Heterogeneity in Damages from a Pandemic.

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Abstract

We use nationally-representative linked survey and administrative data to document socio-economic and demographic disparities in the economic and health effects of the COVID-19 pandemic in the United States during its first two years. Impacts on all-cause mortality and on employment were concentrated in the same racial/ethnic, education, industry, and occupation groups. Black-White and Hispanic-White disparities in mortality impacts narrowed over the two years, but educational disparities persisted. For economic impacts, only Hispanic-White disparities narrowed. Lower-income individuals experienced greater mortality impacts and this gradient steepened in the second year. Our findings, using consistent methods and measures, highlight the pandemic's heterogeneous impacts.

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1 Introduction

The United States has long exhibited striking variation in health and economic well-being across demographic groups, including education, income, race, and ethnicity.[1] The COVID-19 pandemic – which was both a health and an economic crisis – was no exception.

To characterize its heterogeneous impacts, we assemble rich, nation-wide, representative data on both economic and health damages from the pandemic. We document how the economic and health impacts of the pandemic varied across a wide set of pre-pandemic socio-economic characteristics, as well as how these disparities evolved over the course of the first two full years of the pandemic in the U.S. – from March 2020 through February 2022. We define the pandemic's health damages by the increase in all-cause annual mortality relative to what was expected based on the historical linear trend. We define the pandemic's economic damages by the average monthly decline in the employment-to-population ratio, again relative to the historical linear trend. We present estimates of average impacts over the first two years of the pandemic, and also show how these impacts evolved during this time period.

We leverage linked administrative and survey data for the mortality analysis. Specifically, we use the U.S. Census Bureau's version of the Social Security Administration's Numerical Identification database (Census Numident), which provides individual-level data on the date of death (if applicable) for the near universe of the U.S. population. We link these administrative all-cause

[1] There is a vast literature documenting these disparities and investigating causal origins. Examples of the literature on health variation include Fuchs (1974), Case et al. (2002), Deaton (2002), Williams and Jackson (2005), Meara et al. (2008), Currie (2009), Boustan and Margo (2015), Currie (2011), Case and Deaton (2015), Chetty et al. (2016), Lleras-Muney (2022), Polyakova and Hua (2019), Chetty et al. (2020), Bailey et al. (2021), Finkelstein et al. (2021), Schwandt et al. (2021), and Novosad et al. (2022). Examples of the literature on variation in economic well-being include Hoynes et al. (2012), Bayer and Charles (2018), and Derenoncourt et al. (2022).

mortality records to a record of race/ethnicity from the 2010 Decennial Census, and to a rich set of additional, pre-pandemic socio-economic covariates—including education, occupation, industry, and income—for the subset of the population with records in the American Community Survey (ACS). For the employment analysis, we use the IPUMS Current Population Survey (CPS) (Flood et al. 2022). This provides individual-level employment data, together with socioeconomic and demographic covariates, for a representative sample of U.S. households.

All of our analyses are limited to individuals ages 11-99, since information on race and ethnicity is not available in the 2010 Census for children who were under 11 years during the pandemic. For many of our analyses, we further concentrate on the 'working age' population, defined as individuals ages 25-64. We do this for two reasons. First, this restriction is a natural one when examining economic (i.e., employment) damages. Second, some of our covariates – particularly industry and occupation – are not defined or well-measured for the non-working age population; therefore we also limit our mortality analyses of these sub-groups to the working-age population. For a similar reason, our mortality analyses by education focus on individuals ages 25-99, so that we are likely to observe completed educational attainment.

In aggregate, we estimate that the first two years of the pandemic were responsible for an average of 20.5 excess deaths (from any cause) annually per 10,000 people ages 11-99, and for an average decline in monthly employment of 4.2 per 100 people ages 25-64. Excess deaths were increasing in age and concentrated in the older adult (65+) population, while employment losses among working-age adults were decreasing in age. Aggregate employment damages were the largest in the first month of the pandemic and declined gradually over the course of the pandemic's 24 months. The recovery was not complete at the end of the two years, with 1.8 jobs per 100 people ages 25-64 missing in February 2022. In contrast, the time pattern of excess mortality was not monotone, with the highest spikes of excess mortality appearing in December-January of 2021 and January of 2022, with more than 3 monthly excess deaths per 10,000 at each of these peaks.

These mortality increases and employment declines varied substantially across different groups in the population. Consistent with the existing literature (discussed below), we find substantial disparities in both health and economic damages across racial and ethnic groups, with non-Hispanic Black and Hispanic individuals affected more than White and Asian individuals in both economic and mortality terms. We also document that the disparities in mortality impacts by race and ethnicity substantially declined over the first two years of the pandemic, as did the Hispanic-White gap in economic damages, while the Black-White gap in economic damages persisted.

But disparities in damages were not unique to racial and ethnic divides. We also document substantially higher economic and health damages among those with less education, those working in service occupations or entertainment, or those not working in jobs amenable to working from home. Along all of these measures of socio-economic status, health and economic damages tended to be concentrated in the same groups. Differences in damages by education are particularly striking. Excess age-adjusted mortality (among ages 25-99) varied from around 7 to 9 per 10,000 annually for those with more than a Bachelor's degree to around 57 per 10,000 annually for those with less than a high school degree; likewise the average monthly decline in the employment to population ratio (among ages 25-64) was about 1-2 per 100 for those in this highest educational attainment category, compared to over 5 per 100 for those without a high school diploma. The educational divide in the incidence of economic and health damages from the pandemic persisted throughout the first two years.

Finally, we document a strong negative gradient between income and excess mortality. For example, among those ages 25-64, individuals living in households with annual income at 700-750% of poverty (ca. $142,345 to $152,500 for a family of three in 2019) had 5.2 per 10,000 excess age-adjusted deaths in 2020 while those living with income close to poverty (ca. $20,335 for a family of three in 2019) had 13 per 10,000 excess deaths.[2] This negative excess-mortality

[2]Income levels use weighted average (across households of different composition) poverty thresholds as reported by the U.S. Census Bureau: https://www.census.gov/data/tables/time-series/

- income gradient steepens in the second year of the pandemic. Continuing our example above, excess age-adjusted deaths among those with incomes at 700-750% of poverty did not increase (and indeed may have declined slightly) from the first to the second year of the pandemic, but for those at the poverty level excess deaths increased substantially, from 13 to 21 per 10,000. To our knowledge, this is the first evidence of the national income-excess mortality gradient during the pandemic, beyond its initial months. Our findings mirror the strong, negative mortality-income gradients that are well-known in the literature (Chetty et al. 2016; Udalova et al. 2022).

Related literature Our paper contributes to several related literatures. Most narrowly, it adds to the large literature on the health and economic impacts of the COVID-19 pandemic in the United States. This literature, which we do not attempt to fully summarize here, has documented substantial mortality impacts of the pandemic, with more than 6 million years of life estimated to be lost in the U.S. in 2020 (Cronin and Evans 2021) and a loss in quality-adjusted years of life equivalent to half of the annual burden of all cancers combined (Reif et al. 2021). The economic consequences of the pandemic were similarly dramatic, with substantial decreases in consumer spending and business revenues (Chetty et al. 2024), large numbers of layoffs (Forsythe et al. 2022), drastic declines in hours worked (Bartik et al. 2020), and drops in the employment-population ratio (Montenovo et al. 2022; Cowan 2020) during the initial months of the pandemic, as well as continued absences from the labor market in subsequent months (Davis et al. 2021; Cutler 2022; Goda and Soltas 2022; Ziauddeen et al. 2022).

While almost all groups suffered lost years of life due to the pandemic, it has been well-documented that racial and ethnic minorities - including Black people, Hispanic people, and American Indian and Alaskan Native people were disproportionately affected. Minorities experienced greater all-cause mortality during the pandemic's initial months (Hatcher et al. 2020; Miller et

demo/income-poverty/historical-poverty-thresholds.html.

al. 2021; Polyakova et al. 2021; Rossen et al. 2021; Shiels et al. 2021; Mackey et al. 2021), and these gaps persisted through the pandemic's first and, in some estimates, second years (Aburto et al. 2022; Ruhm 2022; Foster et al. 2024; Ruhm 2023).[3] The economic consequences too have disproportionately been felt by racial and ethnic minorities. Racial and ethnic minorities were more likely to become unemployed or leave the labor force in the first few months of the pandemic (Cowan 2020; Montenovo et al. 2022; Lee et al. 2021; Cortes and Forsythe 2023; Polyakova et al. 2020; Couch et al. 2020). Even a full year into the pandemic, non-White workers were more likely than White workers to experience employment declines (Cortes and Forsythe 2023). Our results confirm the findings in this rich literature, providing a unified approach for comparing the incidence of disparities in economic and health damages across groups and over time.

In comparison to the literature on racial and ethnic disparities, evidence on the differential impact of the pandemic along measures of socio-economic status has been sparser. The literature has documented lower excess all-cause mortality in 2020 for those with a BA compared to those without a BA (Case and Deaton 2021), as well as a lower probability of having been diagnosed with COVID-19 among individuals with more education (Rothwell and Smith 2021). Our linkage of the national administrative data on mortality to pre-pandemic socio-economic characteristics in the American Community Survey allows us to replicate and extend this analysis for additional socio-economic measures and for the full first two years of the pandemic. Closest to our work is Miller et al. (2021), who use similar linkages to document national differences in all-cause excess mortality in the first two quarters of 2020 by income and occupation. In addition, a series of studies by Chen and colleagues (Chen, Glymour, Catalano, et al. 2021; Chen, Glymour, Riley, et al. 2021;

[3] It has also been documented that minorities had higher recorded COVID-19 (rather than all-cause) mortality rates during the initial months of the pandemic (Bassett et al. 2020; Ford et al. 2020); these gaps declined but were not eliminated during the pandemic's second year (Aschmann et al. 2022; Lundberg et al. 2022; Truman et al. 2022).

Chen, Matthay, et al. 2022; Chen, Riley, et al. 2022) as well as Schwandt et al. 2022 use detailed data from a single state – California – to document differences in mortality damages by education, occupation, and area income at the onset and over the first two years of the pandemic. Our national estimates of disparities in excess mortality for the first two years are qualitatively consistent with these studies.

We further enrich the work on socio-economic disparities in the pandemic's mortality impacts by asking whether the groups who experienced the highest mortality impacts also experienced greater economic impacts. The existing literature on socio-economic gradients in the economic damages of COVID-19 is more limited. Studies have shown that those with lower levels of education were also more likely to lose their jobs in the pandemic's initial months (Adams-Prassl et al. 2020; Lee et al. 2021; Cowan 2020) and were less likely to participate in the labor force, less likely to be at work, and more likely to be unemployed in 2020 and 2021 (Rothwell and Smith 2021; Goldin 2022; Cortes and Forsythe 2023; Forsythe et al. 2022).

Our findings also contribute to a broader literature examining the relationship between economic conditions and health. This literature has highlighted the complex ways in which aggregate-level economic downturns and individual-level job losses may impact health (Ruhm 2000; 2005; Sullivan and Von Wachter 2009; Ruhm 2015; Stevens et al. 2015; Schwandt and Von Wachter 2020; Finkelstein et al. 2024), and, conversely, how shocks to population health may impact the economy (Adda 2016; Barro et al. 2020; Correia et al. 2022). It has also documented heterogeneity in the prevalence and incidence of health and economic shocks across different groups. For example, Alsan et al. (2021) show that historical health shocks typically had a larger effect on Black than White Americans and Hoynes et al. (2012) show that the economic consequences of recessions have disproportionately impacted racial and ethnic minorities. Those with less education also appear to be more adversely affected economically by recessions (Hoynes et al. 2012), although their health may benefit more (Finkelstein et al. 2024). Naturally, our findings are specific to a particular period in the history of a particular infectious disease. Nonetheless, they complement a growing literature that emphasizes the importance of non-medical factors in driving health inequality (e.g., Fuchs 1974; Case and Deaton 2015; Chetty et al. 2016; Finkelstein et al. 2021; Chen, Persson, et al. 2022).

The rest of the paper proceeds as follows. We describe our data sources, measurement, and the econometric approach in Section 2. Section 3 presents our estimates of damages across groups. Section 4 briefly concludes.

2 Data and Measurement

2.1 All-Cause Mortality

We measure the health impact of the pandemic by its impact on all-cause mortality. This measure is not contaminated by the measurement error in the choice of what to label a "COVID" death (which could systematically vary across groups), and also captures potential indirect impacts of the pandemic on mortality.[4]

We use mortality records from January 2011 through February 2022 from the Census Bureau's version of the Social Security Administration's Numerical Identification (Census Numident) database. The Census Numident includes individual-level data with the date of birth and date of

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[4]For example, indirect effects due to the declines in economic activity (Ruhm 2000; 2005; 2015; Stevens et al. 2015; Finkelstein et al. 2024), effects of individual job loss (Sullivan and Von Wachter 2009), avoidance of medical care (Zhang 2021; Ziedan et al. 2022), or changes in health behaviors such as drug use (Friedman and Akre 2021; Ruhm 2023). Indeed, previous research looking at excess mortality by cause of death has found that the pandemic increased deaths from several non-COVID causes, including deaths from heart disease, Alzheimer's disease, diabetes, strokes, alcohol use, drug use, vehicles, and homicides, as well as deaths during childbirth (Ahmad and Anderson 2021; Woolf et al. 2021; Hoyert 2022; Ruhm 2023).

death (if deceased) for all people with a U.S. Social Security number (SSN). More information about the measurement of mortality in the Census Numident file is available in Finlay and Genadek (2021) and in Appendix A.1. We define the all-cause mortality rate to be the number of people in a well-defined group who died during a given period (either a month or a twelve-month period) divided by the number of people in that group who were alive at the beginning of the period. A key advantage of the Census Numident data is that they provide an internally consistent measure of both the numerator and denominator, as they record not only deceased but also living people at any given moment.

For a subset of the Census Numident population, we obtain additional socio-economic information by merging in responses from the American Community Survey (ACS). The ACS is administered each year to approximately 3 million housing units, and contains rich self-reported demographic variables for all individuals in the household. The ACS surveys a different random sample of U.S. households each year. For each calendar year t, we select the individuals in the Census Numident who were alive on March 1 of year t and for whom we observe an ACS response in at least one year from $t-6$ through $t-2$. For example, for individuals in the Census Numident who are alive as of March 1, 2020, we link ACS responses for each year from 2014-2018. In the rare case that an individual was surveyed more than once during years $t-6$ through $t-2$, we keep the most recent response. Using data from lagged ACS waves avoids capturing responses that are endogenous to the effects of the pandemic in years 2020 and 2021; using data from multiple lagged waves lets us increase our sample size. For those individuals with ACS responses, we retain information on the level of completed education, family income relative to poverty, industry, and occupation.[5] Appendix A.3 provides more information about these variables. For any analyses using the merged ACS-Numident dataset, we use the ACS person sampling weights.

[5]For additional analyses in the Appendix, we also use information on disability status, living arrangements, and whether the person had health insurance.

Sample Restrictions The starting point of our analytic data is the set of individuals in the Census Numident data who were alive on January 1, 2011 (defined as not having a recorded year of death in 2010 or earlier). We keep individuals for whom we can observe race or ethnicity in either the 2010 Decennial Census or the Census Bureau's 2010 Modeled Race File. We can distinguish between Hispanic origin and non-Hispanic origin; within non-Hispanic origin we can further distinguish between White, Black, Asian, American Indian and Alaska Native, Native Hawaiian and Other Pacific Islander people, and people of some other race or two or more races. We exclude individual-years with an address outside of the 50 U.S. states or the District of Columbia, or outside of the age range of 11 to 99. The lower age restriction arises because from the 2010 census we cannot obtain race/ethnicity information for individuals born after 2010. The upper age restriction aims to restrict the measurement error from historic death undercounts in Census Numident. Appendix A.1 provides more detail on all sample restrictions we impose to ensure that we limit our analysis to data where we can reliably observe mortality. Appendix Table C.1 reports how these restrictions change the sample size.

2.2 Employment-to-Population Ratio

We measure economic damages from the pandemic by its impact on the employment-to-population ratio. We use self-reported employment from the publicly available Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) from 2011 to 2022, which harmonizes data across months of the CPS. The CPS samples approximately 60,000 U.S. households each month (one adult responds for all eligible members of the household); households are sampled for four consecutive months, and then another four consecutive months eight months later. We use data from March 2011 through February 2022.

We define the employment-to-population ratio in a given month as the number of people in a well-defined group who reported working either part-time or full-time during the week before the month's survey week, divided by the total number of people surveyed in the same group that month. For each group, we define an annual employment-to-population ratio as the average (across individuals surveyed in that year) proportion of survey months that an individual reported that they were employed. Our annual employment-to-population measure therefore captures an average of monthly employment rates, in contrast to our annual mortality measure which measures cumulative mortality over the year.

The CPS provides self-reported demographic measures, including race/ethnicity, as well as the socio-economic measures similar to those in ACS – education, income, industry, and occupation. For those unemployed or not in the labor force at the time of the survey, the CPS records the most recent industry and occupation. Income is reported for the time period of 12 months prior to the survey. Appendix A.4 provides the full list of variables and their definitions. Unlike in our mortality analysis, in which all variables related to socio-economic status are measured pre-pandemic, a drawback to our analyses using the CPS is that most socio-economic variables are measured contemporaneously with employment, and may be affected by the pandemic. This is particularly problematic for income, which is why our main analysis of pandemic damages by income looks only at mortality damages.

Sample Restrictions We limit our CPS sample to the non-military and non-institutionalized population ages 25 to 64 in any of the 50 United States or the District of Columbia. We use the CPS "final basic" survey weight throughout the analysis to account for sampling procedures and non-random response.

2.3 Summary Statistics

Table 1 reports summary statistics covering the first two years of the pandemic (March 2020 - February 2022) for the demographic variables we can observe in the full Numident dataset, the linked ACS-Numident subset of data, and the CPS, by age groups 11 to 99 (columns 1 and 2) and 25 to 64 (columns 3, 4 and 5). For ages 11 to 99, we have 43.1 million person-year observations in the ACS-Numident linked subset of data, which is 9% of the full Census Numident dataset in Column (1). The distribution of demographics in the ACS-Numident linked data is very similar to the full Numident. In the linked ACS-Numident data, the average person is 46 years old; 48% of individuals are male. 14% of observations are for Hispanic people. 67% are non-Hispanic White, 12% are non-Hispanic Black, 5% are non-Hispanic Asian, 0.8% are non-Hispanic American Indian or Alaskan Native, 0.2% are non-Hispanic Hawaiian or Pacific Islander, and 0.4% have a record of "other or two or more races." The distribution of demographics is very similar in the 25 to 64 age range (except being one year younger on average), where we have 23.9 million person-year observations (accounting for 8% of the full Census Numident for this age range in Column (3)).[6]

The last column of Table 1 provides summary statistics for the CPS sample used in the analyses of economic damages. We have approximately 429,000 person-year observations in the sample for years 2020 and 2021. The composition of the CPS sample is fairly similar in age and sex to ACS-Numident data; the average individual in the CPS sample is 44 years old and 49% are male. There are more notable differences in the composition of race and ethnicity. The CPS sample has a lower share of non-Hispanic White people (59% in the CPS sample compared to 66% in the ACS-Numident data for ages 25 to 64) and a higher share of Hispanic people (19% in the CPS sample relative to 14% in the ACS-Numident data).

2.4 Econometric Framework

Let y_{imt} be an indicator variable for individual i's outcome in month m of year t. For the mortality analysis, this is an indicator for whether the individual died from any cause during month m of year t. For the employment analysis it is an indicator for whether the individual was employed during month m of year t. For both outcomes, the indicator is defined only for people alive at the start of

[6]The distribution remains similar despite the large difference in age ranges, as we are dropping both younger and older cohorts when switching from 11-99 to 25-64 age range.

the month and year in question. In all cases, we define a "year" to be the 12 month period from March to February; the first "year" of the pandemic ($t = 2020$) is thus the 12 months between March 2020 and February 2021 and the second "year" of the pandemic ($t = 2021$) is the 12 months between March 2021 and February 2022. These two years roughly correspond to one year prior to and one year after the introduction of vaccinations.[7]

We measure the impact of the pandemic by estimating the following linear probability model on monthly data from January 2011 through February 2022:

$$y_{imt} = \alpha_m + \beta \times t + \sum_{\mu=m_{-2}}^{\mu=m_{24}} \phi_\mu \mathbb{1}_{\{mt=\mu\}} + \epsilon_{imt} \tag{1}$$

Here, α_m are calendar month fixed effects that account for seasonality; β measures the common annual linear time trend across all months. The sum term indexes over separate indicator variables for 24 months of the pandemic (from March 2020 (m_1) through February 2022 (m_{24}), and the two months prior—from January 2020 (m_{-2}) and February 2020 (m_{-1}). The estimated ϕ_μ coefficients are our measure of damages. They capture deviations from the historical time trend in the months right before and during the COVID-19 pandemic. This measure of damages is equivalent to comparing observed monthly outcomes (mortality or employment) in each month from January 2020 through February 2022 to the predicted level of mortality or employment based on the historical trend, $\hat{y}_{mt} = \hat{\alpha}_m + \hat{\beta} \times t$. We use heteroskedasticity-robust standard errors, as well as relevant survey weights when appropriate.[8]

We also estimate an analogous linear probability model at the annual level to summarize out-

[7]Vaccinations began in December 2020. In February 2021 the share of population that was "fully vaccinated" crossed 5% ("CDC COVID Data Tracker: Vaccination Trends" 2022).

[8]Using survey weights corrects for some of the selection bias attributable to non-random response rates and ACS and CPS. For computational reasons, when we are using the full Census Numident file (rather than the subset that is linked to the ACS) we estimate the mortality regres-

comes over the course of the pandemic's first two years:[9]

$$y_{it} = \alpha + \beta \times t + \sum_{\tau=2020}^{\tau=2021} \theta_\tau \mathbb{1}_{\{t=\tau\}} + \epsilon_{it} \tag{2}$$

Here, α is a common intercept and β measures the common annual linear time trend. θ_{2020} and θ_{2021} are the coefficients of interest and measure how much the outcomes in 2020 and 2021 pandemic years deviated from the historical time trend. The predicted outcome based on the historical time trend can in turn be computed for any year t as $\hat{y}_t = \hat{\alpha} + \hat{\beta} \times t$. We again use heteroskedasticity-robust standard errors, as well as relevant survey weights where appropriate.[10]

The construction and the interpretation of annual *economic* damages differs from annual *mortality* analyses, as there is no natural "cumulative" analogue of annual employment. For mortality estimates, we define y_{it} to be the annual mortality rate. However for employment estimates, we define y_{it} to be the average of y_{imt} indicators across all months m in year t in which person i was surveyed. Thus we estimate the annual total mortality damages but the average monthly employment damages for the year.

To estimate gaps in economic and health damages across different demographic groups (such as by race/ethnicity or by measures of socio-economic status), we allow for all slopes and intercepts

sion in equation 1 using data grouped by year-month-race-sex-county, weighted by the group size. This produces identical point estimates as the individual-level regression, but different standard errors. The latter are equivalent to the standard errors from an individual-level regression clustered at the year-month-race-sex-county level.

[9] Recall year t indexes data from March of that calendar year through the following February.

[10] For computational reasons, when we are using the full Census Numident file (rather than the subset that is linked to the ACS) we again estimate the mortality regression in equation 2 using data grouped by year-race-sex-county, weighted by the group size.

in equations 1 or 2 to be group-specific. This enables us to recover *gaps* in economic and health damages of one group relative to the reference group, and also allows us to compute the *level* of economic and health damages separately for each group. Given the well-documented differences in the age distribution across the different groups we consider and the age-gradients in the pandemic damages (Ford et al. 2020; Polyakova et al. 2020; Alsan et al. 2021; Polyakova et al. 2021, see also Appendix Table C.2), we further allow for differences in levels of each outcome by age group, as well as separate effects of the pandemic by age group.[11]

Specifically, at the annual level we estimate:

$$y_{i(\rho)t} = \alpha_\rho + \gamma_a + \beta_\rho \times t + \sum_{\tau=2020}^{\tau=2021} \left(\theta_{\rho\tau} \mathbb{1}_{\{t=\tau\}} + \lambda_{a\tau} \mathbb{1}_{\{t=\tau\}} \right) + \epsilon_{it} \quad (3)$$

where we let ρ index different categories of each demographic group (e.g., different education levels, or different racial/ethnic groups). Here, α_ρ denotes a group-specific intercept, and β_ρ denotes the group-specific linear time trend. Analogous to the aggregate estimates in equation 2, our primary coefficients of interest are $\theta_{\rho,2020}$ and $\theta_{\rho,2021}$, which now measure the group-specific deviations from the (group-specific) historical trend in the outcome (relative to an omitted reference group). We also allow the levels of each outcome and the effects of the pandemic years to differ across the age groups, with γ_a denoting a vector of fixed effects for five-year age bins, and $\lambda_{a,2020}$ and $\lambda_{a,2021}$ denoting these indicators for five-year age bins interacted with indicators for years $t = 2020$ and $t = 2021$. We report the age-adjusted excess damage for a group ρ in 2020 as $\theta_{\rho,2020} + \sum_a Pr(a) \times \lambda_{a,2020}$ and the age-adjusted excess damage in 2021 as $\theta_{\rho,2021} + \sum_a Pr(a) \times \lambda_{a,2021}$, where $Pr(a)$ is the empirical share of the sample *among all groups* belonging to age bin a. The average level of damage during the first two years of the pandemic for a group ρ is then the

[11] In practice, however, the qualitative results are not sensitive to this age adjustment. For unadjusted group-specific estimates from the pandemic's first year, see the working paper version Finkelstein et al. 2022.

average of its 2020 and 2021 damages.

To examine how gaps across groups change by month, we also estimate a monthly version of Equation 3:

$$y_{i(\rho)mt} = \alpha_{\rho m} + \gamma_a + \beta_\rho \times t + \sum_{\mu=m_{-2}}^{\mu=m_{24}} \left(\phi_{\rho\mu} \mathbb{1}_{\{mt=\mu\}} + \lambda_{a\mu} \mathbb{1}_{\{mt=\mu\}} \right) + \epsilon_{imt} \tag{4}$$

We allow for demographic-group-specific intercepts by month ($\alpha_{\rho m}$) and group-specific annual linear time trends (β_ρ). Our primary coefficients of interest are now the $\phi_{\rho\mu}$ which capture group-specific deviations from the (group-specific) historical trend in the outcome (relative to an omitted reference group) in each month from January 2020 onwards. Once again we allow outcome levels to vary across five-year age bins (γ_a) and we allow the impacts of the pandemic to also vary across 5-year age bins ($\lambda_{a\mu}$).

3 Results: Mortality and Economic Damages

3.1 Aggregate Damages

Damages are measured as the deviation between observed and predicted outcomes over the time period of the pandemic (March 2020 - February 2022). Figure 1A shows observed and predicted annual mortality for individuals aged 11-99 in years 2011 to 2021; predicted mortality is estimated using Equation 2. Mortality was increasing over the pre-pandemic decade with a time trend that is nearly perfectly captured by our linear specification. We find a sharp increase in mortality in 2020 (recall we define 2020 as March 2020 - February 2021), with an observed mortality rate in 2020 of 128.2 deaths per 10,000, compared to the predicted rate of 105.8 deaths per 10,000; that is, observed mortality was 20 percent higher than expected mortality during the first year of the pandemic. In 2021, excess mortality declined slightly to 18.6 per 10,000, from 22.4 per 10,000 in 2020. Figure 1C shows the monthly observed and predicted mortality from January 2020 through

February 2022; monthly predictions are estimated using Equation 1.[12] Observed mortality lines up closely with predicted mortality in January and February 2020, and then visibly diverges starting in March 2020. The differences between observed and predicted mortality peak in December 2020 and January 2021, followed by an additional peak at the end of 2021. Appendix Figure C.1 shows analogous results for individuals aged 25-64, which is the sample we will focus on for some of our heterogeneity analysis. While the level of excess mortality is substantially lower at younger ages, the time patterns for excess mortality are broadly similar.

The remaining two panels show the analogous observed and predicted annual and monthly time patterns for the employment-to-population ratio for individuals aged 25-64. At the annual level, the employment-to-population ratio has been steadily increasing over the last decade, again on an almost perfectly linear trend. We observe a sharp drop in employment from 76 people employed per 100 in 2020 to 71 people employed per 100 in 2021; that is, the average monthly employment-to-population ratio declined by 5 percentage points (about 6.5 percent) during the first year of the pandemic. In 2021, employment rebounded, but only partially, to 74 people employed per 100. At the monthly level, we observe the largest drop in the employment-to-population ratio in April 2020, when it dropped by almost 10 percentage points; it then climbed back up gradually, but had not fully recovered by the end of the pandemic's second year (February 2021).

3.2 Heterogeneity in Damages

Damages by race and ethnicity The health and economic consequences of the pandemic's first two years were markedly unequal by race and ethnicity. Figure 2 shows average annual age-adjusted excess mortality and economic damages from the first two years of the pandemic for

[12] Appendix Figure C.2 shows the annual predicted and observed values of each outcome within selected months. The historical time trend is close to linear for those calendar months.

each racial and ethnic group in our data.[13] The figure shows not only that there was substantial heterogeneity in damages across groups – and that many of these differences are statistically distinguishable – but also that the groups that were hit the hardest economically were also those with the highest excess mortality.[14] The highest average annual excess mortality was experienced by non-Hispanic American Indian/Alaskan people (41 per 10,000), non-Hispanic Black people (37 per 10,000), and Hispanic people (34 per 10,000); in comparison, non-Hispanic White people experienced excess mortality of 16 per 10,000.[15] These were generally also the groups that experienced the largest economic damages. In particular, non-Hispanic Black and Hispanic people experienced an average decline in the employment-population ratio of 6.5 per 100 and 5.7 per 100, respec-

[13] Table C.4 reports the underlying estimates and standard errors.

[14] To benchmark these estimates, Appendix Table C.3 shows the unadjusted predictions for average annual mortality employment by race/ethnicity and educational attainment.

[15] Where we can make reasonable comparisons, our excess mortality estimates by race and ethnicity are similar to those from other papers. Using publicly available data from the CDC's Provisional Death Counts for Coronavirus Disease series and other sources, Ruhm (2023) finds that between March 2020 and February 2022, the ratio of observed to predicted deaths among all individuals in the U.S. is 1.22 overall, 1.18 among non-Hispanic White individuals, 1.29 among non-Hispanic Black individuals, and 1.43 among Hispanic individuals. This is close to our estimates (for comparability, without applying age adjustments), where we find a ratio of observed to predicted deaths of 1.19 overall, 1.15 among non-Hispanic White individuals, 1.29 among non-Hispanic Black individuals, and 1.40 among Hispanic individuals. Using the Census Numident file but a slightly different age group (ages 15-99) and time frame (April 2020 through March 2021), Foster et al. (2024) find that mortality was 1.15 times higher than expected for non-Hispanic White people, 1.32 times higher than expected for non-Hispanic Black people, and 1.48 times higher for Hispanic people; again, these numbers are very close to our estimates.

tively; in comparison, non-Hispanic White individuals experienced a decline of 3.5 per 100. In a population-weighted regression of economic damages on health damages across race/ethnicity groups, the slope is positive and highly statistically significant (slope estimate of 0.126 with a standard error of 0.013).

These disparities were not constant during the two years of the pandemic. Figure 3 shows how they evolved over time for the largest racial and ethnic groups. The Black-White and Hispanic-White age-adjusted mortality gaps declined towards the end of the two year period. After spiking at almost 6 excess deaths per 10,000 in April 2020, the monthly Black-White age-adjusted mortality gap averaged 1.5 excess deaths per 10,000 for the remainder of the first year of the pandemic, and 0.86 excess deaths per 10,000 over the second year of the pandemic. The Hispanic-White monthly age-adjusted mortality gap averaged 1.5 excess deaths per 10,000 over the first year of the pandemic, peaked towards the end of that first year (in January 2021) at 3.9 excess deaths per 10,000 and was substantially lower throughout the second year (average monthly gap of 0.36). The Hispanic-White difference in economic damages had also been erased by the end of the pandemic (panel D), while the Black-White gap in economic damages was substantially more persistent over the course of the pandemic (panel B).

Damages by education Figure 4 shows that there were also stark gradients in both excess mortality and economic damages across groups with different levels of education – many of which are statistically distinguishable – and that both types of damages were concentrated in less educated groups.[16] For example, for the approximately one-quarter of the population whose highest level of education was a high school diploma or GED, age-adjusted average annual economic damage was 5.5 per 100 and age-adjusted average annual excess mortality was 27.3 per 10,000. But among the one-fifth of the population whose highest educational attainment was a Bachelor's degree, eco-

[16]Again, Appendix Table C.5 reports the underlying estimates and standard errors.

nomic and mortality damages were lower, with 3.3 per 100 jobs lost and 11.9 per 10,000 excess deaths. The approximately one-third of the population with some college or an associate's degree experienced economic and mortality damages closer to those with a high school degree or GED. The approximately one-tenth of the population with more than a Bachelor's degree fared slightly better on mortality damages than those with a Bachelor's degree (with excess deaths around 7 to 8 – rather than 12 – per 10,000), and substantially better on economic damages (with an average monthly decline in the employment-to-population ratio of 0.7 to 1.7 instead of 3.3). The approximately 10 percent of individuals with less than a high school degree were a stark outlier in terms of excess mortality, with nearly six times higher age-adjusted excess mortality relative to those with a college degree.

In contrast to the declining time pattern of many racial and ethnic gaps, Figure 5 indicates that gaps by education (splitting the sample by Bachelor's degree attainment) persisted throughout the pandemic. Indeed, the gaps in excess economic damages by Bachelor's degree attainment *grew* into the second year of the pandemic, increasing from a difference of 1.46 missing jobs per 100 in July 2020 to 3.46 missing jobs per 100 in May 2021, before partially decreasing again to 1.65 jobs per 100 by February 2022. Mortality gaps by education fluctuated throughout the first two years of the pandemic, with gaps generally mirroring the overall levels of mortality damage, peaking in December 2020-January 2021, summer 2021, and January 2022.

Damages by industry and occupation For the working-age population, health and economic damages are positively correlated across industries and occupations (Figure 6).[17] Across industries, average annual age-adjusted excess mortality varied between -5 per 10,000 and 12 per 10,000. The industry with the highest excess mortality was administration and support, with mining/quarry/oil/gas

[17] A complete set of estimates for industries and occupations are shown in Appendix Tables C.6 and C.7, respectively.

following closely behind (both above 10 per 10,000). These industries also had substantially above median economic damages, with average annual age-adjusted declines in the employment-to-population ratio of 7.2 and 8.0 per 100, respectively, compared to a median of 2.9 per 100. Arts, entertainment, and recreation, as well as accommodations and food, were large outliers for economic damages, with average annual age-adjusted declines in the employment-population ratio of 20 and 14 per 100 respectively, and they also experienced above-median mortality damages. By occupation, building, grounds cleaning, and maintenance were the occupations with the highest average annual excess mortality (13 per 10,000), and also experienced substantially above-median declines in the employment-to-population ratio. The occupations that experienced the highest declines in the employment to population ratio were food prep and service (13.4 per 100) and personal care and service (9.6 per 100); these also experienced substantially above-median excess mortality.[18]

The figure also shows excess deaths and economic damages across occupations that are classified as being able to work from home or not; that classification follows Dingel and Neiman 2020 in defining those in which at least 50 percent of the jobs within the occupation can be done from home as 'work from home' occupations. Average annual excess mortality was 9.6 per 10,000 for those in occupations that were not classified as work from home, compared to 5.6 per 10,000 for those in work from home occupations; the decline in the employment-to-population ratio was also

[18]For comparison, Miller et al. (2021), used the same linked ACS-Numident data we use but for April-June 2020. During that first quarter of the pandemic, they find the largest age-unadjusted increases in mortality from 2019 to 2020 for installation, maintenance, repair; production; and legal occupations. This differs from our findings of the occupations with the largest excess mortality over the first two years of the pandemic (building, grounds cleaning, and maintenance; installation, maintenance, repair; and material moving).

higher for occupations classified as non work from home (4.9 per 100 compared to 3.2 per 100).[19]

Mortality damages by income Figure 7 plots average annual age-adjusted excess deaths per 10,000 for the working-age population, based on the respondent's pre-pandemic family income relative to poverty thresholds. It plots these damages separately for the first and the second year of the pandemic.[20]

The gradient in mortality damages by income is as striking. In both years, there is a pronounced monotonic relationship in which excess deaths generally decrease at higher levels of family income. Moreover the negative income-damages gradient becomes even more stark in the second year of the pandemic. For example, in the first year of the pandemic, annual age-adjusted mortality was just over 17 per 10,000 for the approximately 10 percent of the population with family income below the poverty line. For individuals with family incomes at 250-299% of the poverty line (roughly the 33rd percentile of the income distribution), age-adjusted excess mortality was less than half that of the poorest individuals, at 8.3 deaths per 10,000, and at 500-550 percent of the poverty line (roughly the 67th percentile of the income distribution), it was about half again, at 4.7. In the second year of the pandemic, mortality damages among most income bins in the top third of the income distribution tended to be similar between 2020 and 2021, and in some cases decreased from the first to second year. Among the bottom two-thirds of the income distribution, however, excess mortality tended to increase from the first to second year. For example, among the group within

[19] We also found lower economic damages among individuals who report a disability in the CPS compared to those who do not, presumably reflecting the fact that individuals with disabilities were less likely to be employed prior to the pandemic. However, individuals with disabilities also experienced greater age-adjusted excess mortality than individuals without disabilities. These estimates are shown in Appendix Table C.9.

[20] Appendix Table C.8 reports the underlying estimates and standard errors.

250-299 percent of the poverty line, age-adjusted excess mortality increased by a factor of 1.6 – to 13.5 excess deaths per 10,000 – and among individuals below the poverty line, an increase of approximately the same proportion resulted in approximately 28 excess deaths per 10,000. As a result, the poorest individuals made up a disproportionate share of the increase in excess mortality observed among 25-to-64 year-olds between the pandemic's first two years.[21]

Potential drivers of disparities These results are primarily descriptive and leave open an important set of questions regarding the *drivers* of the heterogeneous impacts of the pandemic for both health and economic damages. One natural question concerns the role of the rich set of policy interventions implemented during the pandemic. Some of the more compelling causal evidence of policy impacts on pandemic damages comes from exploiting the initial variation in the timing of policies around the first few weeks of the pandemic.[22] However, since most localities eventually adopted some policies during the pandemic, the short-run variation in policy timing is less useful for analyzing drivers of damages over the full first two years of the pandemic.

While there is also variation across localities in the average level of policy stringency over this two year period (Hale et al. 2023), our brief investigation of how much state-level damages were correlated with policy stringency highlighted the challenge of interpreting such results causally. We found that states with more stringent policies experienced higher economic damages and lower

[21] Appendix Figure C.3 shows the corresponding income gradient in economic damages. However, these results should be interpreted with caution, as income for many respondents is measured during the pandemic and therefore is endogenous to the pandemic's effects.

[22] For example, this literature has found that initial stay-at-home orders increased unemployment insurance claims (Baek et al. 2021) and lowered employment (Gupta et al. 2023), while reducing COVID-19 infection rates (Courtemanche et al. 2020) without shifting mortality substantially (Agrawal et al. 2023).

excess mortality and that states with higher vaccination rates (conditional on policy stringency) had lower excess mortality and similar economic damages. Notably, however, states with higher vaccination rates (conditional on policy stringency) experienced lower excess mortality already in the first year of the pandemic, when no vaccines were yet available. This suggests that variation in policy stringency and vaccination rates is likely correlated with other factors—such as both demand for policy and private mitigating behavior—that are also correlated with economic and mortality damages.

Somewhat more promisingly, we explored what observable measures of socio-economic status can—in a statistical sense—explain racial and ethnic disparities in mortality and economic damages during the first two years of the pandemic. In the contemporary public discourse about racial and ethnic disparities in the pandemic's mortality impact, differences in incomes, living arrangements, and the nature of work were frequently suggested as potential drivers.[23] For economic damage, media reports highlighted different rates of employment in service industries and jobs that could be done from home as reasons that could have contributed to racial disparities in the economic impact of the pandemic (Cohen and Casselman 2020; Kurtzleben 2020) In Appendix B, we therefore consider how the measures of industry, occupation, education and income examined above, as well as additional measures designed to capture living arrangements and use of public transit correlate with racial and ethnic disparities in mortality and economic damages during the first two years of the pandemic within the working age population. We find that the observable measures can explain about 40% of the non-Hispanic Black-White gap in excess mortality (Appendix Table C.10), about 60% of the Hispanic-White gap in excess mortality (Appendix Table C.11), and almost 50% of the

[23]For example, Scott (2020) argued that differences in the prevalence of essential jobs and housing disparities were factors that could have contributed to health disparities between non-Hispanic Black and White people during the pandemic while Ray (2020) emphasized greater public transit use and higher population density as potential factors.

gaps in economic damages for the same groups.

4 Summary

Using a consistent set of methods and measures on nationally representative data, our analysis paints a detailed picture of the heterogeneous impacts that the first two years of the COVID-19 pandemic had on both health and economic well-being in the United States. We document substantial variation in the economic and health damages experienced by different groups in the first two years of the COVID-19 pandemic, with both economic and health damages disproportionately concentrated in more disadvantaged groups.

We find substantial disparities in the pandemic's impact on all-cause mortality and employment by race and ethnicity, similar to those documented in prior work. We also find that the pandemic's mortality and economic damages were larger for those with lower socio-economic status, measured using education and the type of occupation and industry. We estimate that the pandemic-induced all-cause mortality was substantially higher among individuals living in lower-income households, reminiscent of the overall income-mortality gradient that has been documented for the U.S. and other countries. Finally, we find that while the mortality gaps in damages across racial and ethnic groups declined over the first two years of the pandemic, some racial/ethnic economic gaps in damages persisted, and both mortality and economic gaps by education persisted. Naturally, an important direction for further work is to explore the factors that contributed to the heterogeneity in pandemic impacts across demographic groups.

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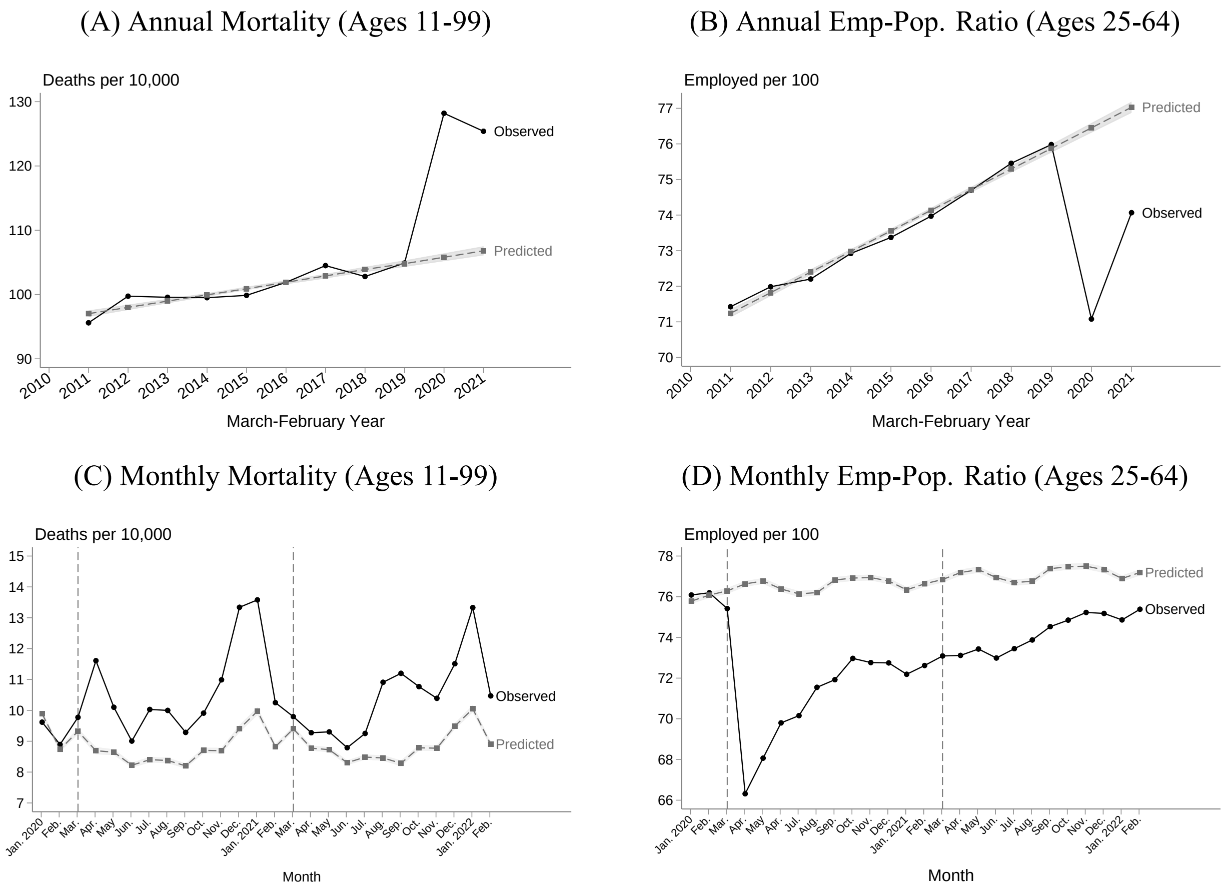
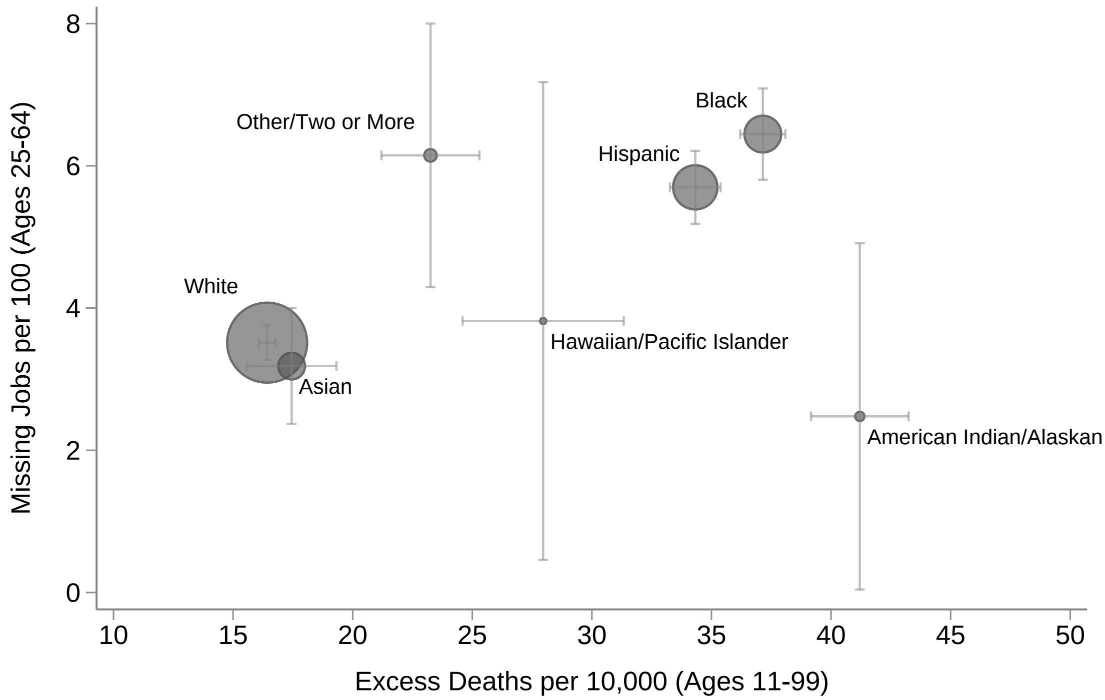
Exhibits

Figure 1: **Aggregate Mortality and Employment**



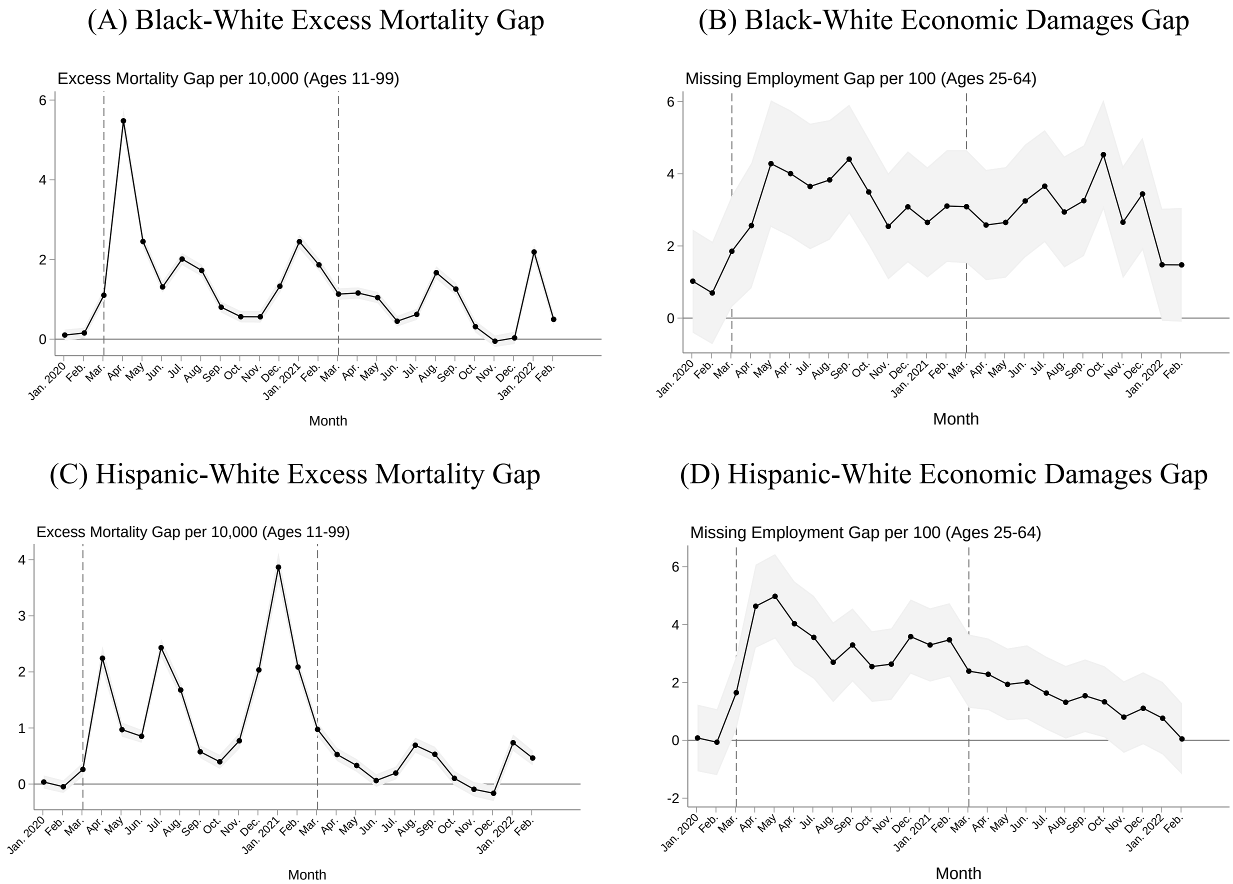
Notes: Panel (A) shows the annual number of observed and predicted deaths per 10,000 people among all individuals ages 11-99 using the full Census Numident dataset. Panel (B) shows observed and predicted number of individuals employed per 100 working-age adults over the same time period. Panels (C) and (D) show the monthly series for the same measures, with dashed vertical lines indicating the start of the first and second year of the pandemic. The annual employment-to-population ratio averages employment-to-population ratio across all months in a given year. A year is defined as 12 months from March to February. Panels (A) and (B) use data from March 2011 to February 2022. Panels (C) and (D) use data from January 2020 to February 2022. The dashed 'prediction' series for mortality and employment-to-population are constructed in Panels (A) and (B) as $\hat{y}_t = \hat{\alpha} + \hat{\beta} \times t$, using the estimates from Equation 2; they are constructed in Panels (C) and (D) as $\hat{y}_{mt} = \hat{\alpha}_m + \hat{\beta} \times t$ based on the estimates from Equation 1. The 95% confidence interval for the prediction is shaded in gray and is based on heteroskedasticity-robust standard errors and CPS survey weights (in B and D). **Source**: Authors' calculations from Census Numident and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure 2: **Age-Adjusted Economic and Health Damages by Race and Ethnicity**



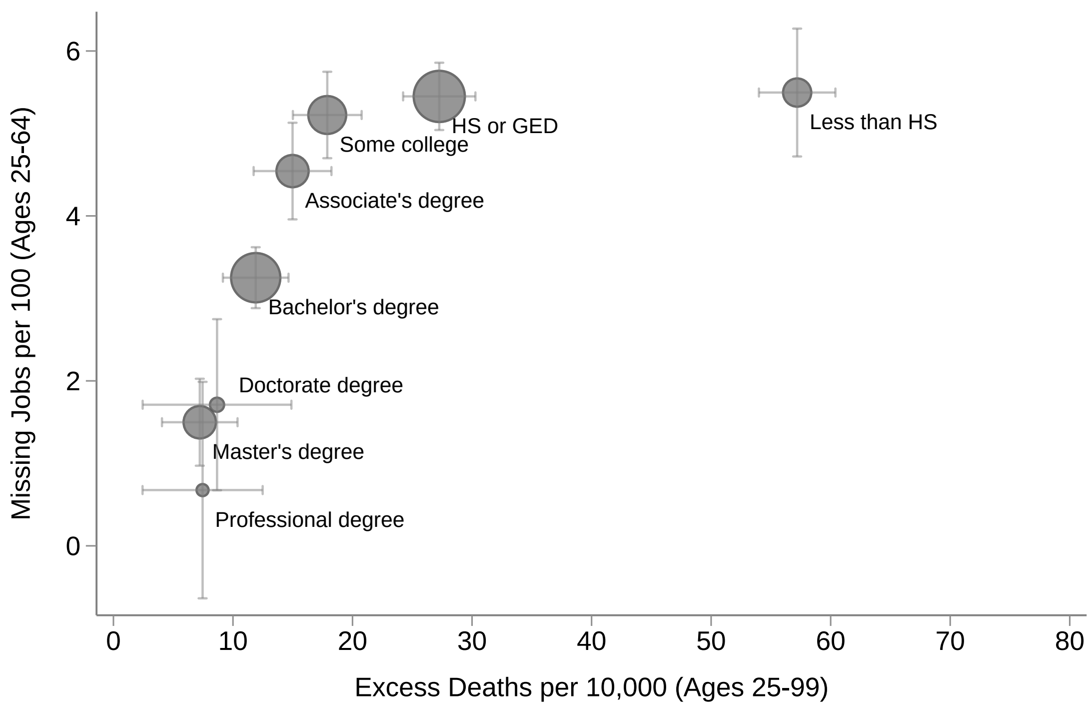
Notes: This graph plots average annual (averaged across the two pandemic years) age-adjusted economic damages (among 25- to 64-year-olds) against average annual age-adjusted excess all-cause mortality (among 11- to 99-year-olds) by race and ethnic group. Lines show the heteroskedasticity-robust 95 percent confidence intervals for each group, using CPS survey weights for economic damages. Each circle represents one group, and the size of each circle is proportional to the weighted group population size aged 25 to 64 in the CPS sample. All groups other than "Hispanic" are limited to Non-Hispanic individuals. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age-adjustment. See Appendix Table C.4 for the point estimates and the standard errors. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure 3: **Age-Adjusted Monthly Gaps in Damages by Race and Ethnicity**



Notes: Panels (A) and (C) show, among individuals ages 11-99, age-adjusted monthly Black-White gaps in excess mortality (Panel A) and Hispanic-White gaps in excess mortality (Panel C). Panels (B) and (D) show, among individuals ages 25-64, age-adjusted monthly Black-White gaps in employment damages (Panel B) and Hispanic-White gaps in employment damages (Panel D). The graph displays estimates for January 2020 to February 2022, with dashed vertical lines indicating the start of the first and second year of the pandemic. The 95% confidence interval for the gap is shaded in gray and is based on heteroskedasticity-robust standard errors and CPS survey weights (in B and D). Damages are estimated as specified in Equation 4. We use the age distribution in the full sample as the benchmark for age-adjustment. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

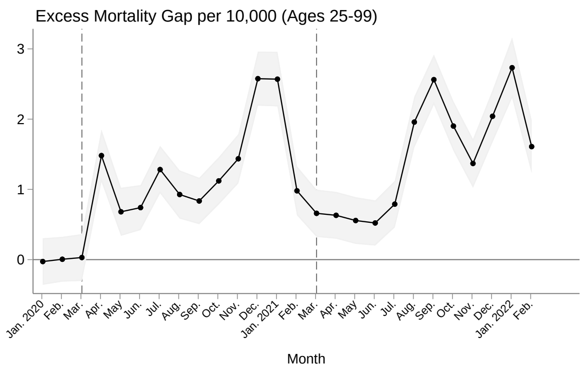
Figure 4: **Age-Adjusted Economic and Health Damages by Education Level**



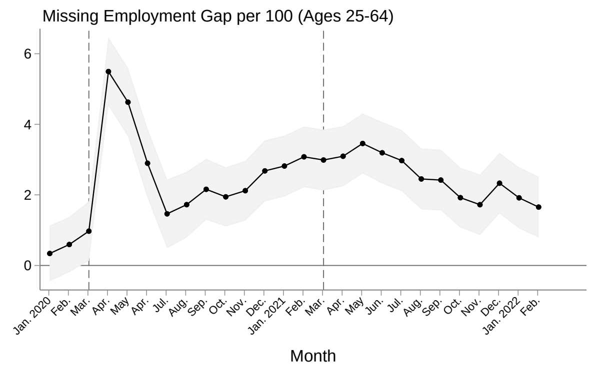
Notes: This graph plots average annual (averaged across the two pandemic years) age-adjusted economic damages (among 25- to 64-year-olds) against average annual age-adjusted excess all-cause mortality (among 25- to 99-year-olds) by the level of educational attainment. Lines show the heteroskedasticity-robust 95-percent confidence intervals for each group, using CPS survey weights for economic damages and ACS person-level weights for health damages. Each circle represents one educational attainment group. The size of each circle is proportional to the weighted group population size aged 25 to 64 in the CPS sample. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age-adjustment. The mortality results use the ACS-Numident linked dataset. See Appendix Table C.5 for the point estimates and the standard errors. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure 5: **Age-Adjusted Monthly Gaps in Damages by Education Level**

(A) Excess Mortality Gap by BA Attainment



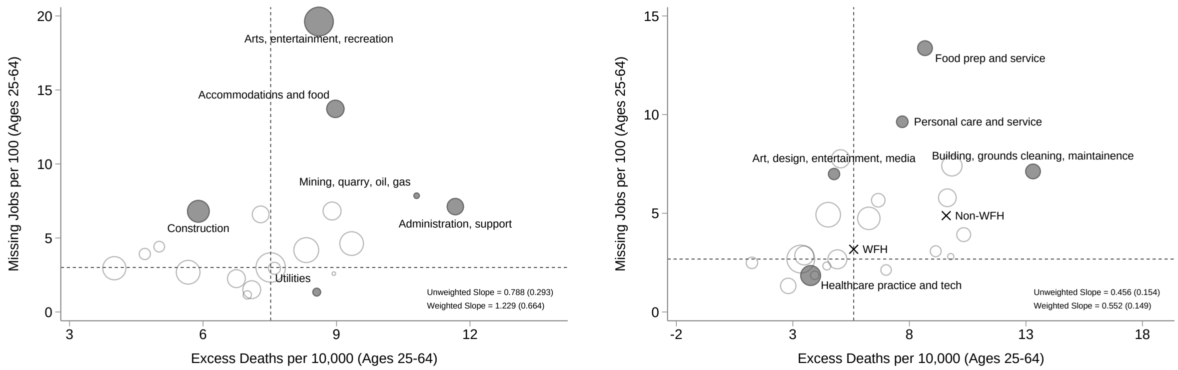
(B) Economic Damages Gap by BA Attainment



Notes: Panel (A) shows, among individuals ages 25-99, age-adjusted monthly gaps in excess mortality for individuals without a bachelor's degree (BA) or higher compared to those with a BA or higher. Panel (B) shows, among individuals ages 25-64, age-adjusted monthly gaps in employment damage for individuals without a BA compared to those with a BA or higher. The graph displays estimates for January 2020 to February 2022, with dashed vertical lines indicating the start of the first and second year of the pandemic. The 95% confidence interval for the gap is shaded in gray and is based on heteroskedasticity-robust standard errors and relevant survey weights (ACS person-level weights in A and CPS survey weights in B). We use the age distribution in the full sample as the benchmark for age-adjustment. Damages are estimated as specified in Equation 4. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

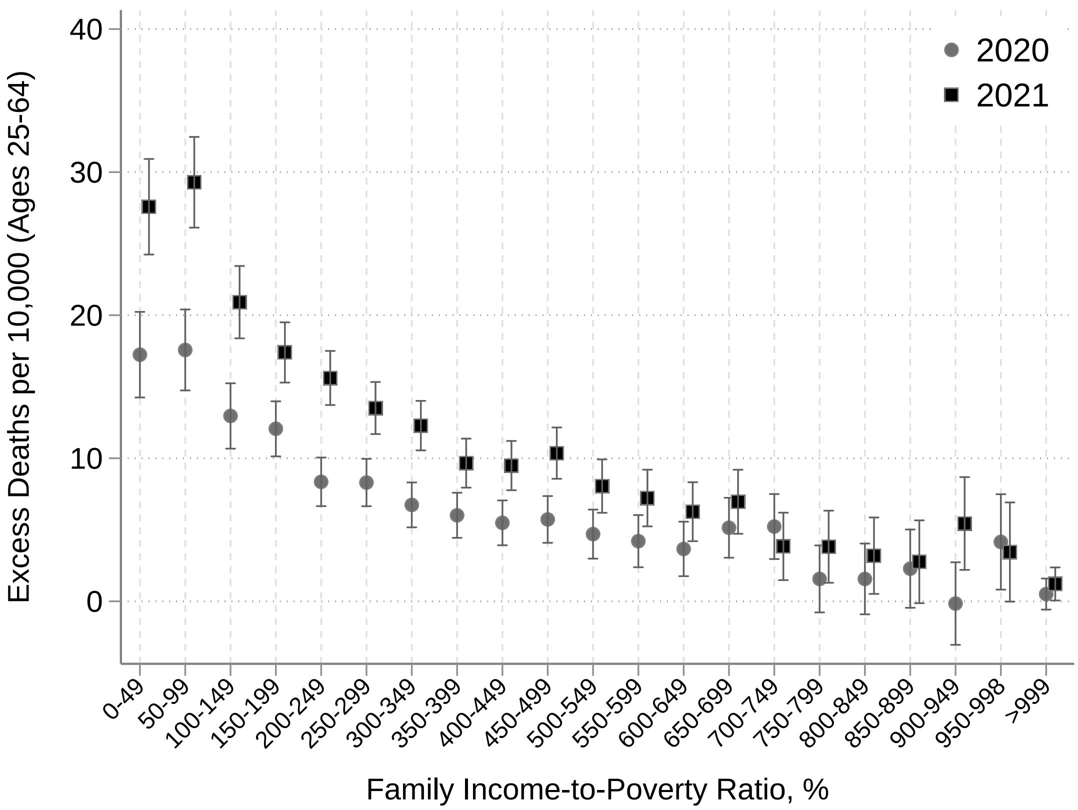
Figure 6: **Age-Adjusted Economic and Health Damages by Industry/Occupation**

(A) Industry | (B) Occupation and Work-from-Home (WFH)



Notes: This graph plots average annual (averaged across the two pandemic years) age-adjusted economic damages (among 25- to 64-year-olds) against average annual age-adjusted excess all-cause mortality (among 25- to 64-year-olds) by industry (Panel A) and occupation and work-from-home status (Panel B). Each circle represents one industry or occupation. The size of each circle is proportional to the weighted group population size aged 25 to 64 in the CPS sample. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age-adjustment. The mortality results use the ACS-Numident linked dataset. See Appendix Tables C.6 and C.7 for the point estimates and the standard errors. To improve readability, one (small) industry "company management," for which we estimate close to zero economic impact and negative excess mortality, is excluded from Panel (A). The dashed vertical and horizontal lines demarcate the level of damages in the population-weighted median industry or occupation. The legend shows the slopes of the unweighted line of best fit and line of best fit weighted by industry or occupation population. Occupations are classified as being able to work from home (WFH) following Dingel and Neiman 2020, as those in which at least 50 percent of the jobs within the occupation can be done from home. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure 7: **Age-Adjusted Health Damages by Income**



Notes: This graph plots annual age-adjusted excess mortality damage (among 25- to 64-year-olds) by family income, separately from March 2020 through February 2021 (in gray circles) and from March 2021 through February 2022 (in black squares). Lines show the heteroskedasticity-robust 95-percent confidence intervals for each income group, using ACS person-level weights. Our income measure is the ratio of a family's income to the poverty threshold, multiplied by 100, as reported in ACS. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age-adjustment. See Appendix Table C.8 for the point estimates and the standard errors. **Source**: Authors' calculations from Census Numident and the 1-Year American Community Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	Ages 11-99		**Ages 25-64**		
	Numident	ACS-Numident	Numident	ACS-Numident	CPS
Person-Years (Unweighted)	483,300,000	43,070,000	285,400,000	23,920,000	429,423
Percent Died	1.26	1.26	0.48	0.45	.
Percent Employed	.	.	.	.	72.56
Average Age	45.21	45.74	44.48	44.72	43.81
% in each category					
Male	48.84	48.41	49.41	48.81	49.17
Hispanic	14.78	14.32	14.53	14.36	18.84
Non-Hispanic White	65.85	67.10	65.07	66.10	58.55
Non-Hispanic Black	12.58	12.02	13.20	12.50	13.28
Non-Hispanic Asian	5.28	5.22	5.63	5.64	6.64
American Indian/Alaskan	0.90	0.82	0.95	0.85	0.83
Hawaiian/Pacific Islander	0.19	0.17	0.21	0.18	0.36
Other/Two or More Races	0.40	0.36	0.41	0.36	1.49

Notes: This table shows summary statistics for our main analytic datasets. The statistics only include data from March 2020 to February 2022. Columns (1) and (3) use the full Census Numident dataset with sample restrictions as outlined in Section 2. Columns (2) and (4) use the linked ACS-Numident dataset, which is a merge between Census Numident and six years of the 1-year American Community Survey (ACS) data. Column (5) is based on the Current Population Survey (CPS). ACS person-level weights and CPS sample weights are used when computing the means in columns (2), (4), and (5). "Person-Years" refers to the unique number of person and year combinations that we observe in each data set. "Percent Died" refers to the share of individual-years in the data for which the individual died. Race and ethnicity categories are based on self-reported race and ethnicity from 2010 Decennial Census or the 2010 Census Modeled Race File. All numbers are rounded according to U.S. Census Bureau disclosure protocols. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Heterogeneity in Damages from a Pandemic

Online Appendices

Amy Finkelstein, Geoffrey Kocks, Maria Polyakova, and Victoria Udalova

A Data Appendix

A.1 Census Numident Data

We use the U.S. Census Bureau's version of the Social Security Administration's Numerical Identification file (Census Numident) (2022 quarter 3 updated vintage) for our mortality analyses. The records are cumulative, adding people as they apply for Social Security numbers upon birth or arrival to the U.S. The date of death is recorded regardless of whether the person died inside or outside the United States, and deceased individuals are not removed from the data. The version of the Census Numident available to us was released October 7, 2022 and is deemed to be a complete record of deaths through March 2022 (Foster et al. 2024). We first restrict that data to individuals who had either no date of death recorded or had a date of death on or after January 1, 2011. Beginning with this dataset of approximately 424 million individuals, we follow Polyakova et al. (2021) and impose the following restrictions in order to ensure that we reliably observe ages and the date of death if applicable. Appendix Table C.1 reports how these restrictions change the sample size:

1. Drop observations for 1.9 million individuals who have a missing year and month of birth; we allow the day of the month be missing. We cannot compute age of individuals (at the beginning of each month) for whom the year and month of birth are missing. After this step, the data consists of approximately 422 million individuals.

2. Drop observations for 0.11 million individuals who have a missing year and month of death;

we allow the day of the month be missing. We cannot assign the month of death for these individuals.

3. Drop observations for 15 million individuals who would have been at least 100 years old prior to 2010. This helps account for historical underreporting of deaths in Numident. As noted in the Online Appendix to Polyakova et al. (2021), deaths only began to be captured systematically in the SSA Numident file beginning in 1962, so many individuals who were deceased prior to this date do not have a recorded death date. After this step, the data consists of approximately 408 million individuals.

4. Drop observations for 60 million individuals if we cannot verify that these individuals were still alive at the start of 2010 using supplementary linked data sources. This procedure is described in more detail in the Online Appendix to Polyakova et al. (2021). Specifically, we exclude individuals if we cannot confirm that they were alive on January 1, 2011 from the death record in Census Numident itself or through any of the 2010 Decennial Census, 2010 Medicare Enrollment Database (EDB), or the 2010 and 2011 MAF-ARF (address) files. The MAF-ARF includes address information obtained from a variety of administrative and Census survey sources (Dillon 2021). We only keep individuals that satisfy at least one of the following conditions: (a) died during January 2011-February 2022 as recorded in the Census Numident file; or (b) were alive in the 2010 Decennial Census; or (c) were alive in the 2010 Medicare EDB; or (d) were included in the MAF-ARF in both 2010 and 2011. After this step, there are approximately 347 million individuals and 3.343 billion individual-years remaining in the dataset.

5. Drop 226 million individual-years (approximately 6.7% of the remaining sample) for individuals if we do not have information on their race and ethnicity – see the description of our sources for race and ethnicity below. This restricts our sample to individuals who are 11 or older, since we do not have race/ethnicity information for individuals born after 2010 (and

hence at the beginning of the last year of our data in 2021 we only observe race/ethnicity for individuals who are at least 11 years old).

6. Drop 303 million individual-year observations for which an address is not recorded in the MAF-ARF file or for which the address is outside of the 50 U.S. states or the District of Columbia.

The resulting "full" Census Numident dataset for years 2011-2021 consists of 2.6 billion individual-years between the ages of 11 and 99 and 1.6 billion individual-years between the ages of 25 and 64. This corresponds to 483.3 million unique individual-years aged 11-99 years and 285.4 million unique individual-years aged 25-64 years in years 2020 and 2021. Out of these individual-years, we are able to locate American Community Survey survey responses for 228.1 million individual-year observations between the ages of 11 and 99 and 130.5 million individual-year observations between the ages of 25 and 64. These in turn correspond to 43.1 million (age 11-99) and 23.9 million (age 25-64) individual-year observations in 2020 and 2021.

A.2 Race and Ethnicity Data

Our information on race and ethnicity comes from two sources: the 2010 Decennial Census and the 2010 Modeled Race file produced by the Census Bureau. We first link the Census Numident to the 2010 Decennial Census. We thus require the individuals to be present in the U.S. in 2010. This merge uses a unique individual-level anonymous identifier common across all Census data sources, called a Protected Identification Key (PIK). PIKs are created using personally identifiable information (PII) and probabilistic record linkage (Wagner, Lane, et al. 2014). Individuals do not receive PIKs if either their PII are of low quality to assign a valid unique PIK or because they do not have a social security number (SSN). When race/ethnicity is not available in Decennial Census, we use the race/ethnicity variable recorded in the Census Bureau's 2010 Modeled Race File. The 2010 Modeled Race file is based on information from the 2000 Decennial Census, the 2010 Decennial

Census, the Census Numident, the Indian Health Services, and other administrative records. We use the race/ethnicity information from the 2010 Decennial Census when available, and if it is not available in this file, we use the race/ethnicity variable recorded in the Modeled Race File. As noted in the Online Appendix to Polyakova et al. (2021), we do not use the direct measure of race/ethnicity recorded in the Census Numident file due to limitations in the SSA's race/ethnicity records for the oldest and youngest individuals. We use the following categories of race and ethnicity: Hispanic; non-Hispanic White; non-Hispanic Black; non-Hispanic Asian; non-Hispanic Hawaiian or Pacific Islander; non-Hispanic American Indian or Alaskan Native; or Other or Two or More Races.

A.3 ACS Data

We use the following variables from the American Community Survey (years 2005-2019) in our main analysis. For all variables, missing values are counted as a separate category.

- **Education**: The education variable includes following categories: less than a high school diploma or equivalent; high school or GED; some college but not a degree; associate degree; bachelor's degree; master's degree; professional degree; and doctoral degree.

- **Industry**: 23 broad industry categories based on NAICS codes – agriculture; forestry and fishing; mining, quarrying, oil, and gas; utilities; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing; information; finance and insurance; real estate, rental, and leasing; professional, scientific, and technical services; company management; administrative and support; educational services; healthcare and social assistance; arts, entertainment, and recreation; accommodation and food services; other services (except public administration); public administration; active military duty; and unemployed. Some unemployed individuals or those not in the labor force may be coded under the most recent industry where they worked, if applicable.

- **Occupation**: 24 broad occupation categories based on Standard Occupation Classification groups following Census occupation codes – management; business and financial; computer and mathematical; architecture and engineering; life, physical, and social science; community and social service; legal occupations; education, instruction, and library; art, design, entertainment, and media; healthcare practitioners and technical; healthcare support; protective service occupations; food preparation and serving; building and grounds cleaning and maintenance; personal care and service; sales and related; office and administrative support; farming, fishing, forestry; construction and extraction; installation, maintenance, and repair; transportation; material moving; military; and unemployed. Some unemployed individuals or those not in the labor force may be coded under the most recent industry where they worked, if applicable.

- **Work-from-home status**: an indicator for work-from-home status as defined in Dingel and Neiman (2020), based on broad occupation categories. An occupation is considered to be "work-from-home" if at least 50% of the jobs within the occupation can be done from home based on survey evidence as described in Dingel and Neiman (2020).

- **Income**: 21 bins for the ratio of a family's income to the poverty index, multiplied by 100: 0-49, 50-99, 100-149, ..., 950-998, 999 or higher.

- **Disability status**: with or without a disability. Individuals are considered to have a disability if they responded "yes" to at least one of the following: having hearing difficulties, vision difficulties, self-care difficulties, independent living difficulties, ambulatory difficulties, or cognitive difficulties.

We use the following ACS variables in the analysis reported in Appendix B:

- **People per room**: 6 indicators for the ratio of people in the household to the number of rooms in the house: less than 0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0, at least 1.0.

- **Housing type**: one-family home, apartment building, or other (e.g., mobile home, boat, or RV).

- **Group quarters**: 4 broad categories based on the group quarter type – health group quarters (e.g., nursing facilities/skilled nursing facilities, psychiatric facilities, and in-patient hospice facilities); non-health group quarters (e.g., correctional facilities, group homes for juveniles, college/university student housing, and military quarters); other non-institutional facilities (e.g., emergency and transitional shelters, soup kitchens, and maritime vessels); and non-group quarters.

- **Mode of transportation to work**: car, truck, or van; subway, elevated train, rail, or streetcar; walking, bike, or motorcycle; work from home; or other (e.g., ferry or taxi).

- **Essential worker status**: an indicator for essential worker status as defined in Kearney, Pardue, et al. (2020), based on a crosswalk of detailed industry codes to the Department of Homeland Security's list of essential jobs. Kearney, Pardue, et al. (2020) base their definition on a March 2020 memo from the Department of Homeland Security with a list of essential jobs, which they then match to 2017 Census industry codes.

- **Health insurance**: indicator variable for having any type of health insurance coverage. This variable is only available in the ACS beginning in 2008; earlier years of data are coded to have a missing value.

A.4 CPS Data

For economic analyses using the IPUMS CPS files (Flood et al. 2022), we start with the sample between January 2011 and February 2022 of non-institutionalized individuals who live in any of the 50 United States or the District of Columbia; this sample consists of 16,688,009 individual-month observations. We then limit our CPS sample to the non-military population (resulting in 16,631,120 individual-months remaining), those who are at least 25 years old (resulting in 12,438,442 individual-months remaining), and those who are younger than 65 years (resulting in 9,647,381 individual-months remaining).

For each individual in CPS, we typically observe four months of data over a twelve month period. We average monthly data for our annual analyses. For continuous variables, such as age, we define the annual value to be the mean of the variable (for example, mean age) reported across different response months. For categorical variables such as race/ethnicity, education, industry, and occupation, income categories, and disability status, we use the individual's modal response over the twelve month period. In cases where there is a tie (for example, the person works in industry A for half of the time, and in industry B for the other half), we randomly assign the person to one of the two groups. For employment, we take the (unweighted) proportion of the number of months in which the individual reported being employed (among all months in which the individual was surveyed).

Below we list all CPS variables used in our analysis. For all variables, missing values are coded as a separate category.

- **Race/Ethnicity**: This variable includes the following categories of race and ethnicity: Hispanic; non-Hispanic White; non-Hispanic Black; non-Hispanic Asian; non-Hispanic Hawaiian or Pacific Islander; non-Hispanic American Indian or Alaskan Native; or non-Hispanic Other or Two or More Races.

- **Education**: The education variable includes following categories: less than high school; high school or GED; some college; associate degree; bachelor's degree; master's degree; professional degree; and doctoral degree.

- **Industry**: 22 broad industry categories based on NAICS codes – agriculture; forestry and fishing; mining, quarrying, oil, and gas; utilities; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing; information; finance and insurance; real estate, rental, and leasing; professional, scientific, and technical services; company management; administrative and support; educational services; healthcare and social assistance; arts, entertainment, and recreation; accommodation and food services; other services (except public administration); public administration; and unemployed. The CPS asks unemployed individuals or those not in the labor force to provide the most recent industry where they worked, if applicable.

- **Occupation**: 23 broad occupation categories based on Standard Occupation Classification groups following Census occupation codes – management; business and financial; computer and mathematical; architecture and engineering; life, physical, and social science; community and social service; legal occupations; education, instruction, and library; art, design, entertainment, and media; healthcare practitioners and technical; healthcare support; protective service occupations; food preparation and serving; building and grounds cleaning and maintenance; personal care and service; sales and related; office and administrative support; farming, fishing, forestry; construction and extraction; installation, maintenance, and repair; transportation; material moving; and unemployed. The CPS asks unemployed individuals or those not in the labor force to provide the most recent occupation where they worked, if applicable.

- **Work-from-home status**: an indicator for work-from-home status as defined in Dingel and Neiman (2020), based on broad occupation categories. An occupation is considered to be "work-from-home" if at least 50% of the jobs within the occupation can be done from home based on survey evidence as described in Dingel and Neiman (2020). Unemployed individuals or those not in the labor force are coded under their most recent job's work-from-home status, if applicable. Otherwise, we coded these individuals as non-work-from-home workers.

- **Income**: annual family income during the past 12 months of the survey, in 17 categories:

blank (missing); under $5,000; $5,000-$7,499; $7,500-$9,999; ...; $150,000 and over.

- **Disability status**: with or without a disability. Individuals are considered to have a disability if in CPS they report having any physical or cognitive difficulty measured as a combination of having responded 'yes' to at least one of CPS' six physical or cognitive difficulties: hearing, eye, remembering, physical, mobility, personal care limitations.

In Appendix B, we additionally use the following variables:

- **Essential worker status**: an indicator for essential worker status as defined by Kearney, Pardue, et al. (2020), based on a crosswalk of detailed industry codes to the Department of Homeland Security's list of essential jobs. Kearney, Pardue, et al. (2020) base their definition on a March 2020 memo from the Department of Homeland Security with a list of essential jobs, which they then match to 2017 Census industry codes. Similar to the industry definition. Unemployed individuals or those not in the labor force are coded under their most recent job's essential status if applicable. Otherwise, we coded these individuals as non-essential workers.

- **Young child**: indicates whether a person's own child (if any) resides with them and is under the age of 13.

B Correlates of Racial and Ethnic Disparities in Damages

We examine the ability of various observable factors to explain – in a statistical sense – the racial and ethnic disparities in mortality and economic damages that we estimate. We focus on the working age population – ages 24-64 – and the average damages over the first two years of the pandemic.[24]

[24] Our decomposition is similar in spirit to Alsan et al. (2021) who decompose differences in COVID-19 hospitalizations (as measured in claims data from a large insurer) by race/ethnicity

B.1 Econometric Framework

We quantify the explanatory power of observable factors by estimating a variant of Equation 3 that further adjusts for additional covariates (X) that take on values x:

$$y_{i(\rho)t} = \alpha_\rho + \gamma_a + \eta_x + \beta_\rho \times t + \sum_{\tau \in \{2020,2021\}} \Big(\theta_{\rho\tau} \mathbb{1}_{\{t=\tau\}} + \lambda_{a\tau} \mathbb{1}_{\{t=\tau\}} + \zeta_{x\tau} \mathbb{1}_{\{t=\tau\}} \Big) + \epsilon_{it} \tag{5}$$

Like Equation 3, this specification controls for differences in the age distribution (a) using five-year age bin fixed effects. We now also include fixed effects for each value of X and interactions of those fixed effects with indicators for pandemic years 2020 and 2021, allowing for both separate levels (η_x) and pandemic effects ($\zeta_{x\tau}$) by these covariates. Our main quantity of interest is how the $\theta_{\rho,2020}$ and $\theta_{\rho,2021}$ (which, recall, measures age-adjusted gaps in damages across racial/ethnic groups) change when we either include individual covariates for X or jointly include all covariates. This captures how much our observable factors, either separately or in aggregate, can (statistically) explain the racial/ethnic gaps in the pandemic's impact.[25] We average $\theta_{\rho 2020}$ and $\theta_{\rho 2021}$ when reporting our results.

For the analyses of gaps in excess mortality, we consider the following X: state, the number of people per room, housing type, being in group quarters, the mode of transportation to work (we refer to these variables as "living arrangement" measures), as well as fixed effects for industry, occupation, indicator for the (likely) ability to work from home, and indicator for (likely) being

during the first three quarters of 2020 and to Cortes and Forsythe (2023) who decompose Black-White differences in year-on-year job displacement probabilities in the CPS during April 2020 and February 2021.

[25]Similar approaches have been used to consider the role of covariates in racial gaps in consumption smoothing (Ganong et al. 2020), racial gaps in exposure to air pollution (Currie et al. 2020), and geographic gaps in infant mortality (Chen et al. 2016).

an essential worker (we refer to these variables as "nature of work" measures). These variables can all be thought of as proxying for differences in the risk of exposure to the pandemic. Our data are fairly rich on measures of exposure risk, but substantially less so for measures of severity conditional on exposure. We are able to add only a few covariates that likely capture severity conditional on exposure: disability status, sex, and having health insurance. We also report how our estimates change with the inclusion of family income; this is strongly correlated with both the risk of exposure as well as the factors that contribute to severity of impact.

As in our baseline analysis, we use lagged measures of covariates defined prior to the start of the pandemic. This has the advantage of avoiding endogenous changes in the covariates due to the pandemic itself. However, this may weaken the explanatory power of the variables if their values change between the time of measurement and the start of the pandemic.

For the analysis of gaps in economic damages, X includes the following measures that proxy for differences in the risk of exposure: state (we do not observe any other information about living arrangements in CPS), industry, occupation, and indicators for the ability to work from home and being an essential worker. We similarly report how our estimates are affected by the inclusion of variables that likely correlate with the determinants of the economic impact severity such as sex, disability status, and having a young child in the household which could affect parental labor force participation when schools close, as well as family income.

B.2 Results

Table C.10 shows the results of estimating Equation 5 for non-Hispanic Black-White gaps in both health and economic damages among ages 25-64. The "Gap" column shows the difference in average damages (by year for mortality and month for employment) among non-Hispanic Black people relative to non-Hispanic White people. The "Reduction relative to baseline" column shows the percent difference in the estimate of the average of the θ_ρ coefficients for different values of X relative to the "Age Adjusted" row. The average annual unadjusted Black-White gap among 25-

to 64-year-olds in March 2020 - February 2022 is 9.7 per 10,000 for excess mortality and 3.0 per 100 for missing employment.[26] Adjusting for age results in a slight increase in the Black-White gap in excess mortality from 9.7 per 10,000 to 10.2 per 10,000, and a slight decrease (from 3.0 to 2.9 extra missing jobs) in economic damages, consistent with the non-Hispanic Black population being on average younger than the non-Hispanic White population.

Subsequent panels add individual covariates to the regression. The "exposure" covariates – living arrangements (panel B) and nature of work (panel C) – individually account for between 2 and 11 percent of the excess mortality gap. Together, the living arrangement and nature of work variables explain approximately 25 percent of the Black-White excess mortality gap (panel F); this suggests that our proxies of exposure differences are an important piece of the gap, but that a substantial share remains unexplained. We note that income and education, which we would expect to be correlated with both exposure risk and the severity conditional on exposure, can, on their own, explain about 25% and 19% of the gap in excess mortality, respectively. Including all of our variables together leaves about 60 percent of the mortality gap unaccounted for

Next, looking at the Black-White gap in economic damages, we find that industry and occupation alone can each explain 20-26% of the gaps (Panel C). All together, differences in exposure can account for 28% of the employment gap and even with all covariates included, more than half of the Black-White gap in employment damages remains unexplained.

We then show the same results for Hispanic-White gaps in each outcome. Adjusting for age again increases the estimated average annual mortality gap, from 5.0 per 10,000 to 5.7 per 10,000. About 25 percent of this gap can be explained by our measures of exposure in Panel B and C; we can explain approximately two-thirds of the gap when we include all observed covariates. For economic

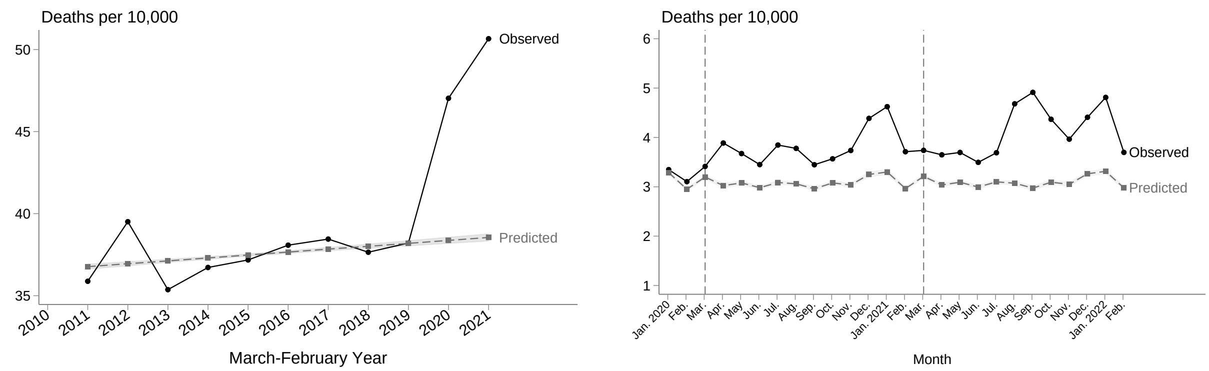
[26] This mortality gap differs from that reported in Table C.4 because here we use ages 25-64 among the linked ACS-Numident dataset rather than ages 11-99 within the full Census Numident data.

damages, the age-adjusted gap is 2.2 per 100, and about 18 percent of that can be explained by our measures of exposure. All of the covariates can together explain 47% of this gap; income appears individually to be the most important (reducing the gap by 50%), but we note that some of this relationship could be mechanical as for some individuals in CPS income is measured during the time of the pandemic.

C Appendix Exhibits

Figure C.1: **Annual and Monthly Mortality, Ages 25-64**

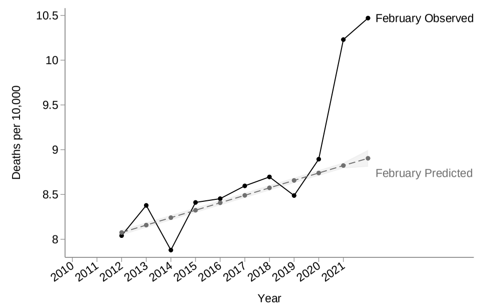
(A) Annual Mortality, 2011-2021 (B) Monthly Mortality, 2020-2021



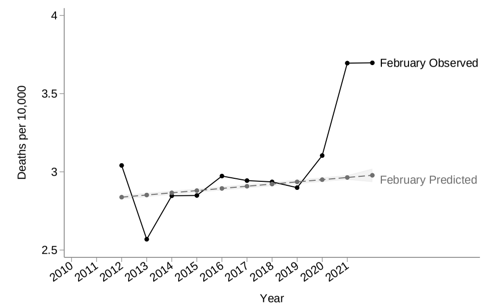
Notes: These figures show the annual (Panel A) and monthly (Panel B) number of observed and predicted deaths per 10,000 people among working-age adults (ages 25-64) using the full Census Numident dataset. A year is defined as 12 months from March to February. Panel (A) displays estimates from March 2011 through February 2022 and Panel (B) displays estimates from January 2020 through February 2022. The dashed linear trend lines are estimated as specified in Equations 2 (Panel A) and 1 (Panel B). Dashed vertical lines in Panel (B) indicate the start of the first and second year of the pandemic. The dashed 'prediction' series are constructed in Panel (A) as $\hat{y}_t = \hat{\alpha} + \hat{\beta} \times t$, using the estimates from Equation 2; they are constructed in Panel (B) as $\hat{y}_{mt} = \hat{\alpha}_m + \hat{\beta} \times t$ based on the estimates from Equation 1. The 95% confidence interval for the prediction is shaded in gray and is based on heteroskedasticity-robust standard errors. **Source**: Authors' calculations from Census Numident. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure C.2: **Monthly Mortality and Employment, 2011-2020, for selected months (continues on next page)**

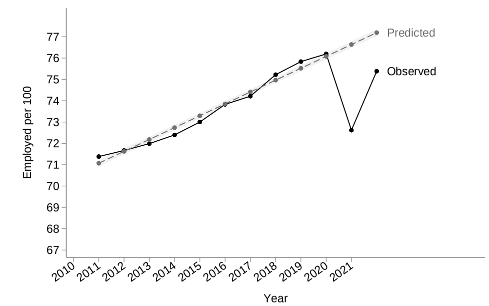
(A) Mortality per 10,000 (Ages 11-99) February



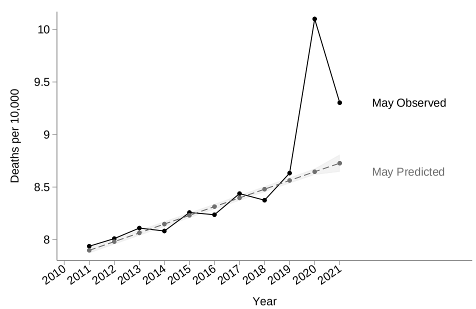
(B) Mortality per 10,000 (Ages 25-64) February



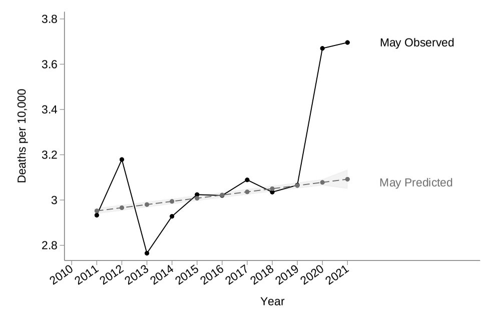
(C) Employment per 100 (Ages 25-64) February



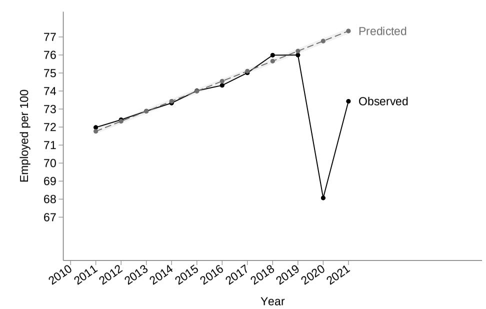
(D) Mortality per 10,000 (Ages 11-99) May



(E) Mortality per 10,000 (Ages 25-64) May



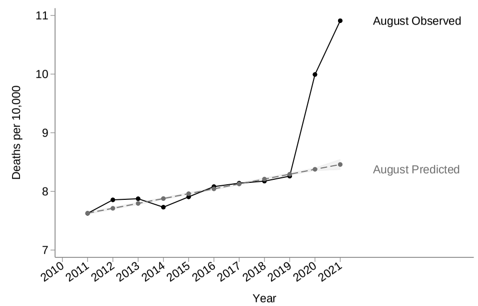
(F) Employment per 100 (Ages 25-64) May



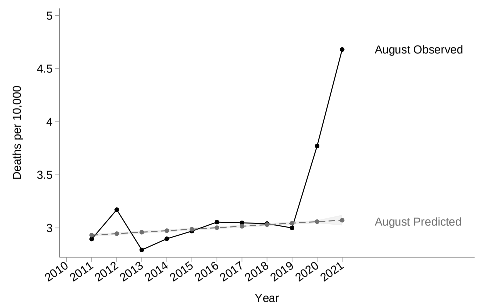
Notes: Panels show the number of monthly observed and predicted deaths per 10,000 people among all individuals ages 11-99 (Panel A,D,G,J) and among working-age adults (ages 25-64) (Panels B, E, H, K) using the full Census Numident dataset. Panels (C, F, I, L) show the observed and predicted number of individuals employed per 100 working-age adults over the same time period. Each row of panels is restricted to one calendar month – February in the first row, May in the second, August in the third, and November in the fourth. The dashed 'prediction' series are constructed as $\hat{y}_{mt} = \hat{\alpha}_m + \hat{\beta} \times t$ based on the estimates from Equation 1. The 95% confidence interval for prediction is shaded in gray and is based on heteroskedasticity-robust standard errors and CPS survey weights (in Panels C, F, I, L). **Source**: Authors' calculations from Census Numident and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure C.2: **Monthly Mortality and Employment, 2011-2020, for selected months (continued)**

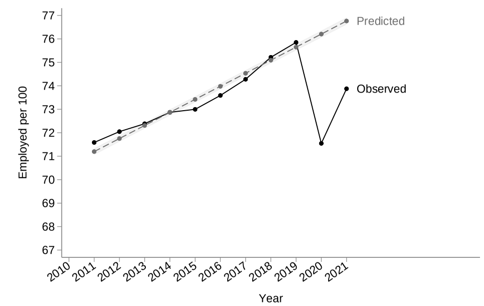
(G) Mortality per 10,000 (Ages 11-99) August



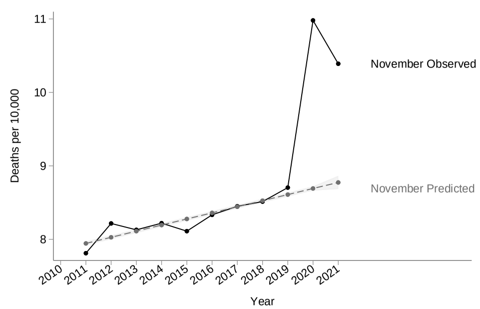
(H) Mortality per 10,000 (Ages 25-64) August



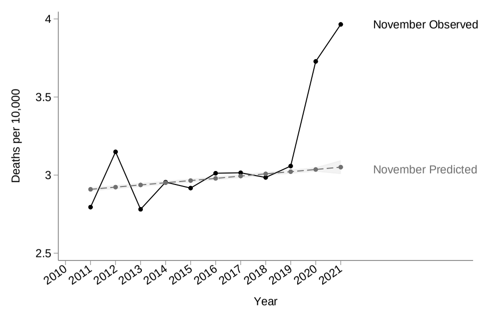
(I) Employment per 100 (Ages 25-64) August



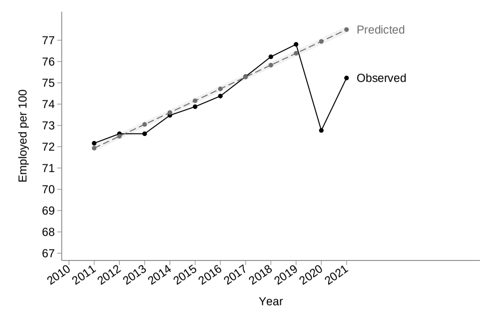
(J) Mortality per 10,000 (Ages 11-99) November



(K) Mortality per 10,000 (Ages 25-64) November

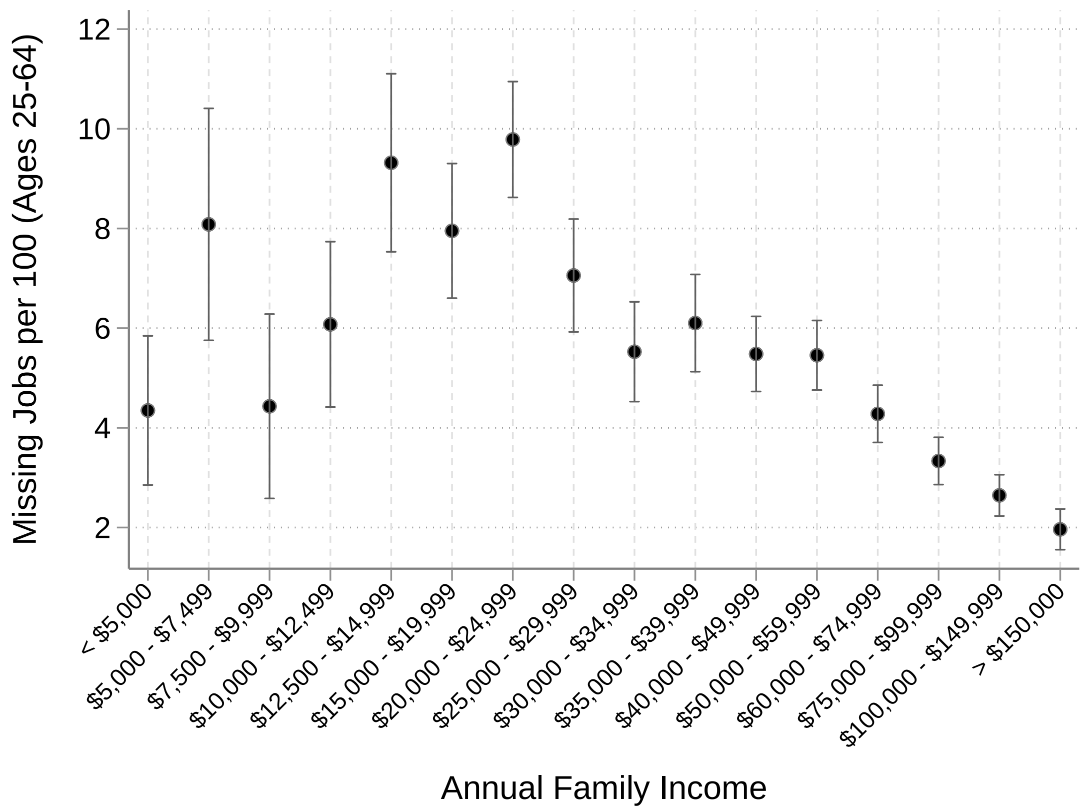


(L) Employment per 100 (Ages 25-64) November



Notes: Panels show the number of monthly observed and predicted deaths per 10,000 people among all individuals ages 11-99 (Panel A,D,G,J) and among working-age adults (ages 25-64) (Panels B, E, H, K) using the full Census Numident dataset. Panels (C, F, I, L) show the observed and predicted number of individuals employed per 100 working-age adults over the same time period. Each row of panels is restricted to one calendar month – February in the first row, May in the second, August in the third, and November in the fourth. The dashed 'prediction' series are constructed as $\hat{y}_{mt} = \hat{\alpha}_m + \hat{\beta} \times t$ based on the estimates from Equation 1. The 95% confidence interval for the prediction is shaded in gray and is based on heteroskedasticity-robust standard errors and CPS survey weights (in Panels C, F, I, L). **Source**: Authors' calculations from Census Numident and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Figure C.3: **Age-Adjusted Economic Damages by Income**



Notes: This graph plots average annual (averaged across two pandemic years) age-adjusted economic damages (among 25- to 64-year-olds) by family income. Lines show the heteroskedasticity-robust 95 percent confidence intervals for each income group, using CPS survey weights. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age-adjustment. **Source**: Authors' calculations from Current Population Survey.

Table C.1: **Mortality Analysis Sample Size with Restrictions**

	(1)	(2)	(3)	(4)	(5)	(6)
Restriction	**Individuals Remaining**	**Individuals Dropped at step**	**Individual-Years Remaining (Numident)**	**Individual-Years Remaining in 2020 and 2021 (Numident)**	**Individual-Years Remaining (ACS-Numident)**	**Individual-Years Remaining in 2020 and 2021 (ACS-Numident)**
Numident File without Death before 2010	424,300,000					
Require Birth Month and Year	422,400,000	1,893,000				
Require Death Month and Year if Died	422,300,000	111,000				
Drop Individuals at Least 100 Before 2010	407,700,000	14,560,000				
Require Can Verify Alive Start of 2010	347,300,000	60,470,000				
Initial Person-Year Sample			3,343,000,000	618,400,000	266,600,000	50,220,000
Drop if Missing Race			3,117,000,000	54,100,000	258,600,000	4,6700,000
Drop if not in the US			2,814,000,000	487,000,000	240,000,000	43,370,000
Ages 11–99 Sample			2,624,000,000	483,300,000	228,100,000	43,070,000
Ages 25–64 Sample			1,582,000,000	285,400,000	130,500,000	23,920,000

Notes: This table shows the size of our main analytic datasets and the number of individuals dropped for each restriction described in Appendix A.1. A year is defined as 12 months from March to February. The linked ACS-Numident dataset is a merge between Census Numident and six years of the 1-year American Community Survey (ACS) data. All reported numbers were rounded following the Census Bureau guidelines. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, 2010-2020 Master Address File-Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, and 2010 Modeled Race File. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.2: **Health and Economic Damages by Age Group**

	(1)	(2)	(3)	(4)	(5)	(6)
Age Group	**Annual Excess Mortality (per 10,000)**	**Annual Predicted Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**Predicted Employment (per 100)**	**(SE)**
10–19	0.80	3.89	(0.05)	.	.	.
20–29	2.37	11.38	(0.09)	6.73	74.65	(0.22)
30–39	4.67	15.92	(0.11)	4.72	81.42	(0.19)
40–49	9.51	24.43	(0.15)	4.33	81.43	(0.20)
50–59	15.37	54.25	(0.28)	3.13	74.25	(0.21)
60–69	27.57	125.05	(0.56)	2.64	45.98	(0.25)
70–79	57.15	280.70	(1.15)	.	.	.
80–89	108.10	773.50	(3.07)	.	.	.
90–99	210.95	1874.50	(7.20)	.	.	.

Notes: This table reports average unadjusted annual (averaged across two pandemic years) excess all-cause mortality and average unadjusted annual economic damages, by age group. Damages are estimated as specified in Equation 3, omitting the age bin adjustment terms. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical linear trend. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using CPS survey weights for employment damage. The mortality results use the full Numident dataset.
Source: Authors' calculations from Census Numident and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.3: **Annual Predictions by Race/Ethnicity and Education**

	(1)	(2)
Group	**Predicted Annual Mortality (per 10,000)**	**Predicted Employment (per 100)**
Panel A: Race/Ethnicity		
Non-Hispanic White	123.65	77.89
Hispanic	53.85	76.41
Non-Hispanic Black	96.40	73.57
Non-Hispanic Asian	55.55	76.12
Non-Hispanic American Indian/Alaskan	111.90	64.05
Non-Hispanic Hawaiian/Pacific Islander	71.85	76.20
Other/Two or More	56.95	77.54
Panel B: Education		
Less than HS	258.05	59.64
HS or GED	181.40	70.98
Some college	112.30	75.23
Associate's degree	83.50	79.55
Bachelor's degree	74.55	83.18
Master's degree	79.65	85.63
Professional degree	91.15	87.29
Doctorate degree	105.15	90.42

Notes: This table reports predictions of unadjusted average annual (averaged across two pandemic years) all-cause mortality (ages 11-99 for race/ethnicity and ages 25-99 for education) and unadjusted average annual economic damage (ages 25-64 for all groups) by race/ethnicity and educational attainment. Predictions are computed based on Equation 3, omitting the age bin adjustment terms. Heteroskedasticity-robust standard errors are shown in parentheses, using CPS survey weights for employment damage and ACS person-level weights for mortality damage by education. All race/ethnicity groups other than "Hispanic" are limited to Non-Hispanic individuals. The mortality predictions by race/ethnicity use the full Numident dataset and the mortality predictions by education use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.4: **Annual Health and Economic Damages by Race/Ethnicity**

	(1)	(2)	(3)	(4)
Group	**Annual Excess Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**(SE)**
Non-Hispanic White	16.43	(0.18)	3.51	(0.12)
Hispanic	34.33	(0.54)	5.70	(0.26)
Non-Hispanic Black	37.15	(0.48)	6.45	(0.33)
Non-Hispanic Asian	17.45	(0.95)	3.18	(0.42)
Non-Hispanic American Indian/Alaskan	41.20	(1.04)	2.48	(1.24)
Non-Hispanic Hawaiian/Pacific Islander	27.96	(1.72)	3.82	(1.71)
Other/Two or More	23.25	(1.04)	6.15	(0.95)

Notes: This table reports average annual (averaged across two pandemic years) age-adjusted excess all-cause mortality (among 11- to 99-year-olds) and average annual age-adjusted economic damages (among 25- to 64-year-olds) by race/ethnicity. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age adjustment. All race/ethnicity groups other than "Hispanic" are limited to Non-Hispanic individuals. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using CPS survey weights for economic damages. The mortality results use the full Numident dataset. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.5: **Annual Health and Economic Damages by Education**

	(1)	(2)	(3)	(4)	(5)	(6)
Group	**Annual Excess Mortality (per 10,000)**	**(SE)**	**Population Share, Ages 25-99**	**Annual Economic Damage (per 100)**	**(SE)**	**Population Share, Ages 25-64**
Less than HS	57.20	(1.63)	12.57	5.50	(0.40)	11.44
HS or GED	27.26	(1.54)	27.14	5.45	(0.21)	25.87
Some college	17.89	(1.47)	20.59	5.22	(0.27)	20.95
Associate's degree	14.98	(1.66)	8.37	4.54	(0.30)	9.07
Bachelor's degree	11.90	(1.40)	19.38	3.25	(0.19)	20.75
Master's degree	7.22	(1.61)	8.52	1.50	(0.27)	8.63
Professional degree	7.46	(2.56)	2.07	0.68	(0.67)	2.03
Doctorate degree	8.67	(3.17)	1.36	1.71	(0.53)	1.27

Notes: This table reports average annual (averaged across two pandemic years) age-adjusted excess all-cause mortality (among 25- to 99-year-olds) and average annual age-adjusted economic damages (among 25- to 64-year-olds) by educational attainment. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age adjustment. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using ACS person-level weights for health damages and CPS survey weights for economic damages. The mortality results use the ACS-Numident linked dataset. Columns (3) and (6) show the shares of the population in the indicated age group in the 2016 IPUMS ACS with the given educational attainment, using relevant person weights. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.6: **Annual Age-Adjusted Health and Economic Damages by Industry**

	(1)	(2)	(3)	(4)
Industry	**Annual Excess Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**(SE)**
Administration, support	11.67	(1.85)	7.19	(0.38)
Mining, quarry, oil, gas	10.80	(3.47)	8.03	(0.98)
Retail trade	9.34	(1.50)	4.66	(0.22)
Accommodations and food	8.97	(1.64)	13.52	(0.38)
Forestry, fishing	8.94	(5.16)	2.65	(1.47)
Transportation, warehousing	8.90	(1.84)	6.86	(0.31)
Arts, entertainment, recreation	8.61	(1.98)	19.93	(0.51)
Utilities	8.55	(2.65)	1.17	(0.45)
Manufacturing	8.32	(1.50)	4.23	(0.19)
Wholesale trade	7.61	(1.91)	3.13	(0.38)
Healthcare, social assistance	7.52	(1.43)	2.93	(0.15)
Other services	7.29	(1.69)	6.60	(0.31)
Public administration	7.09	(1.62)	1.50	(0.20)
Agriculture	7.00	(1.88)	0.93	(0.62)
Finance, insurance	6.75	(1.55)	2.17	(0.21)
Construction	5.89	(1.69)	6.80	(0.25)
Education	5.67	(1.43)	2.58	(0.17)
Information	5.01	(1.85)	4.33	(0.46)
Real estate, rental, leasing	4.69	(2.10)	4.25	(0.41)
Professional, scientific, technical	4.01	(1.47)	2.97	(0.18)
Company management	–5.30	(4.65)	0.64	(1.93)

Notes: This table reports average annual (averaged across two pandemic years) age-adjusted excess all-cause mortality (among 25- to 64-year-olds) and average annual age-adjusted excess economic damage (among 25- to 64-year-olds), by industry. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age adjustment. Results are presented in descending order by annual excess mortality. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using ACS person-level weights for health damages and CPS survey weights for economic damages. The mortality results use the ACS-Numident linked dataset.
Source: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.7: **Annual Age-Adjusted Health and Economic Damages by by Occupation and Work-from-Home (WFH) Status**

	(1)	(2)	(3)	(4)
Group	**Annual Excess Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**(SE)**
Panel A: Occupation				
Building, grounds cleaning, maintenance	13.30	(1.60)	7.12	(0.39)
Installation, maintenance, repair	10.33	(0.92)	3.92	(0.32)
Material moving	9.82	(1.74)	7.41	(0.29)
Farming, fishing, forestry	9.78	(3.34)	2.81	(0.95)
Transportation	9.63	(1.55)	5.79	(0.29)
Protective service	9.13	(1.55)	3.08	(0.38)
Food prep and service	8.67	(1.18)	13.37	(0.44)
Personal care and service	7.70	(1.19)	9.64	(0.47)
Community and social service	7.00	(1.47)	2.13	(0.36)
Healthcare support	6.67	(1.35)	5.66	(0.40)
Sales and retail	6.26	(0.76)	4.74	(0.22)
Construction, extraction	5.04	(1.29)	7.76	(0.31)
Business, financial	4.91	(0.84)	2.67	(0.22)
Art, design, entertainment, media	4.77	(1.26)	6.99	(0.46)
Office and admin support	4.52	(0.66)	4.93	(0.20)
Life, physical, social science	4.46	(1.71)	2.33	(0.50)
Legal	3.94	(1.58)	1.86	(0.40)
Healthcare practice and tech	3.76	(0.75)	1.85	(0.16)
Education, library	3.49	(0.70)	2.86	(0.21)
Management	3.34	(0.49)	2.68	(0.13)
Computer, mathematical	2.80	(1.05)	1.32	(0.24)
Architecture, engineering	1.25	(1.32)	2.49	(0.31)
Panel B: WFH Status				
Non-work from home	9.58	(0.27)	4.88	(0.14)
Work from home	5.61	(0.34)	3.18	(0.08)

Notes: This table reports average annual (averaged across two pandemic years) age-adjusted excess all-cause mortality (among 25- to 64-year-olds) and average annual age-adjusted excess economic damage (among 25- to 64-year-olds), by occupation and work-from-home (WFH) status. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age adjustment. Results are presented in descending order by annual excess mortality. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using ACS person-level weights for health damages and CPS survey weights for economic damages. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.8: **Age-Adjusted Health Damages by Income**

	(1)	(2)	(3)	(4)	(5)	(6)
Poverty Index Bin	**Annual Excess Mortality, 2020 (per 10,000)**	**(SE)**	**Annual Excess Mortality, 2021 (per 10,000)**	**(SE)**	**Lower Income Percentile**	**Approximate Annual Income for Family of Three, 2019**
0–49	17.24	(1.53)	27.58	(1.70)	2.08	$0
50–99	17.57	(1.44)	29.29	(1.62)	5.25	$10168
100–149	12.96	(1.17)	20.91	(1.29)	11.85	$20335
150–199	12.06	(0.98)	17.40	(1.07)	19.21	$30503
200–249	8.35	(0.87)	15.61	(0.96)	26.97	$40670
250–299	8.30	(0.84)	13.51	(0.93)	35.15	$50838
300–349	6.74	(0.80)	12.28	(0.88)	42.53	$61005
350–399	6.01	(0.80)	9.66	(0.87)	49.74	$71173
400–449	5.49	(0.80)	9.49	(0.88)	56.02	$81340
450–499	5.72	(0.83)	10.35	(0.91)	62.27	$91508
500–549	4.70	(0.87)	8.05	(0.95)	67.44	$101675
550–599	4.21	(0.93)	7.22	(1.01)		$111843
600–649	3.66	(0.97)	6.26	(1.05)		$122010
650–699	5.14	(1.07)	6.96	(1.14)		$132178
700–749	5.22	(1.16)	3.84	(1.20)		$142345
750–799	1.57	(1.19)	3.82	(1.29)		$152513
800–849	1.56	(1.26)	3.19	(1.36)		$162680
850–899	2.28	(1.40)	2.76	(1.48)		$172848
900–949	–0.16	(1.47)	5.44	(1.66)		$183015
950–998	4.15	(1.70)	3.44	(1.77)		$193193
999 or Higher	0.51	(0.55)	1.21	(0.59)		$203147

Notes: This table reports annual age-adjusted excess all-cause mortality (among 25- to 64-year-olds) by family income, separately for pandemic years 2020 (March 2020 - February 2021) and 2021 (March 2021 - February 2022). Our income measure is the ratio of a family's income to the poverty threshold, multiplied by 100, as reported in the ACS. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample in the ACS-Numident linked dataset as the benchmark for age adjustment. Heteroskedasticity-robust standard errors are shown in parentheses, using ACS person-level weights for health damages. Column (5) shows the share of 25- to 64-year-olds in the 2016 IPUMS ACS with a family income value at or below the lower limit of the indicated poverty index bin, using relevant person weights. Percentiles are not shown above the poverty index bin beginning at 500 due to top-coding in the public ACS data. Column (6) shows the approximate annual income for a family of three in 2019 associated with the lower limit of the indicated poverty index bin, using poverty thresholds available from the Census Bureau at: https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html. **Source**: Authors' calculations from Census Numident and the 1-Year American Community Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.9: **Age-Adjusted Health and Economic Damages by Disability**

	(1)	(2)	(3)	(4)
Group	**Annual Excess Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**(SE)**
Not Disabled	8.48	(0.87)	4.55	(0.10)
Disabled	22.25	(1.19)	0.93	(0.38)

Notes: This table reports average annual (averaged across two pandemic years) age-adjusted excess all-cause mortality (among 25- to 64-year-olds) and average annual age-adjusted excess economic damages (among 25- to 64-year-olds), by disability status. For economic damages, disability is defined from the CPS as having any physical or cognitive difficulty (measured as a combination of having responded 'yes' to at least one of the six physical or cognitive difficulties in the CPS). For health damages, disability is defined from the ACS as responding "yes" to at least one of the following: having hearing difficulties, vision difficulties, self-care difficulties, independent living difficulties, ambulatory difficulties, or cognitive difficulties. Damages are estimated as specified in Equation 3. We use the age distribution in the full sample as the benchmark for age adjustment. The damages measure the deviation of observed outcomes relative to the linear trend-based prediction. Heteroskedasticity-robust standard errors are shown in parentheses, using ACS person-level weights for health damages and CPS survey weights for economic damages. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.10: **Decomposition of Gaps in Damages between Black and White Individuals**

	(1)	(2)	(3)	(4)	(5)	(6)
	Excess Deaths per 10,000			Missing Jobs per 100		
Specification	Gap	(SE)	Reduction relative to baseline	Gap	(SE)	Reduction relative to baseline
Panel A: Baseline						
Age-Adjusted	10.19	(0.98)	baseline	2.93	(0.35)	baseline
Unadjusted	9.65	(0.97)	5.3%	3.01	(0.36)	–2.6%*
Panel B: Living Arrangement Variables						
State	9.48	(0.99)	6.9%	3.05	(0.36)	–3.8%
People per Room	9.71	(0.98)	4.7%			
Housing Type	9.77	(0.98)	4.1%			
Group Quarters	9.86	(0.98)	3.2%			
Panel C: Nature of Work Variables						
Mode of Transportation to Work	9.88	(0.97)	3.0%			
Industry	9.65	(0.98)	5.3%	2.32	(0.20)	20.8%
Occupation	9.09	(0.98)	10.8%	2.17	(0.20)	25.9%
Work from Home	9.38	(0.97)	7.9%	3.14	(0.33)	–7.1%
Essential Worker	9.91	(0.97)	2.7%	2.47	(0.31)	15.8%
Panel D: Severity Variables						
Disability	9.80	(0.97)	3.7%	3.14	(0.33)	–7.2%
Sex	10.47	(0.98)	–2.8%	2.96	(0.35)	–0.8%*
Young Child				2.98	(0.35)	–1.6%
Health Insurance	10.19	(0.98)	0.0%*			
Panel E: Income and Education						
Income	7.62	(0.98)	25.2%	2.31	(0.33)	21.2%
Education	8.24	(0.98)	19.0%	2.69	(0.34)	8.4%
Panel F: Variable Combinations						
Living Arrangements	8.35	(0.99)	18.0%	3.05	(0.36)	–3.8%
Nature of Work	9.04	(0.98)	11.2%	2.09	(0.19)	28.6%
Living Arrangements and Nature of Work	7.64	(1.00)	25.0%	2.12	(0.20)	27.7%
All Variables	6.10	(1.00)	40.1%	1.63	(0.19)	44.3%

* The reduction is not statistically significant at 5% level.

Notes: This table shows the estimated differences—between non-Hispanic Black and non-Hispanic White individuals—in excess average annual (averaged across two pandemic years) all-cause mortality and average annual economic damages, both among 25- to 64-year-olds. Mortality estimates are based on the linked ACS-Numident dataset. Differences in damages are estimated as specified in Equation 5. Each row includes covariates specified in Panels B, C, D, E, and F. All rows except the "Unadjusted" row control for 5-year age bins. Regressions are weighted with ACS or CPS survey weights. Heteroskedasticity-robust standard errors are reported in parentheses. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.

Table C.11: **Decomposition of Gaps in Damages between Hispanic and White Individuals**

	(1)	(2)	(3)	(4)	(5)	(6)
	Excess Deaths per 10,000			Missing Jobs per 100		
Specification	Gap	(SE)	Reduction relative to baseline	Gap	(SE)	Reduction relative to baseline
Panel A: Baseline						
Age-Adjusted	5.67	(0.71)	baseline	2.18	(0.29)	baseline
Unadjusted	4.97	(0.70)	12.4%	2.47	(0.29)	–12.9%
Panel B: Living Arrangement Variables						
State	6.41	(0.74)	–13.1%	1.87	(0.30)	14.6%
People per Room	4.69	(0.72)	17.3%			
Housing Type	5.50	(0.71)	3.0%			
Group Quarters	5.71	(0.71)	–0.7%			
Panel C: Nature of Work Variables						
Mode of Transportation to Work	5.37	(0.71)	5.2%			
Industry	4.75	(0.71)	16.2%	2.24	(0.15)	–2.5%*
Occupation	4.17	(0.71)	26.5%	2.04	(0.15)	6.5%
Work from Home	4.78	(0.71)	15.8%	2.38	(0.28)	–9.0%*
Essential Worker	5.34	(0.71)	5.9%	2.04	(0.26)	6.5%*
Panel D: Severity Variables						
Disability	5.87	(0.71)	–3.5%	1.92	(0.28)	12.1%
Sex	5.66	(0.71)	0.2%*	2.21	(0.28)	–1.3%*
Young Child				2.25	(0.29)	–3.0%
Health Insurance	5.73	(0.71)	–1.1%*			
Panel E: Income and Education						
Income	3.95	(0.72)	30.3%	1.09	(0.28)	50.0%
Education	2.35	(0.72)	58.6%	2.15	(0.29)	1.6%*
Panel F: Variable Combinations						
Living Arrangements	5.44	(0.75)	4.1%*	1.87	(0.30)	14.6%
Nature of Work	4.09	(0.71)	27.9%	2.00	(0.15)	8.3%
Living Arrangements and Nature of Work	4.18	(0.76)	26.2%	1.80	(0.16)	17.8%
All Variables	2.26	(0.77)	60.1%	1.17	(0.16)	46.5%

* The reduction is not statistically significant at 5% level.

Notes: This table shows the estimated differences—between Hispanic and non-Hispanic White individuals—in excess average annual (averaged across two pandemic years) all-cause mortality and average annual economic damages, both among 25- to 64-year-olds. Mortality estimates are based on the linked ACS-Numident dataset. Differences in damages are estimated as specified in Equation 5. Each row includes covariates specified in Panels B, C, D, E, and F. All rows except the "Unadjusted" row control for 5-year age bins. Regressions are weighted with ACS or CPS survey weights. Heteroskedasticity-robust standard errors are reported in parentheses. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, the 1-Year American Community Survey, and Current Population Survey. All results were approved for release by the Census Bureau, auth. no. CBDRB-FY22-POP001-0104, CBDRB-FY22-POP001-0117, CBDRB-FY23-POP001-0001.