The Covid Pandemic and Cohort Mortality: Causal Estimates from the US and France

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September 2025

Abstract

Previous analyses of excess mortality from the Covid-19 pandemic have relied on period approaches. We take a novel cohort approach that follows specific birth cohorts through the pandemic. Our approach compares observed mortality trajectories, estimated from cohort mortality rates derived from monthly counts of deaths and populations by sex, to multiple estimated counterfactual trajectories. Confidence intervals are constructed via permutation tests. The approach results in some findings are well-known from period estimates – *e.g.* effects were far larger in the US than in France – and others that are novel – *e.g.* we find effects of Covid for much younger cohorts than previously reported. Our cohort approach to estimating causal effects reveals demographic consequences obscured by period methods, and has broad applicability to future analyses of mortality shocks.

Introduction

The COVID-19 pandemic has fundamentally altered global mortality patterns, creating an unprecedented need to understand its long-term demographic consequences. A study of 29 countries that included most of Europe, the United States and Chile documented that 27 of 29 experienced drops in period life expectancy at birth in 2020 relative to 2019, with the United States experiencing the largest drop of 2.1 years (Schöley et al. 2022). To date, studies assessing the impact of Covid-19 have almost exclusively adopted a period approach. While period-based mortality analyses provided immediate snapshots of excess deaths and age-specific mortality rates, they offer an incomplete picture of the pandemic's true demographic impact. This study employs a cohort-based approach to mortality analysis, which provides critical insights into how COVID-19 has affected the cumulative mortality experiences of specific birth cohorts rather than simply capturing mortality patterns at discrete points in time.

The distinction between period and cohort approaches to mortality analysis is particularly crucial when examining the effects of a temporally-concentrated health crisis like COVID-19. Period mortality measures, such as life tables constructed for specific calendar years, reflect the mortality conditions that would hypothetically affect a synthetic cohort if current rates remained constant throughout their lifetime. While useful for immediate policy responses and international comparisons, period measures can misrepresent the long-term mortality consequences for actual birth cohorts who experienced the pandemic at different life stages (Lleras-Muney and Moreau 2022).

A cohort-based analysis reveals how the pandemic's mortality effects are distributed across cohorts that have different numbers of remaining years of life. Birth cohorts that experienced COVID-19 during vulnerable life stages may show permanently elevated mortality risks that extend beyond the acute pandemic period, while other cohorts might exhibit different patterns of mortality displacement or long-term health sequelae. Additionally, measures of cohort mortality are not subject to distortions from population growth and aging that can influence period estimates of excess deaths (Shiels et al. 2021). Unlike age groups, cohorts are a coherent entity consisting of the same individuals (minus deaths, plus migration) throughout a study period.

Crucially, the cohort-based methodology enables identification of plausibly causal effects of COVID-19 on mortality under minimal identifying assumptions. By comparing mortality outcomes across birth cohorts and over time, this approach leverages exogenous variation in pandemic exposure timing to identify causal impacts. Unlike period analyses focused on life expectancy or excess deaths, cohort comparisons do not rely on cross-sectional synthetic measures, and can isolate the differential impact of COVID-19 on individual cohort while taking secular mortality trends into account. This identification strategy requires only that pandemic timing was exogenous to pre-existing cohort-specific mortality trajectories—a plausible assumption given the unpredictable emergence and global spread of Covid-19. The methodology we developed for this approach has broad applicability to analyses of other mortality shocks.

Literature

To our knowledge, only one study to date has adopted a cohort approach to studying Covid-19, with this study using published forecasts of cohort mortality to estimate population-level years of life lost (Goldstein and Lee 2020).

Another area where a cohort approach has, to our knowledge, not been used pertains to the estimation of excess mortality itself. A standard approach, used by the Center for Disease Control (CDC) to estimate excess deaths (Rossen et al. 2020, 2021) relies on algorithms first developed by Farrington et al. (1996) and augmented by Noufaily et al. (2013) These algorithms predict counts of deaths for a given population at a given point in time or geographical area using data from the same population at earlier time points and overdispersed Poisson generalized linear models with spline terms to account for trends and seasonality. The goal of such modern surveillance methods is to detect disease outbreaks and spikes for fine-grained spatial and temporal data. Notably, they do not incorporate information about trends in population size and age structure, and rely entirely on period data.

Other approaches generally follow the same playbook of comparing predicted to observed deaths (or death rates). These approaches provide different estimates, often incorporating covariates when available in linear regressions with fixed effects (Stokes et al. 2021), regression trees (Economist 2023), least absolute shrinkage and selection operator regression (IHME 2022), and complex Bayesian models (Kontis et al. 2020). These methods have the advantage of flexibly incorporating large amounts of data in ways that make multiple-country estimation feasible, but their relatively opaque nature can make it unclear why alternative estimates might differ (see, e.g., the recent critique of results reported by IHME9 that noted highly implausible estimates of death counts for a number of countries (Schöley et al. 2023)). Here also, these methods have been applied to period data only.

What have we learned from research on mortality in the US and France? One recent study of French mortality during the Covid-19 pandemic estimated excess mortality and years of life lost using period data (Moulaire et al. 2025). Using a Poisson regression model, they calculate expected mortality in the pandemic period (years 2020–2023) as a function of trends in age-specific mortality in years 2010–2019. They find excess mortality beginning at age 51 for men and around age 65 for women. Some excess mortality is observed at much younger ages in the US, but impacts are not statistically significant until age 35+ (Foster et al. 2024). As in France, excess mortality among US women was lower than among men, and began at later ages. Some models of excess mortality do estimate statistically significant impacts for ages 15-44 in both the USA and Europe (Rossen et al. 2022), but not disaggregated by sex or finer age groups.

Not visible in any existing analysis, however, is the cumulative effect of the pandemic on the mortality of cohorts. Doing so would require (a) accumulating mortality effects across multiple time points for an individual cohort and (b) a model of mortality that takes previous cohort trends into account. Our methodology is designed to address both of these issues and to provide credible confidence intervals such that we can interpret the results as the causal effect of the Covid-19 Pandemic on the cumulative mortality of cohorts in the US and France.

Data

The data required for our analyses of single-year birth cohorts of males and females are publicly-available secondary data from two sources. We require micro-mortality data on individual deaths and corresponding population counts for France and the United States for (at least) 2015 up to the present. Table 1 provides information for the portion of the data covering the years 2013 onward. These data include exhaustive individual-level databases on deaths. Combined with corresponding population counts, they allow us to estimate cohort-specific mortality rates at the national level for each month since 2015 by sex for France and the United States.

Cohort populations are estimated using Census estimates for July populations, interpolated to obtain monthly estimates. This procedure account for cohort mortality

Table 1: Data sources for the years 2013 onwards

	Individual Deaths			Population Counts		
	Years	Variables	Source	Years	Variables	Source
France	2013–2021	Sex Date of Birth Date of Death	INSEE*	2015-2023 (Jan 1)	Sex Single Year of Age	INSEE*
USA	2013–2021	Sex Single Year of Age at Death Year and Month of Death	NCHS**	2013-2021 (July 1)	Sex Single Year of Age	US Census Bureau

Note: * National Institute of Statistics and Economic Studies. **National Center for Health Statistics.

Methods

Consider a cohort born in year c. The causal effect of a period shock on cohort mortality would be equal to the difference between the cohort's mortality rates in the post-shock period and a counterfactual mortality rate schedule that would have occurred in the absence of the shock.

Let μ_c^1 denote the mortality rate in cohort c during the covid period and let μ_c^0 denote the mortality rate in cohort c that would have been observed under a no-covid counterfactual. Define the average treatment effect (ATE) of the covid pandemic for cohort c to be

$$\Delta_c = \mu_c^1 - \mu_c^0. \tag{1}$$

Because the counterfactual is fundamentally unobservable, we need to estimate it. We do so using using two strategies. The first, which we call "horizontal", estimates the counterfactual by extrapolating the trend in age-specific mortality among adjacent older cohorts (e.g. cohorts born in year $c-1, c-2, etc.$) when they were the age at which cohort c was affected by the shock (thus extrapolating horizontally along the Lexis diagram). The second, which we call "oblique," estimates the counterfactual by extrapolating along the Lexis diagonal of cohort c's age-specific mortality rates. In both approaches, cohort-specific effects are then estimated by comparing the counterfactual with the observed mortality rates.

An important difference between this approach and traditional estimates of excess mortality, such as those employed by Rossen et al. (2022) is that we do not specify a baseline of no excess deaths from which deviations are measured. Instead, the fluctuations in observed pre-Covid mortality are interpreted as statistically important - these are deaths that are part of the regular variation in mortality that we would observe in the absence of the treatment we are interested in estimating the effects of. As such, our estimates of uncertainty are larger than those around traditional estimates of excess deaths.

A second important difference is that our cohort model, by design, is not sensitive to period changes in age structure or population size. By using cohort data, and estimating effects on individual cohorts, we do not make additional assumptions about trends in populations.

Horizontal Approach

To estimate effects during the initial covid period in 2020 (March–December 2020), the no-covid counterfactual for cohort c will rely on the 10 monthly mortality rates observed during periods beginning in March and ending in December. For the "horizontal" approach we use with five pre-covid cohorts consisting of cohorts $c-1, \ldots, c-5$.

We also specify a set fixed effects for the 10 monthly observations in our local linear regressions because of seasonality in mortality, with deaths more likely in some calendar months than others.

Let r_{jk} denote the $50 = 10 \times 5$ monthly mortality rates for cohorts j and month $k, k = 1, ..., 10$.

Let t_{jk} denote these calendar months, with $t_{jk} = 1$ corresponding to March 2015, $t_{jk} = 2$ to April 2015, ..., and $t_{jk} = 50$ to December 2020. Then the local linear regression for cohort c can be written compactly as

$$r_{jk} = \beta_c t_{jk} + \beta_c t_{jk}^2 + \gamma_k + \epsilon_{jk}, \qquad \begin{aligned} &j = c-1, ..., c-5\,, \\ &k = 1, ..., 10\ , \end{aligned} \tag{2}$$

where the γ_{ck} denote the 10 fixed effects.

Setting $j = c$ in the above yields the predicted, counterfactual, monthly mortality rates for cohort c

$$\hat{r}_{ak} = \hat{\beta}_c t_{ck} + \hat{\beta}_c t_{ck}^2 + \hat{\gamma}_k, \quad k = 1, ..., 10\,. \tag{3}$$

Then the ATE is calculated as:

$$\begin{aligned} \widehat{\Delta}_c &= \sum_{k=1}^{10} r_{ck} - \sum_{k=1}^{10} \hat{r}_{ck} \\ &= \sum_{k=1}^{10} (r_{ck} - \hat{r}_{ck}) \end{aligned} \tag{4}$$

This method can be illustrated graphically by observing age-specific mortality rates for cohorts before and after the shock. Figure shows these rates for the 1940 cohort and corresponding cohorts $c-1 = 1939, c-2 = 1938, \ldots c-5 = 1935$ for men and women in the US and France.

Oblique Approach

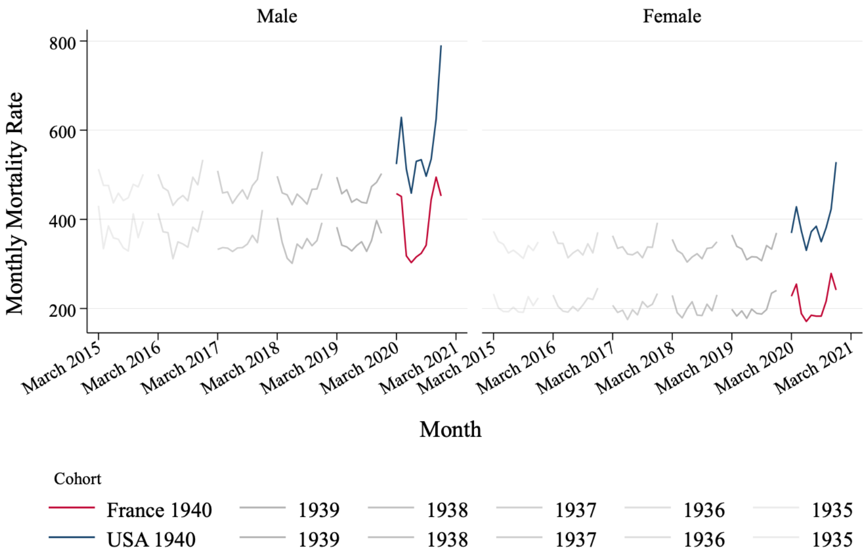
For the “oblique” approach, we use the five previous years of monthly mortality rates of cohort c, thus substituting single year ages $a, a-1, a-2, \ldots a-5$ in place of cohorts $c, c-1, \ldots c-5$. Thus Eqs. 2–4 can be rewritten as:

$$r_{jk} = \beta_a t_{jk} + \beta_c t_{jk}^2 + \gamma_k + \epsilon_{jk}, \qquad \begin{aligned} &j = a-1, ..., a-5\,, \\ &k = 1, ..., 10\ , \end{aligned} \tag{5}$$

and

$$\hat{r}_{ak} = \hat{\beta}_a t_{ak} + \hat{\beta}_a t_{ak}^2 + \hat{\gamma}_k, \quad k = 1, ..., 10\,. \tag{6}$$

Figure 1: Monthly mortality rates, Mar–Dec, for the 1940 and five earlier cohorts, Men and Women, USA and France



Then

$$
\begin{aligned}
\widehat{\Delta}_c &= \sum_{k=1}^{10} r_{ak} - \sum_{k=1}^{10} \hat{r}_{ak} \\
&= \sum_{k=1}^{10} (r_{ak} - \hat{r}_{ak}) \qquad (7)
\end{aligned}
$$

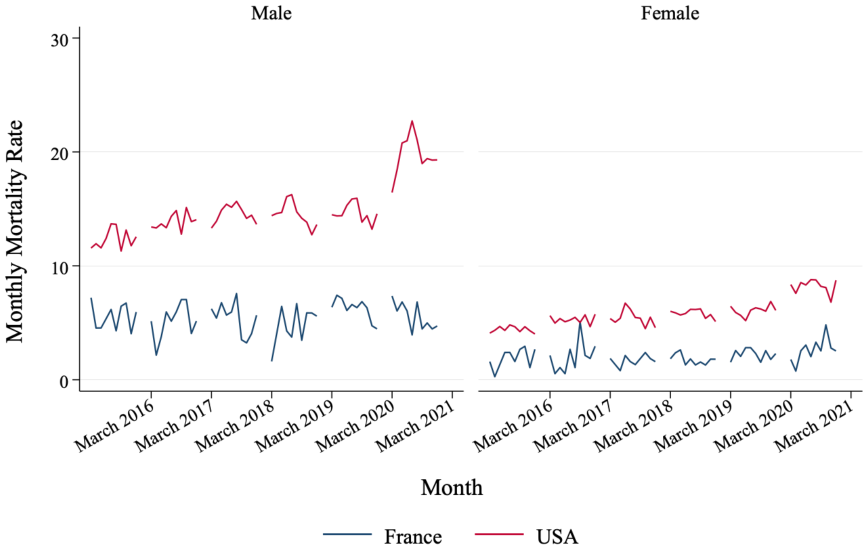
This method can be illustrated graphically by observing age-specific mortality rates for the 1940 cohort before and after the shock. Figure shows these rates for men and women in the US and France.

Extending to Multiple Covid Years

When extending treatment beyond 2020 to 2021, we extend the treatment period from 10 to 22 months. This requires two changes to the modeling strategy. First, it requires shifting the "control" years to one year earlier, thus $j = a-2, ..., a-6$. This is to observe cohorts over a longer pre-treatment period of consecutive months without overlapping with the treatment period.

Second, the fixed effect γk now takes values $1, ..., 22$. This continues to account for month-specific effects, while at the same time accounting for trends in the 22-month period. For the horizontal method, 12 of the 22 months will

Figure 2: Monthly mortality rates, Mar–Dec, 1940 cohort 2015–2020, Men and Women, USA and France



now overlap across adjacent cohorts. Since the deaths that occur in the same month but across adjacent cohorts will be at different ages, the fixed effect adjusts for monthly variation while continuing to allow for differences between cohorts.

Confidence Intervals

We rely on permutation methods to construct confidence intervals (CIs). These methods, rely on the statistical notion of exchangeability; that if samples are drawn from the same distribution, then randomly exchanging the observations from the samples does not, on average, change the characteristics of either sample (Fisher 1935). It follows that whether this null hypothesis is consistent with the observed data is testable by computing a test statistic (e.g. a difference in means) over all possible permutations of observations. Permutation tests are exact because it is possible to compute all possible permutations of observations, thereby allowing computation of the exact number of values in the permutation distribution that are more extreme than the observed statistic of interest. They are also distribution-free because the null requires only that observations in the two groups be drawn from a common distribution, with no restrictions on the form of that distribution.

In the case of covid effects on cohort mortality, the null hypothesis is that the average difference between the predicted values and the observed values (the residuals from the regression Eq. 3 or Eq. 5.) is the same in the pre-covid period and the post-covid period. Under the null hypothesis, exchanging the residuals from the post-covid period with those of the pre-covid period should not change the estimated ATE.

More precisely, consider a null that posits that the observations in B differ from those A by some constant μ, but that the observed y_A and $y_B^* = y_B - \mu$ are otherwise drawn from the same unknown F. Then under this null, $1 - \alpha$ permutation CIs can be constructed by finding the values $\mu_{\alpha/2}$ and $\mu_{1-\alpha/2}$ such that a proportion α of the permutation distribution lies between these two bounds (Garthwaite 1996; Ernst 2004). Note also that unlike frequentist CIs, permutation CIs need not be symmetric about point estimates.

We use packages developed by Nguyen (2009) to implement computationally-efficient procedures for obtaining permutation CIs.

Results

Figures 3–6 illustrate effects of the covid-19 pandemic on cohorts of men and women born 1933–2015 in the US and France, using both the oblique and horizontal methods. In line with existing period estimates, effects on cohorts in the US were larger than for those in France, for both men and women. There are two components to this difference. First, impacts were significant among cohorts in the US that were younger when the pandemic began. There were significant impacts on French men born through 1983, and on French women born before 1960. For French cohorts born after these years, we estimate that the pandemic had mortality effects that were not statistically different from what would have been expected given existing trends. The picture is sharply different in the US. US cohorts of both men and women born all the way into the mid 2000's experienced higher mortality than expected.

The differences in effects across countries were largest in absolute terms for men, but in relative terms for women. This is primarily because there was practically no effect of Covid on the mortality of French women born after the late 1950's. For French men, effects are statistically different from zero for cohorts born up to about 1970. In the US, even cohorts born in the early 2000's were impacted.

For older cohorts effects were more similar across countries, though they remained consistently larger in the US. The 95% confidence intervals on the estimates for US and French men overlap for a number of cohorts, particularly those born in the 1930's. But for women there is practically no overlap. Covid's impact on the mortality of US women was was unambiguously far worse than on French women for almost every cohort.

For the most part, the horizontal and oblique methods performed similarly, with a few exceptions. Effect sizes from the horizontal method often exhibit more variation, except perhaps with respect to men in 2021. The horizontal method also, on average, estimated slightly smaller effects.

Figures 5 and 6 decompose the impacts of the pandemic into impacts in years 2020 and 2021. Figure 5 shows how effects evolved from 2020 to 2021 for cohorts born 1933-1960. For these cohorts, effects were relatively evenly divided between 2020 and 2021. Figure 6 shows the same set of results for cohorts born 1961–2015. There was very little effect of the pandemic on the mortality of French cohorts, but where there was mortality it too was evenly divided by year. For the US, however, effects on younger cohorts were considerably larger in the second year than in the first. Thus the impacts on younger US cohorts were driven by 2021.

Figure 3: Cumulative Effect of Covid-19 Pandemic on Cohort Mortality for Men, US and France, March 2020–December 2021

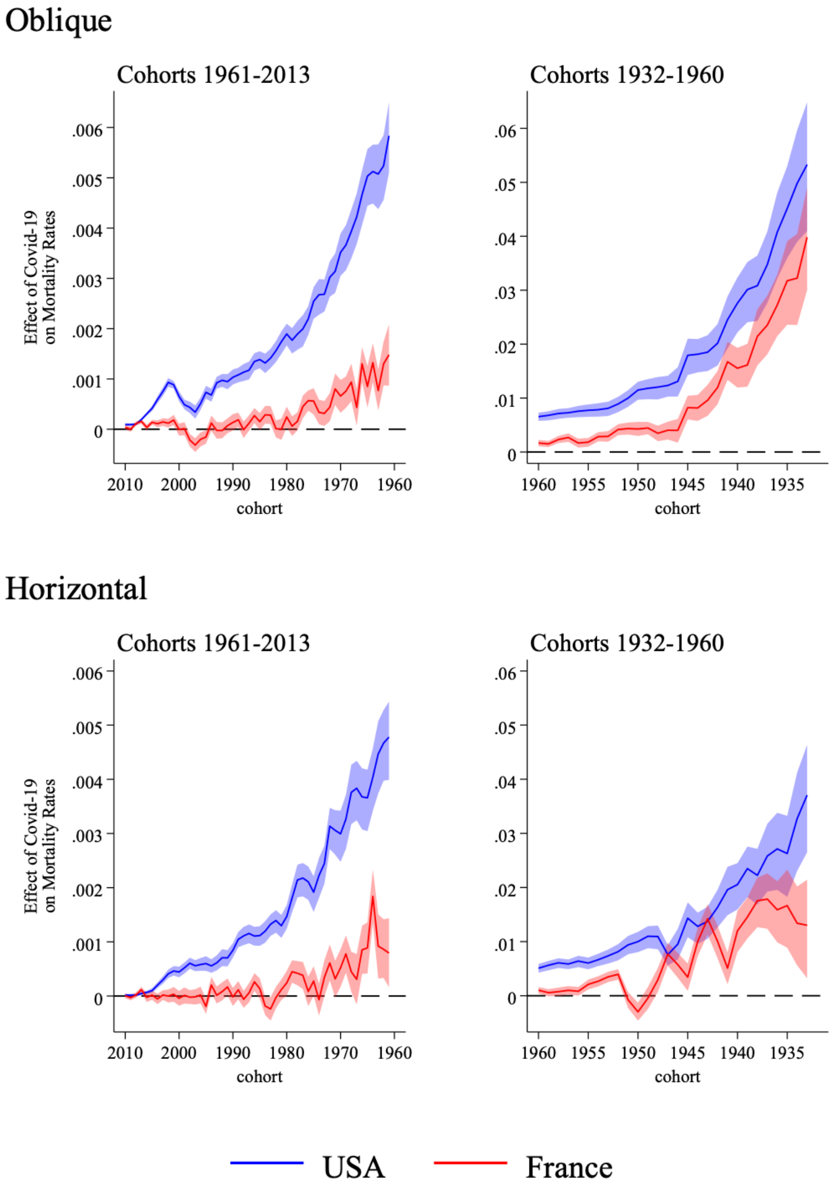


Figure 4: Cumulative Effect of Covid-19 Pandemic on Cohort Mortality for Women, US and France, March 2020–December 2021

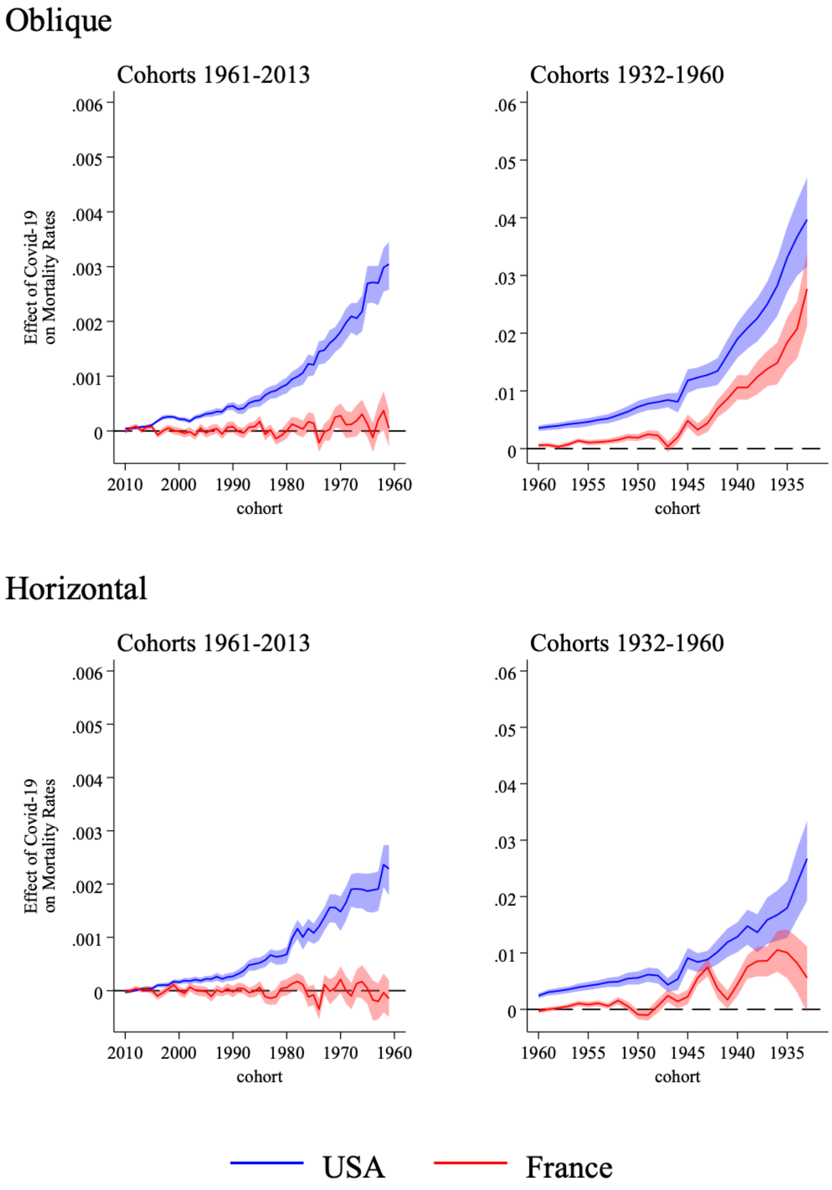


Figure 5: Decomposition of Effect of Covid-19 Pandemic on Cohort Mortality for Cohorts 1933–1960, US and France, Men and Women, March 2020–December 2021

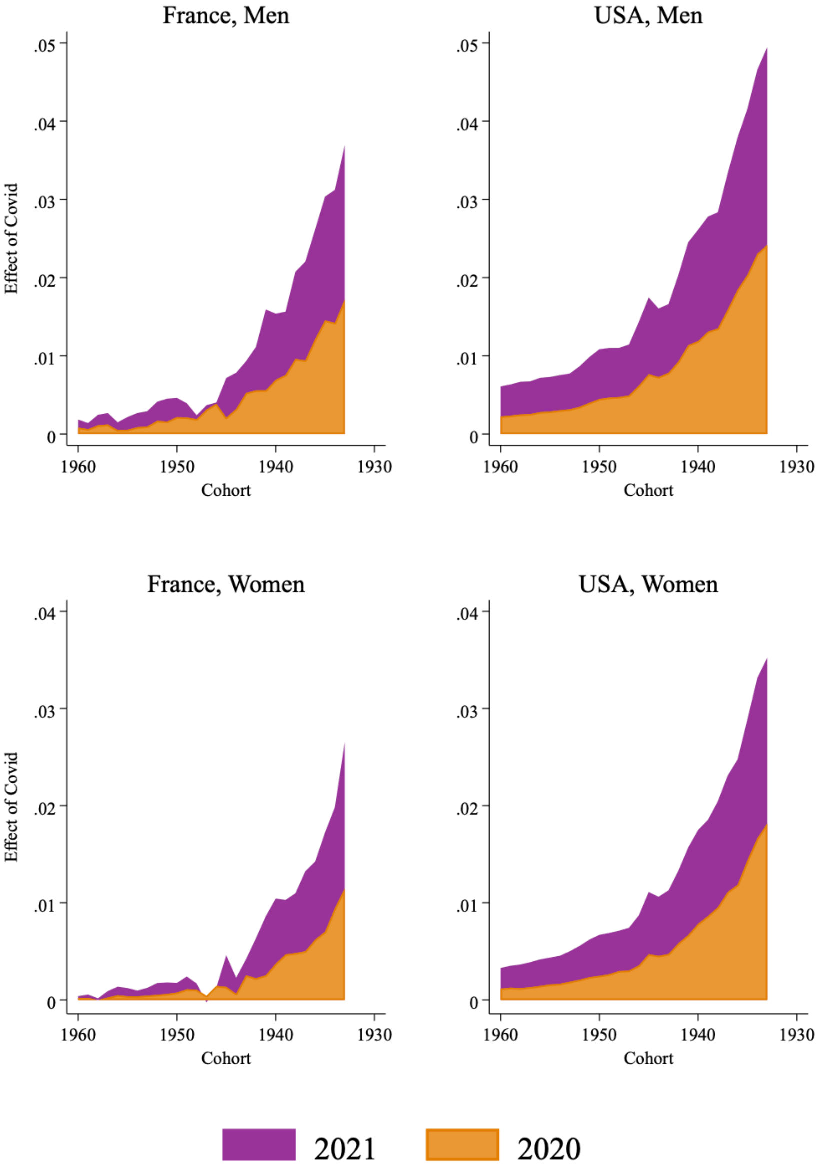
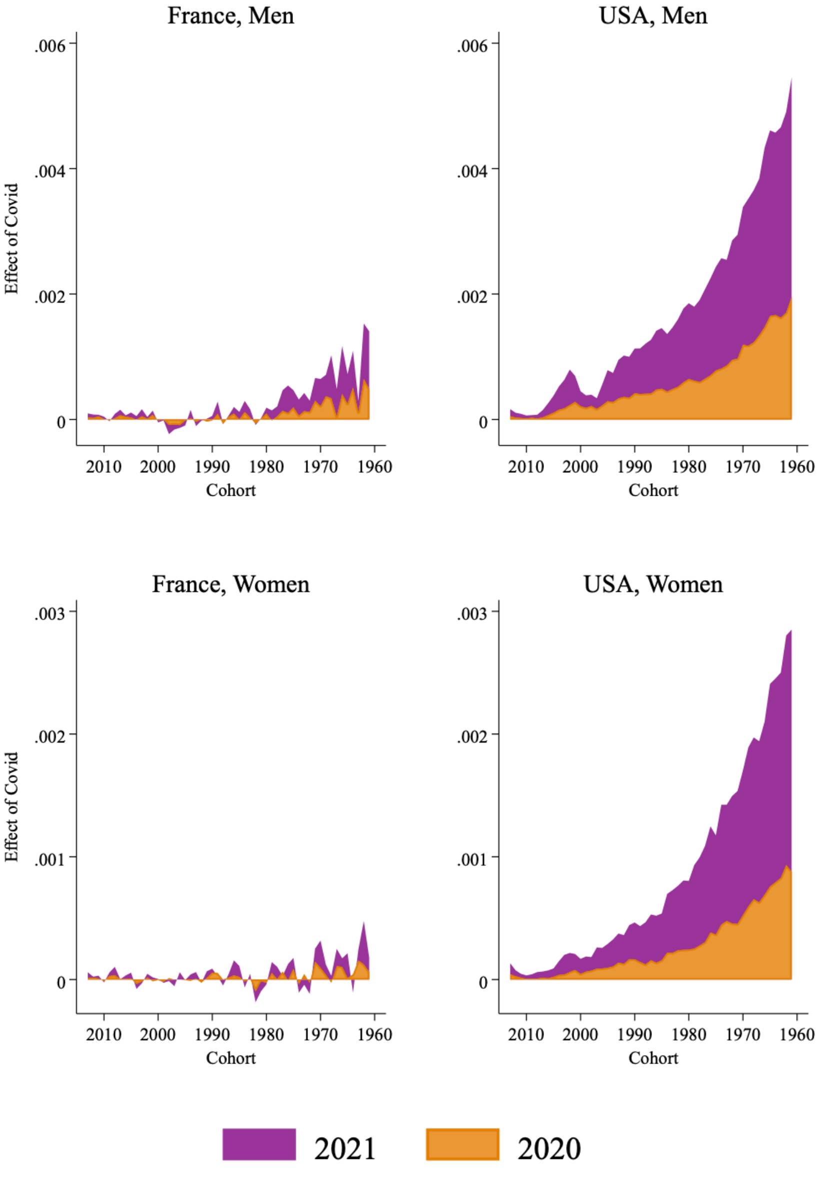


Figure 6: Decomposition of Effect of Covid-19 Pandemic on Cohort Mortality for Cohorts 1961–2015, US and France, Men and Women, March 2020–December 2021



Discussion

In line with past literature, we find substantial impacts of COVID (2020-2021) on mortality in the US and France, with much larger impacts in the US than in France. Beyond this findings, a few results stand out.

First, we find that the effects on French men emerged for younger cohorts than has previously been reported. While Moulaire et al. (2025) found impacts on men who were age 50+ when the COVID pandemic occurred in 2020, we find impacts on cohorts of men born on or before 1983, who were in their late 30's or older at the start of the pandemic. These effects are statistically significant at the 95% level. We did not observe corresponding patterns of effects on French women. The mortality of cohorts of French women born after 1960 was not affected by the pandemic.

Second, we also find statistically significant and substantively important impacts on cohorts of US men and women who were very young (15+) at the start of the pandemic. This too is a novel result, as earlier accounts found effects only at older ages (Foster et al. 2024) or on aggregated age groups (Rossen et al. 2022). The substantial effects on the mortality of US cohorts who were very young has implications for aggregate measures of cohort survival, such as the Cross-Sectional Average Length of Life (Guillot 2003), because large effects on the survival of cohorts when they are young have outsize influence on aggregate survival statistics.

There are at least two possible explanations for the differences between our estimates and those from period analyses. A first explanation is that our estimates are aggregated over a 22-month period (March 2020–December2021). Even though individual monthly impacts may be small and variable, the aggregate is substantial, so we are able to detect smaller effects even on individual cohorts. A second is that the cohort design, in which mortality effects accumulate across adjacent ages, accounts for changes in cohort size and in cohort aging. Our results are not contaminated by changes in the exposure variable (except to the small extent that our estimates of monthly cohort populations may be biased).

Our cohort methods have a number of advantages over traditional period measures of excess mortality. First, unlike period measures that provide snapshots at discrete time points, our cohort approach tracks the accumulated mortality experience of specific birth cohorts as they age through the pandemic. This allows us to assess how COVID-19 has permanently altered the mortality trajectories of cohorts at different life stages.

Second, our cohort methods represent effects on real, not synthetic, cohorts. Cohorts represent coherent demographic entities—the same individuals (minus deaths, plus migration) followed over time. Our estimates are therefore not subject to distortions from population growth, aging, or changing age structure that can influence period-based excess death counts. Our cohort approach measures actual mortality experiences of real populations rather than constructing hypothetical synthetic cohorts, providing a more accurate assessment of the pandemic's demographic consequences than period measures which are difficult to interpret outside of the cross-section.

Third, our cohort estimates facilitate more meaningful international comparisons between populations that have different age distributions because cohort measures follow specific birth cohorts rather than age groups at a point in time. Period estimates of excess deaths can be heavily influenced by whether a country has proportionally more people in high-risk age groups at the time of the mortality shock. By following specific cohorts through time, our estimates are intrinsically comparable across populations regardless of their current age composition.

Fourth, the cohort design naturally accumulates small age-specific effects that period approaches might miss when examining single calendar years or age groups in isolation. By aggregating mortality effects across multiple adjacent ages within a cohort over the 22-month pandemic period, our approach is able to detect impacts on younger populations. This allowed us to identify significant mortality effects among US cohorts born into the early 2000s and French men born through 1983—younger than previous studies using period data had been able to detect with statistical confidence.

Fifth, our methodology relies on minimal, transparent assumptions to obtain plausibly causal estimates. Our approach models counterfactual cohort-specific mortality trajectories in an easily replicable and communicable way. This approach allows us to account for secular trends in mortality improvement that may vary by cohort without reliance on opaque algorithms, and allows us to easily examine deviations from expected outcomes. Our methodology also produces appropriately conservative confidence intervals via permutation tests, incorporating genuine uncertainty in counterfactual mortality. Our methodology thus has broad application to future analyses of mortality shocks.

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Online Supplement

Estimates in Tabular Form