs} - M_x^i)^2}{b-a}} \right)$$

where a is the start of the age range for a given cohort and b is the endpoint, as identified in the first step. Since mortality generally increases by age for adults, the RMSD to be minimized will give more weight to older ages (i.e., the same proportional error will increase the RMSD more at older than younger ages). This is a desirable property in this application because the model will extrapolate to older ages, so accuracy closer to the starting point of the extrapolation interval is particularly important. The third and final step in the procedure is to fit a Brass relational logit model [24] using the selected UN model life table as the standard. The following equation is fit:

$$\log\left(\frac{M_x^{obs}}{1-M_x^{obs}}\right) = \alpha + \beta \cdot \log\left(\frac{M_x^{std}}{1-M_x^{std}}\right)$$

where M_x^{obs} are the observed and M_x^{std} the standard age-specific mortality rates. As for the selection of the model life table, the model is only fit between ages a and b, as defined above. Notice also that a more accurate model specification would relate the logit of age-specific probabilities of dying q_x in the two populations, but this would

complicate the analysis by requiring first the conversion of mortality rates into probabilities of death and then to convert predicted probabilities back to rates. In practice whether the logit of rates or probabilities are used is unlikely to matter for the age ranges being modeling since*:

$$q_x = e^{Mx} - 1 \approx (1 + M_x) - 1 = M_x$$

where the approximation holds if $M_x \approx 0$. Equipped with these models, fit separately by birth cohort and sex, extrapolate the age-specific mortality rates from the last age unaffected by the pandemic are extrapolated to age 95. Age 95 was chosen as an upper threshold because mortality at the oldest ages becomes harder to predict.

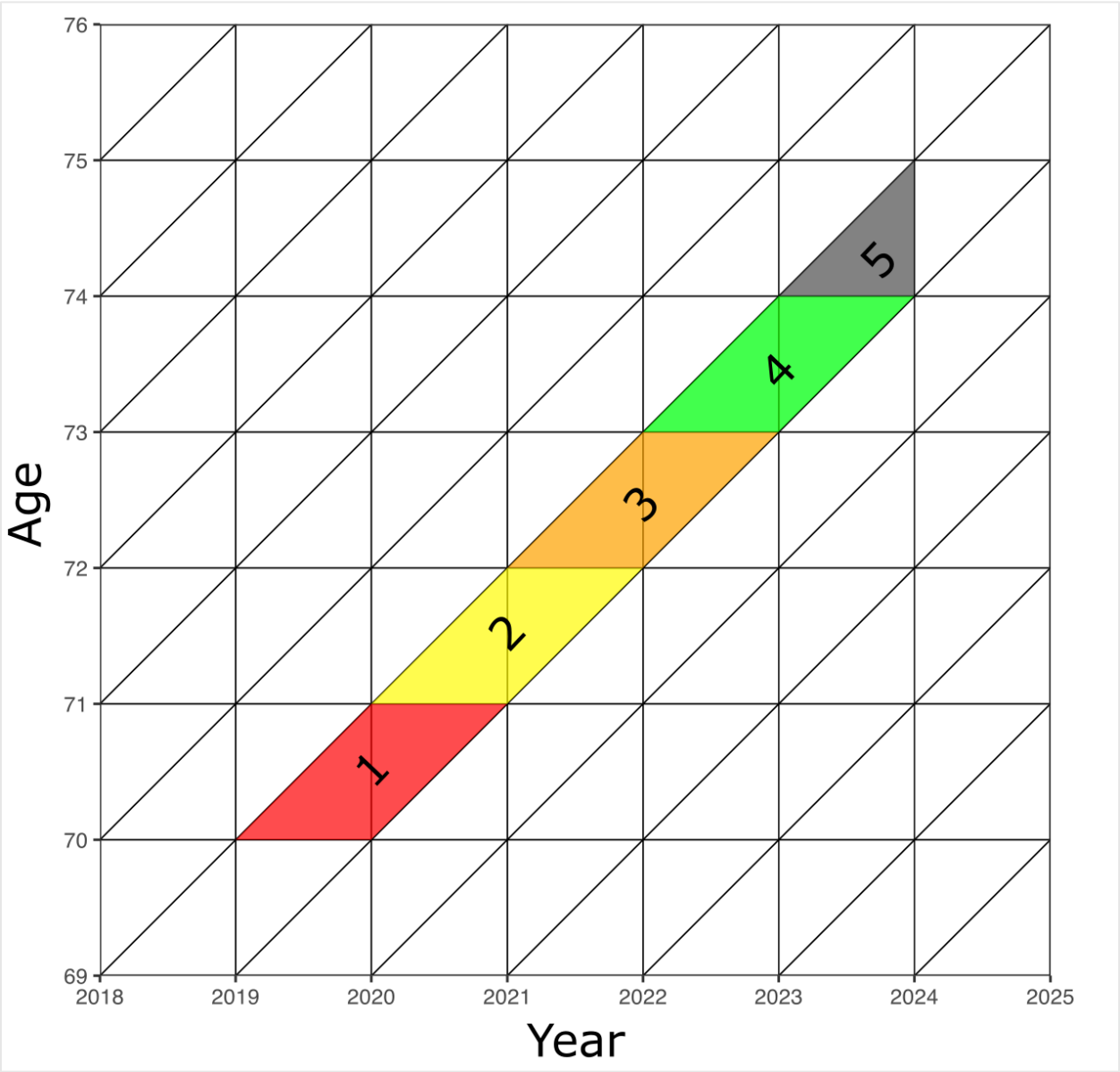
2.3 MEASURING AND QUANTIFYING THE IMPACT OF THE PANDEMIC ON COHORT MORTALITY TRAJECTORIES

To quantify the impact of the pandemic on cohort mortality, the expected age-specific mortality rates are compared to the observed rates for the four ages affected by the COVID-19 pandemic within each cohort. For example, for the 1949 cohort, mortality at ages 70 to 74 (which occurred between 2020 and 2023) was affected by the pandemic; for the 1935 cohort, the affected ages were 85 to 89. For each cohort, the mortality for the last age is still incomplete because some of the deaths and exposures will have occurred in 2024, for which data is not yet available. Figure 1 illustrates the study design using the 1949 cohort as an example. Looking at the Lexis diagram, it can be seen that, for the 1949 cohort, mortality at age 70 will occur between 2019 and 2020, mortality at age 71 will occur between 2020 and 2021, mortality at age 72 between 2021 and 2022, mortality at age 73 between 2022 and 2023, and mortality at age 74 between 2023 and 2024. It is thus important to keep in mind that each age- and cohort-specific mortality rate reflects deaths and exposures for two consecutive calendar years.

* The expression below is valid when the mortality rate M_x or $_1M_x$ is constant between age x and $x + 1$, which is not a strong assumption for adult ages and when using one-year intervals.

Figure 1

ILLUSTRATION OF STUDY DESIGN ON A LEXIS DIAGRAM USING THE 1949 BIRTH COHORT AS AN EXAMPLE



Notes: The graph shows the 1949 cohort as it ages and enters the pandemic period. Mortality at four ages (70-74) is affected by the first four years of the pandemic. This discrepancy between the number of years and ages affected by the pandemic arises because, from a cohort perspective, mortality at a given age can occur across two consecutive years. For the fifth age affected by the pandemic, 74 for the 1949 cohort, the data is incomplete because part of mortality at that age will have occurred in 2024, for which data is not yet available. By treating it as other data points, it is implicitly assumed that the data for 2023 is representative of that for the full 2023-2024 period.

For each cohort, four different scenarios were constructed, which were compared to the baseline of no deviation from the pre-pandemic trend. In each scenario, mortality rates are allowed to increase as observed for the ages affected by the pandemic (e.g., 70-74 for the 1949 cohort). It is assumed excess mortality would decline to half of its 2023-2024 value (partially observed) in 2024-2025 (age 75 for the 1949 cohort). This adjustment is based on excess mortality estimates for 2023 and 2024.[25,26]

From the 2024-2025 data point, different assumptions about the number of years it will take for the rates to go back to the pre-pandemic trend are made: 1) mortality returns to the expected trend in five years (with a linear decline), 2) mortality returns to the expected trend in ten years (with a linear decline), 3) mortality only returns to the pre-pandemic trend in 30 years (with a linear decline), or 4) mortality remains permanently above the pre-pandemic trend. These scenarios align roughly with those in a similar analysis of potential long-term trends in mortality following the COVID-19 pandemic.[25] Scenario (1) is referred to as the best-case scenario, scenario (2) the average scenario, scenario (3) the pessimistic scenario, and scenario (4) the worst-case scenario.

Under each scenario, two metrics are calculated: 1) the ratio between the average age-specific mortality rate under the scenario and in the baseline (rate ratio), and 2) the percentage reduction in the probability to reach age 95 for those alive in January 2020 compared with the baseline. For example, for the 1949 cohort, the probability of reaching age 95 for those who survived to age 70 is calculated under mortality rates in each of the scenarios and contrasted with the same probability under the baseline rates. These probabilities are obtained by constructing truncated cohort life tables with standard techniques and assuming deaths occur in the middle of each age interval.[27]

2.4 ESTIMATING THE CORRELATION BETWEEN EXCESS MORTALITY IN CONSECUTIVE YEARS

Having estimated age- and cohort-specific mortality deviations from the expected mortality trajectories, the question of whether deviations at one age are associated with deviations at later ages can be considered. To simplify the analysis, excess mortality at the age affected by the pandemic in 2020-2021 will be compared to excess mortality at the age affected by the pandemic in 2021-2022. For example, for the 1949 cohort, excess mortality at age 71 is compared to excess mortality at age 72. Since mortality is higher at older ages, looking at absolute excess can be problematic because the data points will be heteroskedastic. To alleviate this issue, excess ratios, i.e., excess/expected ratios or p-scores will be assessed. Using separate models by sex, the ratio in the age affected by 2021-2022 mortality, R_{21-22}, is related to the ratio in the age affected by 2020-2021 mortality, R_{20-21}. To simplify the interpretation of the coefficients, the average of the 2020-2021 ratios is subtracted from both quantities and the result is multiplied by 100. This does not affect the slope of the model but makes the intercept easily interpretable:

$$R_{21-22,c} = \alpha + \beta \cdot R_{20-21,c} + \varepsilon_{1,c}$$

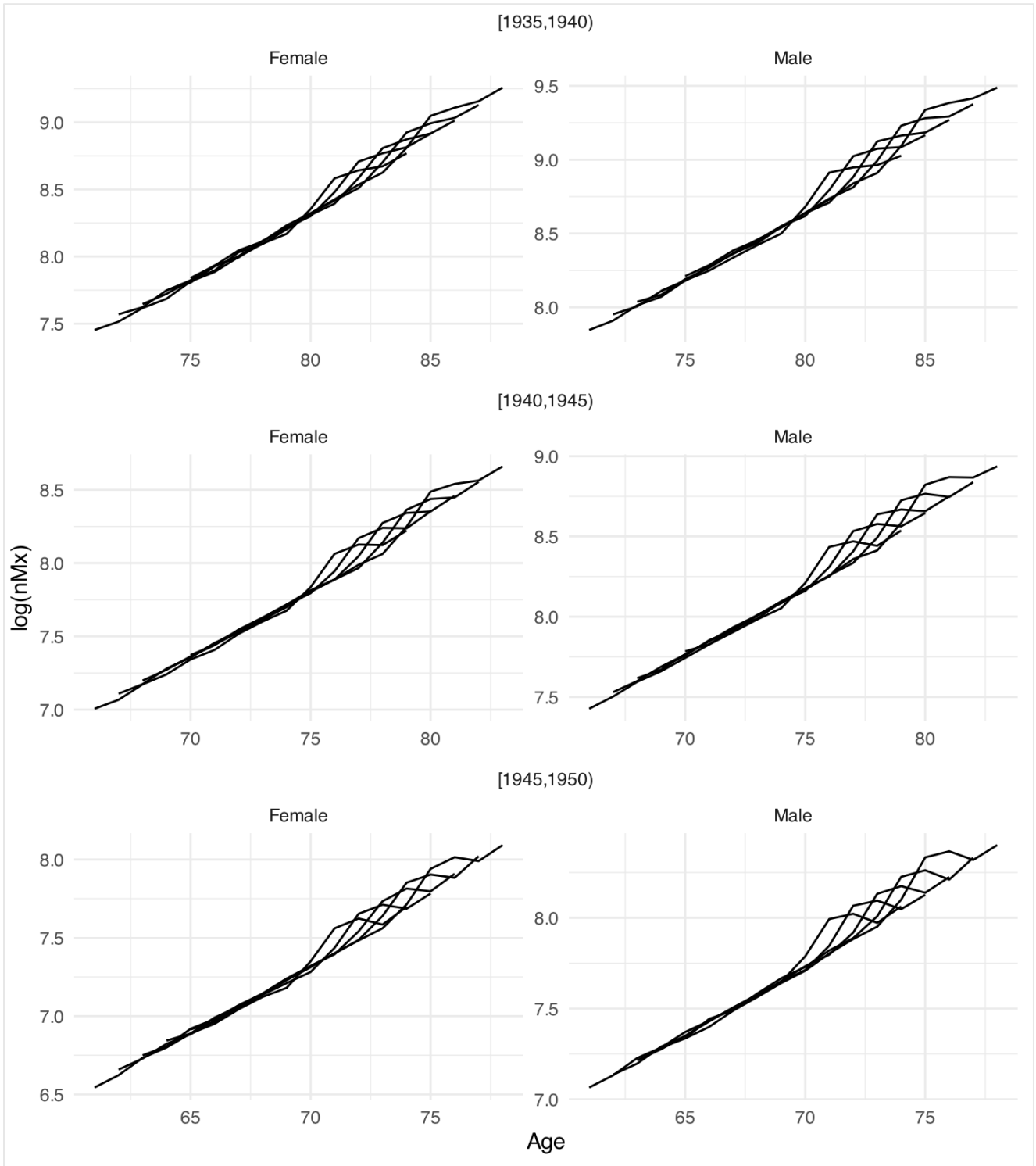
where the c subscript indicates cohort c. The presence of an intercept and the transformation from absolute to relative excess measures make the assumption, $\varepsilon_c \sim Normal(0, \sigma^2)$, more plausible by reducing the heteroskedasticity of the residuals. The intercept of this equation, α, indicates the average difference in percentage points between the 2021-2022 ratios and the 2020-2021 ratios. Positive values indicate that excess mortality declined over time, while positive values indicate that they have increased. The slope of the model, β, indicates how many additional percentage points of excess mortality in 2021-2022 are associated with an additional percentage point of excess mortality in 2020-2021. In the presence of correlated environments, it would be expected for w β to be close to 1, indicating that accounting for overall declines or increases in excess mortality cohorts with higher excess in one period also had higher excess in the next one. Because the transformation of the excess ratios, $\beta - 1$ also represents the expected change in the excess ratio between 2020-2021 and 2021-2022 associated with a 1% increase in 2020-2021. Positive values of $\beta - 1$ would indicate that higher excess in 2020-2021 predicts an increase in excess mortality in 2021-2022 (net of the average change) and suggest the presence of scarring effects. On the contrary, negative values of $\beta - 1$ would indicate that higher excess in 2020-2021 predicts a decrease in excess mortality in 2021-2022 (net of the average change) and, thus, suggests the presence of acquired immunity or positive selection.

Section 3 Results

3.1 EXPECTED AND OBSERVED COHORT-SPECIFIC MORTALITY RATES

Figure 2 shows age-specific mortality rates by cohort and sex for years 2010-2023. The age range included for each cohort depends on its age in 2010, so that earlier cohorts are observed at older ages and more recent cohorts at younger ones. Within each panel, containing mortality rates for cohorts born within five years of each other, there is little between cohort variability for ages unaffected by the pandemic. The small differences manifest as vertical deviations from a common trend rather than as differences in the rate of mortality increase over age, as indicated by the lines being approximately parallel. This pattern indicates that, in the absence of the pandemic, a roughly linear increase in the log-mortality rates would have been expected. Each of the 15 cohorts included in the study saw a sharp mortality increase in 2020 (i.e., ages 70 and 71 for the 1949 cohort). For all cohorts, and particularly for the younger ones, while mortality at ages affected by the second year of the pandemic (ages 71 and 72) and the third (ages 72 and 73) returned closer to the pre-pandemic trend, it remained elevated. Mortality at ages affected by the fourth year of the pandemic (i.e., age 74) did not show clear convergence towards the pre-pandemic trend for most cohorts.

Figure 2
AGE-SPECIFIC MORTALITY RATES BY SEX AND COHORT (1935-1949)

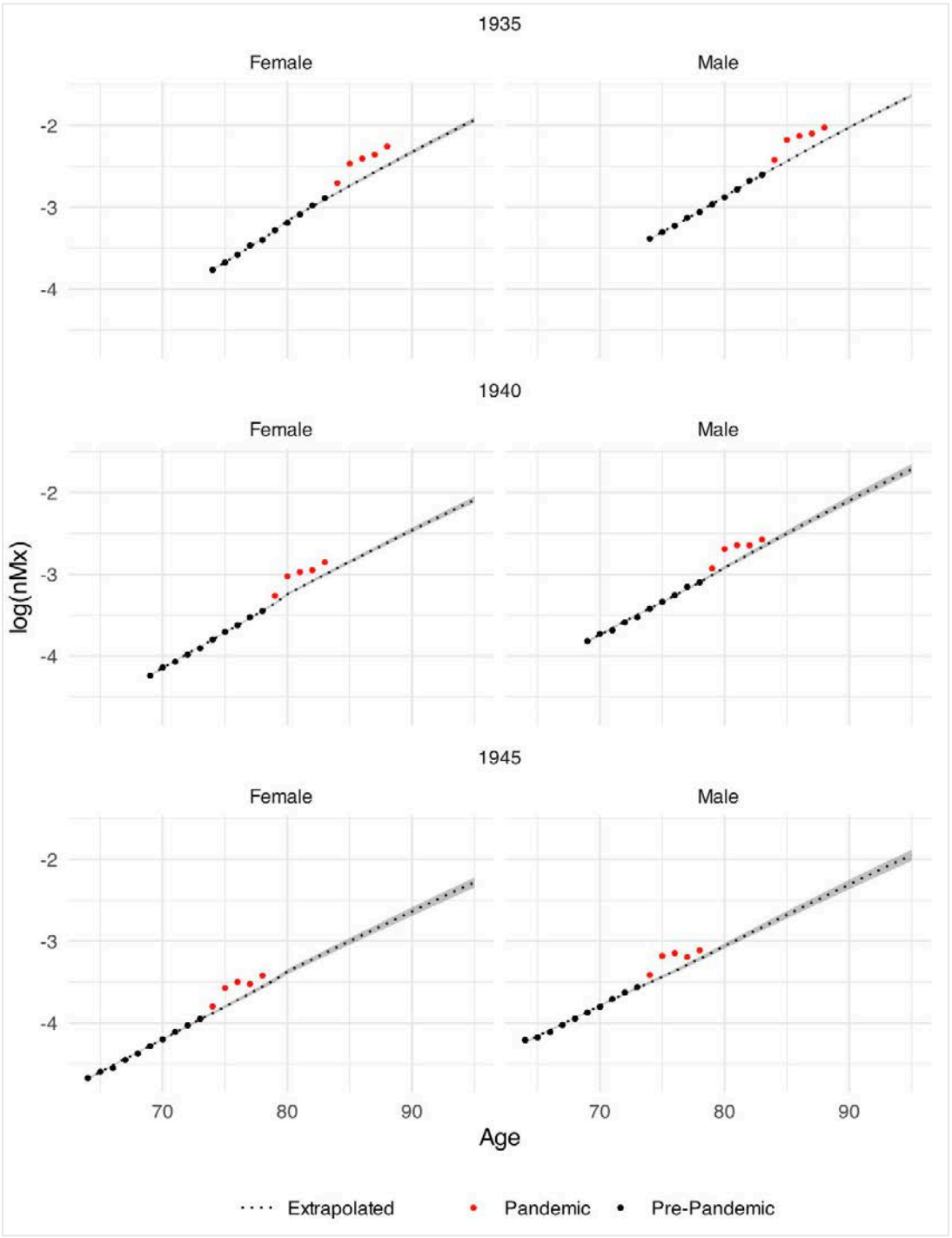


Notes: Each line represents the log age-specific mortality rates (single ages) for a different birth cohort. To simplify the visualization, the line for each cohort starts ten years before the pandemic so all lines have the same length.

Figure 3 shows predicted and observed mortality rates for three cohorts (1935, 1940, and 1945). Figure 4 shows the difference between the two series (observed minus predicted). To reduce the complexity of the figures, only the ages used to fit the model and those affected by the pandemic are included. As seen in Figure 3, the fit is close to perfect for both older and younger cohorts, and the confidence intervals around the estimated rates confirm that differences between expected and observed rates fall outside expected variation. This analysis confirms that, for each of the six cohorts, mortality rates at ages affected by the pandemic are higher than expected and the differences are significant. Figure 4 also confirms that, while the deviations from the trend were larger for ages affected by 2020 and 2021 mortality compared to ages affected by 2021 and 2022 mortality, and it continued to decline at ages affected by 2022 and 2023 mortality, it subsequently stabilized, showing limited signs of convergence to the pre-pandemic trend for most cohorts.

Figure 3

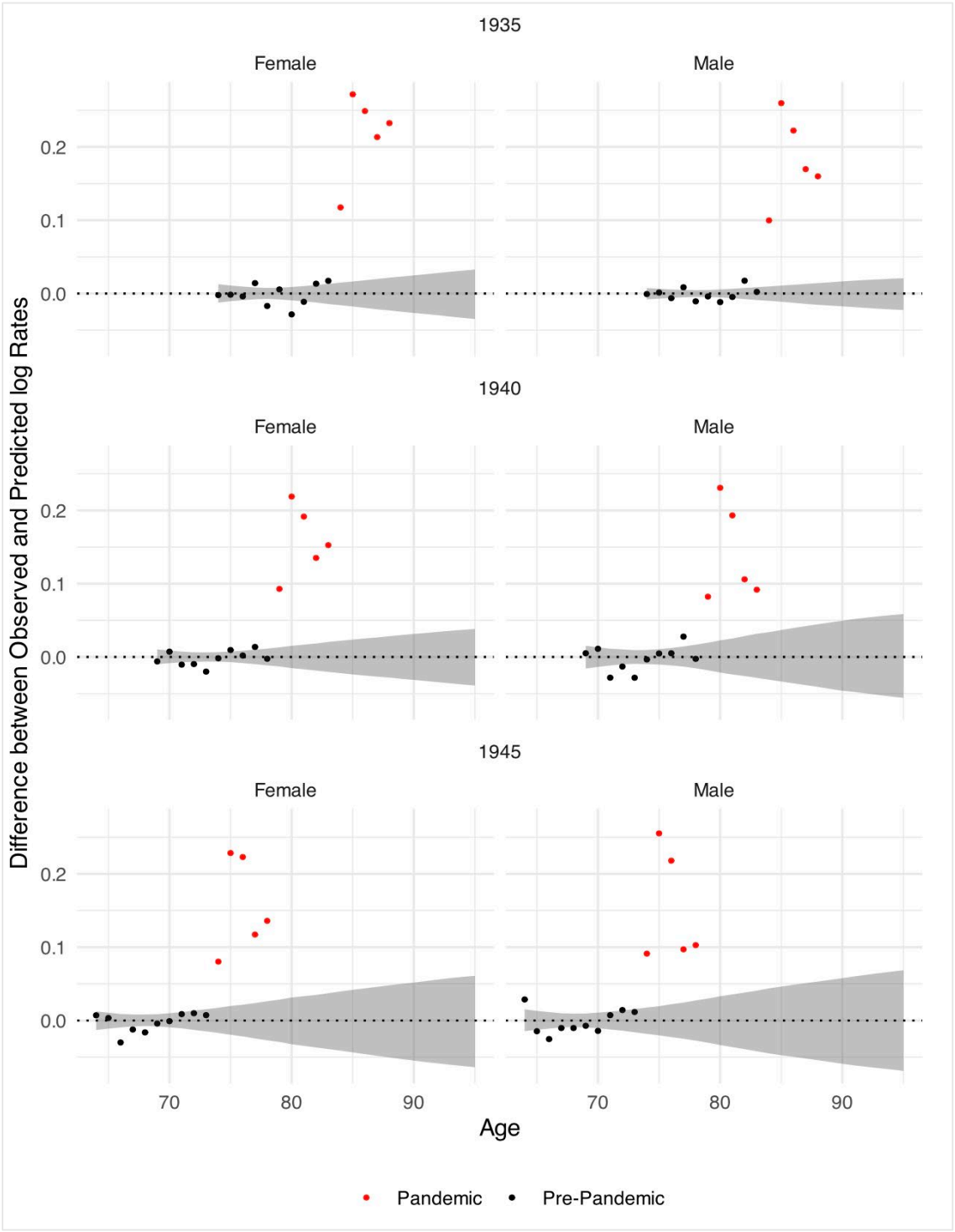
FITTED, OBSERVED, AND EXTRAPOLATED AGE-SPECIFIC MORTALITY RATES BY COHORT AND SEX



Notes: The dotted lines represent the expected age-specific mortality rates. The shaded areas around the dotted line are 90% confidence intervals. Dots reflect observed rates, with color indicating observations unaffected by the pandemic (black) and those affected (red).

Figure 4

OBSERVED DEVIATIONS FROM THE EXPECTED RATES BEFORE AND AFTER THE COVID-19 PANDEMIC BY COHORT AND SEX



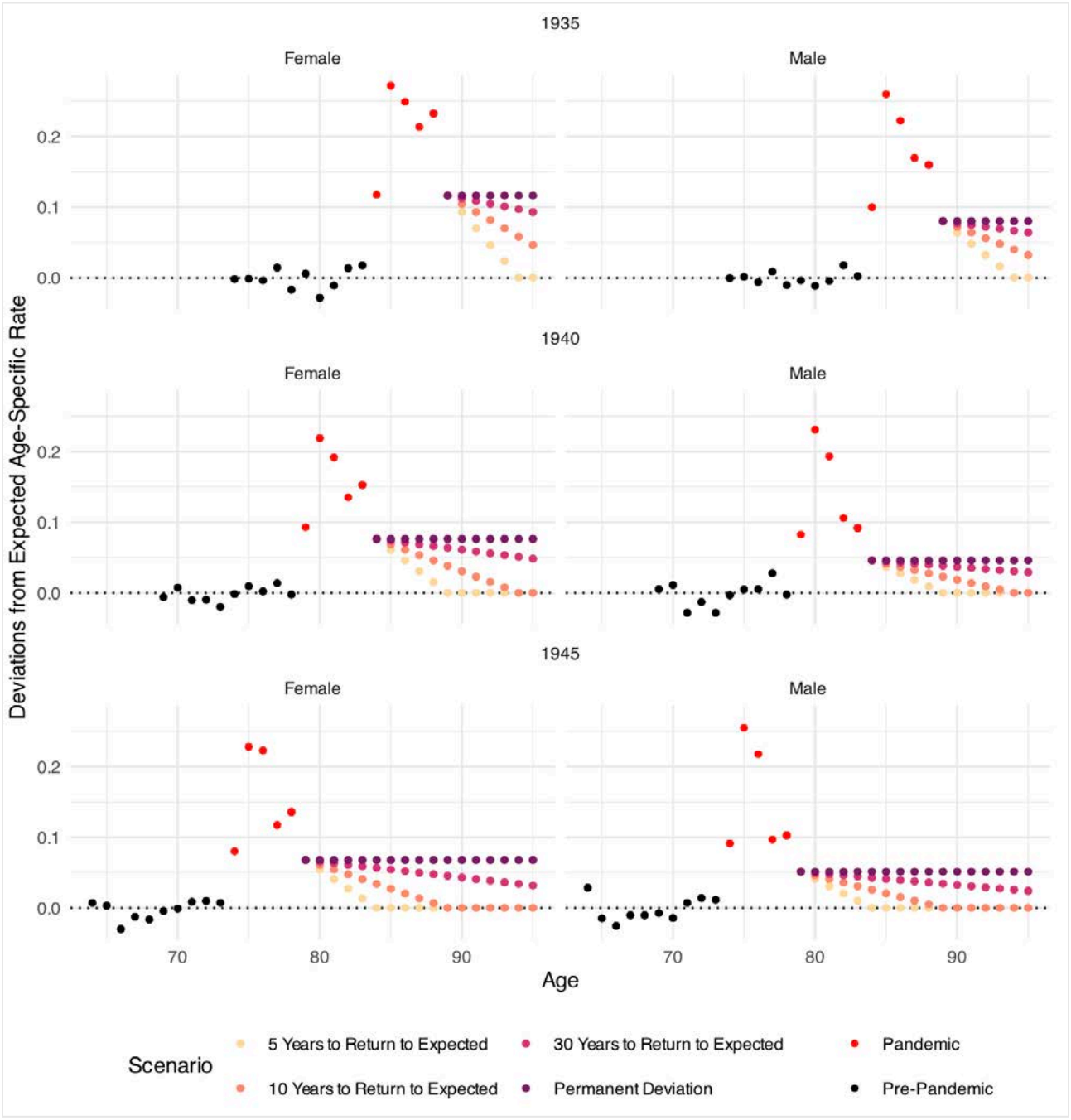
Notes: The dotted horizontal lines represent the expected age-specific mortality rates. The shaded areas around the dotted line are 90% confidence. Dots reflect observed rates, with color indicating observations unaffected by the pandemic (black) and those affected (red).

3.2 MORTALITY TRENDS UNDER FOUR SCENARIOS

Figure 5 illustrates the four scenarios in terms of deviations from the expected trend and with respect to the observed rates up to 2023. Only three cohorts (1935, 1940, and 1945) are included to simplify the visualization, but the scenarios are identically constructed for all cohorts. All the scenarios, except the "Permanent Deviation" scenario, converge back to the pre-pandemic trend but approach it at different speeds, with "5 Years to Return to Expected" being the fastest and "30 Years to Return to Expected" being the slowest. While the structure of each scenario is the same for all cohorts, the starting point is determined by the observed deviation from the expected rates in the last data point (deaths and exposures that occurred in 2023).

Figure 5

SCENARIOS OF FUTURE EVOLUTION OF AGE-SPECIFIC MORTALITY RATES FOR COHORTS AFFECTED BY THE COVID-19 PANDEMIC



Notes: The dotted horizontal lines represent the expected age-specific mortality rates. The solid, colored line represents the expected mortality rates under each of the scenarios. Dots reflect observed rates up to 2023, with color indicating observations unaffected by the pandemic (black) and those affected (red).

Panel A in Figure 6 and Table 1 show the scenario/baseline mortality rate-ratios for each of the cohorts included in the study. The ratios are computed by averaging mortality rates for all ages potentially affected by the pandemic under each scenario and under the baseline, with age 95 as the last age included. For the oldest cohort in the study

(1935), this means looking at the ratio of average rates between ages 85 and 95. For the youngest cohort (1949), this means looking at the ratio of average rates between ages 70 and 95. All rate-ratios are above 100, indicating higher-than-expected mortality and are generally larger for older cohorts. The ratios increase with movement from the best-case to the worst-case scenario. In the best-case scenario, which mostly reflects losses in longevity that have already materialized, the rate-ratios expressed as percentages (baseline is 100) range from 101.1 to 110.6 for females and from 101.1 to 108.3 for males, with average rate ratios of 104.2 for females and 103.2 for males. In the worst-case scenario, the ratios range from 105.1 to 116.1 for females and from 103.4 to 111.9 for males, with average rate ratios of 109.5 for females and 106.8 for males. The difference between the two extreme scenarios provides a measure of how much of the additional decline in longevity could be averted by a faster return to pre-pandemic trends.

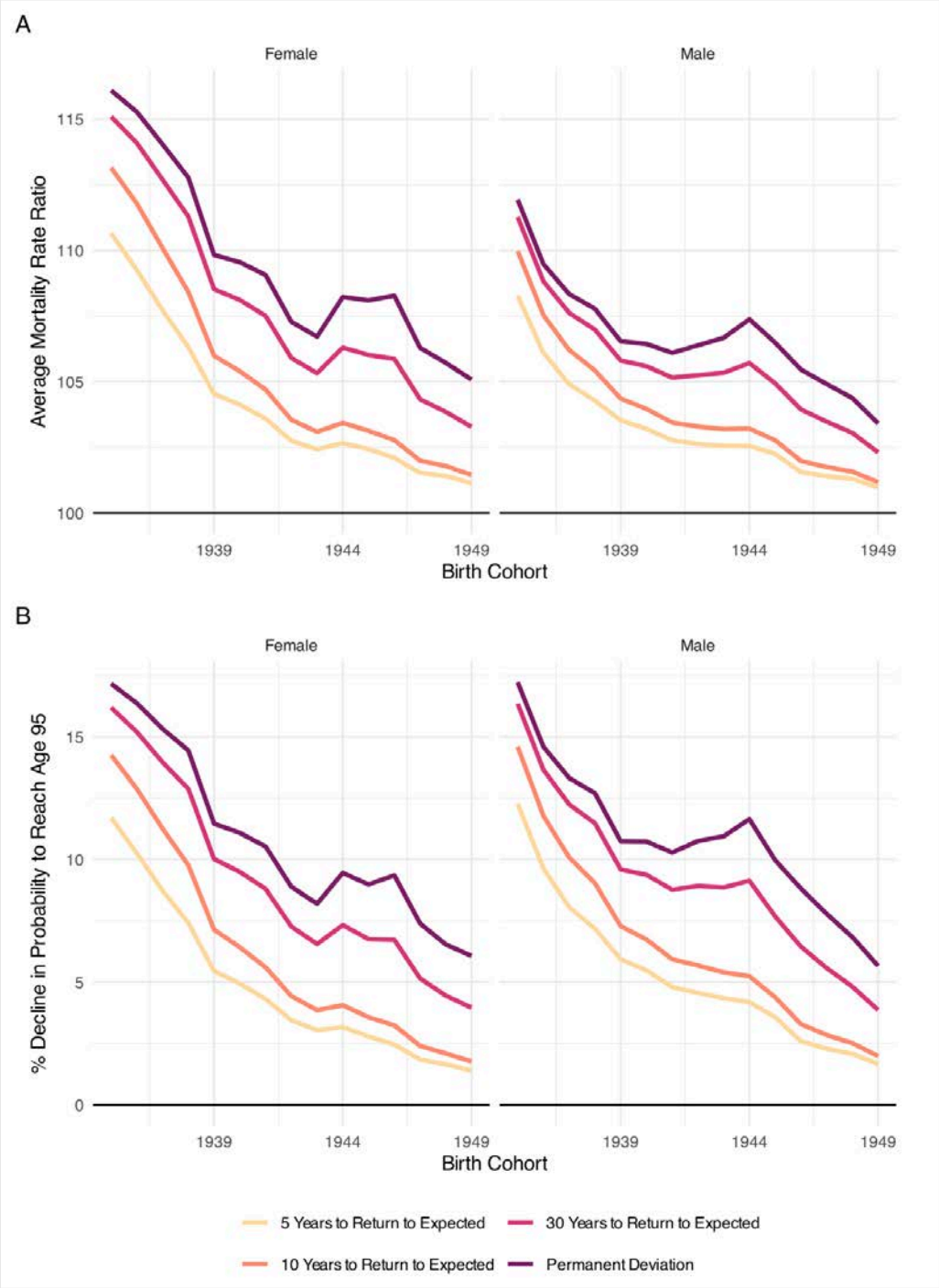
Table 1

MORTALITY RATE RATIOS UNDER DIFFERENT FUTURE SCENARIOS RELATIVE TO BASELINE RATES BY COHORT AND SEX

Scenario	Average Mortality Rate Ratios Relative to Pre-Pandemic Baseline				
	Average	Maximum	80th Percentile	20th Percentile	Minimum
Female					
5 Years to Return to Expected	104.2	110.6	106.6	102.0	101.1
10 Years to Return to Expected	105.4	113.2	108.7	102.6	101.4
30 Years to Return to Expected	107.9	115.1	111.6	105.1	103.3
Permanent Deviation	109.5	116.1	113.0	106.6	105.1
Male					
5 Years to Return to Expected	103.2	108.3	104.4	101.5	101.0
10 Years to Return to Expected	104.0	110.0	105.6	101.9	101.2
30 Years to Return to Expected	105.7	111.3	107.1	103.9	102.3
Permanent Deviation	106.8	111.9	107.9	105.4	103.4

Figure 6

MORTALITY RATE RATIOS (PANEL A) AND PERCENTAGE DECLINES IN PROBABILITY OF SURVIVAL TO AGE 95 (PANEL B) UNDER DIFFERENT FUTURE SCENARIOS RELATIVE TO BASELINE RATES BY COHORT AND SEX



Panel B in Figure 6 and Table 2 translate rate-ratios into proportional reductions in the probability of reaching age 95 for those surviving to the beginning of the pandemic. The patterns are similar to those in Panel A, but this alternative metric offers a more interpretable measure of the individual-level impact of the pandemic. In the best-case scenario, the reduction in the probability to reach age 95 ranges from 1.4% to 11.7% for females and 1.7% to 12.3% for males, with an average decline of 4.8% for females and 5.2% for males. In the worst-case scenario, the decline ranges from 6.1% to 17.2% for females and 5.7% to 7.2% for males, with an average decline of 10.8% for both sexes. For each cohort, these declines correspond to additional deaths among its members before reaching age 95 (Table 3). There would be an additional 206,253 deaths among females and 113,083 among males under the best-case scenario. Under the worst-case scenario, they would grow more than two-fold among both females (505,208 deaths) and males (259,840 deaths).

Table 2

PERCENTAGE DECLINES IN PROBABILITY OF SURVIVAL TO AGE 95 UNDER DIFFERENT FUTURE SCENARIOS RELATIVE TO BASELINE RATES BY COHORT AND SEX

Scenario	Percentage Declines in the Probability of Reaching Age 95				
	Average	Maximum	80th Percentile	20th Percentile	Minimum
Female					
5 Years to Return to Expected	-4.8	-11.7	-7.7	-2.3	-1.4
10 Years to Return to Expected	-6.2	-14.3	-10.1	-3.1	-1.8
30 Years to Return to Expected	-9.0	-16.2	-13.1	-6.3	-4.0
Permanent Deviation	-10.8	-17.2	-14.6	-8.0	-6.1
Male					
5 Years to Return to Expected	-5.2	-12.3	-7.4	-2.5	-1.7
10 Years to Return to Expected	-6.5	-14.6	-9.2	-3.2	-2.0
30 Years to Return to Expected	-9.1	-16.4	-11.6	-6.3	-3.9
Permanent Deviation	-10.8	-17.2	-12.8	-8.6	-5.7

Table 3

EXPECTED AND EXCESS DEATHS BEFORE AGE 95 ASSOCIATED WITH EACH SCENARIO ON FUTURE MORTALITY

Expected and Excess Deaths before Age 95 (reference: pre-pandemic trends)								
Scenario	1935-1939		1940-1944		1945-1949		All Cohorts	
	Expected	Excess	Expected	Excess	Expected	Excess	Expected	Excess
Female								
5 Years to Return to Expected	2,693,256	99,638	3,967,261	59,755	5,472,171	46,860	12,132,688	206,253
10 Years to Return to Expected	2,693,256	126,746	3,967,261	76,948	5,472,171	60,456	12,132,688	264,149
30 Years to Return to Expected	2,693,256	157,205	3,967,261	125,430	5,472,171	125,725	12,132,688	408,360
Permanent Deviation	2,693,256	172,550	3,967,261	153,682	5,472,171	178,976	12,132,688	505,208
Male								
5 Years to Return to Expected	2,365,787	45,218	3,772,210	36,965	5,516,903	30,900	11,654,900	113,083
10 Years to Return to Expected	2,365,787	55,442	3,772,210	45,891	5,516,903	38,022	11,654,900	139,355
30 Years to Return to Expected	2,365,787	66,800	3,772,210	72,164	5,516,903	72,170	11,654,900	211,135
Permanent Deviation	2,365,787	72,476	3,772,210	87,581	5,516,903	99,783	11,654,900	259,840

Notes: Expected deaths refer to the number of deaths that would have occurred based on pre-pandemic trends as projected by statistical models.

3.3 ASSOCIATION BETWEEN EXCESS MORTALITY IN 2020-2021 AND 2021-2022

Table 4 reports the results from the regression analysis relating excess mortality in 2021-2022 to excess mortality in 2020-2021. Looking at the intercepts for the sex-specific models, the average excess mortality ratios in 2021-2022 were 5.7% [5.0, 6.4] lower than in 2020-2021 among females, and 8.2% [7.6, 8.8] lower among males. Looking at the slope associated with the excess mortality ratio in 2020-2021, and adjusting for the differences in the level, a 1% increase in excess mortality in 2020-2021 is associated with a 1% increase in excess mortality in 2020-2021 (0.9 among males). Although the excess mortality ratios in 2020–2021 accurately predict the overall level, subtracting one from both slopes and analyzing the confidence intervals reveals that they do not predict the change in excess mortality between 2020–2021 and 2021–2022. This suggests that common factors explain the severity of excess mortality for a given cohort in consecutive ages (correlated environments) but that neither selection, acquired immunity, nor scarring played a large role or, if they played one, they offset each other perfectly.

Table 4

SUMMARY OF REGRESSION MODELS RELATING EXCESS RATIOS IN 2021-2022 AND 2020-2021

Characteristic	Females			Males		
	Beta	95% CI[1]	p-value	Beta	95% CI[1]	p-value
(Intercept)	-5.7	-6.4, -5.0	<0.001	-8.2	-8.8, -7.6	<0.001
Excess Ratio 2020	1.0	0.81, 1.3	<0.001	0.89	0.65, 1.1	<0.001
R^2	0.880			0.836		
No. Obs.	15			15		
σ	1.26			1.02		

[1]CI = Confidence Interval

Section 4 Discussion

This study demonstrates that the COVID-19 pandemic has already had a significant impact on the survival of individuals born between 1935 and 1949. Even under an optimistic scenario, the average decline in the probability of reaching age 95 will decline by 4.8% among female cohorts and by 5.2% among male cohorts. These losses are largely already realized. Further loss of life expectancy can be limited with a fast return to the pre-pandemic trends. However, the projected consequences of a slow return will be severe. In the case of a ten-year delay, the average decline in the probability of reaching age 95 will be 6.2% among female cohorts and 6.5% among male cohorts. In the case of a 30-year delay in the return to the baseline, the average decline among female cohorts will increase to 9.0% and the one among male cohorts will rise to 9.1%. In the worst-case scenario, there will be a 10.8% decline for both females and males. Each further decline in the probability of reaching age 95 corresponds to additional deaths from 2020 to 2045. There will be 319,336 such deaths under the best-case scenario and 765,048 under the worst-case scenario.

Analyzing the relationship between excess mortality rates in 2020-2021 and 2021-2022, the level of excess mortality in 2020-2021 predicts almost perfectly the level in 2021-2022, net of average declines in excess mortality between 2020-2021 and 2021-2022. This finding suggests that common factors explain differences in excess mortality across cohorts in both periods. These factors would encompass 1) prevalence of individual-level risk factors, including socioeconomic characteristics, health-related behaviors such as smoking and alcohol consumption, and pre-existing conditions such as hypertension, diabetes, or heart disease, and 2) area-level factors such as population density, age structure, and mobility. In contrast, the level of mortality in 2020-2021 does not predict changes in excess between 2020-2021 and 2021-2022, suggesting that experiencing higher-than-average excess mortality in the first two years of the pandemic was unrelated to the probability of experiencing higher-than-average excess in the second and third years of the pandemic. This finding suggests the absence of both selection or acquired immunity – i.e., direct or indirect mechanisms linking higher mortality in one year to mortality declines in the subsequent year – and scarring – i.e., direct mechanisms such as increased risk of death from other causes following a COVID-19 infection, that would link higher mortality in one year to increases in mortality in the next one. It is also possible that these two mechanisms counteracted each other but the absence or small magnitude of strong selection/scarring effects would be predicted by both mathematical models,[28] and an empirical investigation of mortality shocks in the past.[5,29] These findings suggest that mortality compression or harvesting is unlikely to play a significant role in shaping temporal patterns of excess mortality.

4.1 LIMITATIONS

Limitations of the study include the uncertainty of long-term forecasts of mortality rates. While, as can be seen in Figure 3, within-model uncertainty is relatively small, different modeling choices can lead to a wider range of predictions. To reduce the sensitivity of conclusions to the use of different models, the cohorts included in the study were limited to those for which mortality can be observed up to age 69. A second limitation comes from the unavailability of data for more recent years, which required making assumptions about cohort mortality deviations from pre-pandemic trends in 2024. Mitigation of the arbitrariness of these assumptions was attempted by relying on previous reports, but it is possible that when the required data becomes available, it will show more or less severe excess mortality in 2024.

Section 5 Acknowledgments

The authors' deepest gratitude goes to those without whose efforts this project could not have come to fruition: the volunteers who generously shared their wisdom, insights, advice, guidance, and arm's-length review of this study prior to publication. Any opinions expressed may not reflect their opinions nor those of their employers. Any errors belong to the authors alone.

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