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HETEROGENEITY IN DAMAGES FROM A PANDEMIC

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Heterogeneity in Damages from A Pandemic
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ABSTRACT

We use linked survey and administrative data to document and decompose the striking differences across demographic groups in both economic and health impacts of the first year of the COVID-19 pandemic in the United States. The impacts of the pandemic on all-cause mortality and on employment were concentrated in the same racial, ethnic, and education groups, with non-White individuals and those without a college degree experiencing higher excess all-cause mortality as well as a greater employment loss. Observable differences in living arrangements and the nature of work – which likely affected exposure to the virus and to economic contractions – can explain 15 percent of the Hispanic-White difference in excess mortality, almost one-quarter of the non- Hispanic Black-White difference, and almost half of the difference between those with and without a Bachelor's degree; they can also explain 35 to 40 percent of the differences in economic damages between these groups. These findings underscore the importance of non-medical factors in contributing to the disparate impacts of public health shocks.

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1 Introduction

The United States has long exhibited striking variation in health and economic well-being across demographic groups, including geography, education, income, race, and ethnicity.[1] The COVID-19 pandemic – which was both a health and an economic crisis – was no exception. It had well-documented differential impacts on both health and economic well-being across different parts of society. Broadly speaking, there are two main classes of explanations for the differences in the pandemic's impacts across demographic groups. One set of explanations focuses on differences in exposure to the pandemic – either to the virus itself or to the economic contractions it produced. The other focuses on existing differences in health capital and in human capital which can affect outcomes conditional on exposure.

We document how economic and health damages varied across different groups and explore how much observable differences in the risk of exposure can explain the heterogeneity in impacts that we estimate. We focus on the first 12 months of the pandemic in the U.S. – from the start of the pandemic in March 2020 through February 2021 – which marked the period prior to widespread vaccination.[2] We define the pandemic's health damages to be the increase in all-cause twelve-month mortality relative to what was expected based on the historical trend. We define the pandemic's economic damages to be the average monthly decline in the employment-to-population ratio over these same twelve months, again relative to expectations.

For the mortality analysis, we leverage linked administrative and survey data. The ad-

[1]There is a vast literature documenting these disparities and investigating causal origins. Some examples of this research and syntheses of it for variation in health across groups include Fuchs (1974), Case et al. (2002), Deaton (2002), Williams and Jackson (2005), Meara et al. (2008), Currie (2009), 2011, Boustan and Margo (2015), Case and Deaton (2015), Chetty et al. (2016), Weinstein et al. (2017), Lleras-Muney (2022), Polyakova and Hua (2019), Chetty, Hendren, et al. (2020), Bailey et al. (2021), Finkelstein et al. (2021), Schwandt et al. (2021), and Novosad et al. (2022). For variation in economic well-being across groups, see for example Hoynes et al. (2012), Bayer and Charles (2018), and Derenoncourt et al. (2022).

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

ministrative data provide information on the full U.S. population of decedents and survivors. Specifically, we use the U.S. Census Bureau's version of the Social Security Administration's Numerical Identification database (Census Numident). This provides individual-level data on the date of death (if applicable) for the near universe of the U.S. population; we link these administrative records to a record of race/ethnicity from the Decennial Census, and to a rich set of socio-economic covariates – including education, occupation, industry, income, and housing situation – 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.

Overall, we estimate that, over its first year, the pandemic was responsible for 22.3 excess deaths (from any cause) per 10,000 people ages 11-99, and for an average decline in monthly employment of 5.4 per 100 people ages 25-64. Excess deaths were concentrated among the older adults, while (mechanically) employment declines were concentrated in the under-65 population. We document substantial variation in mortality effects and in employment declines across states, as well as by industry, occupation, and income. Economic and health damages were uncorrelated across states; states that experienced higher excess mortality did not necessarily have higher economic damages and vice versa. By contrast, industries and occupations that experienced high economic damages were also the ones with high health damages. Similarly, we observed that economic and health damages were concentrated in lower income groups.

When we look across demographic groups – specifically by race, ethnicity and educational attainment – we find that, consistent with the existing literature, impacts on employment and on mortality were concentrated in the same groups. In particular, non-White individuals and those without a college degree experienced higher excess mortality as well as higher rates of employment loss. Age-adjusted excess annual all-cause mortality was 11.2 per 10,000 higher for non-Hispanic Black people than non-Hispanic White people, and age-adjusted average annual employment displacement was 3.2 per 100 higher. For Hispanic people relative to non-Hispanic White people, the comparable gap in excess mortality was 9.8 per 10,000; in employment displacement it was was 3.0 per 100. For people without a Bachelor's degree (BA) relative to those with a BA or higher, these gaps were 7.6 per 10,000 for mortality and 2.8 per 100 for employment displacement.

We explore the extent to which observable differences in exposure to the pandemic – measured by where and how people live and work – can explain these differences in the pandemic's (age-adjusted) impacts by demographic group. Differences in living arrangements and the nature of work were frequently suggested as potential drivers of disparities in the impact of the pandemic in the contemporary public discourse.[3] Our rich data allow us to explore the quantitative role of such "exposure-based" explanations.

For this analysis we limit our data to prime age workers (ages 25-64) where economic damages – and our exposure measures – are well-defined. This age group is responsible for the entirety of the economic damage estimates (by construction) but less than one quarter of the estimated overall excess mortality (excess mortality of 5.4 per 10,000 in the age 25-64 group compared to 22.3 per 10,000 in the age 11-99 group); however the gaps in excess mortality by race, ethnicity, and education are even larger proportionally within the younger age group.[4] Our measures of exposure include location (state), living arrangements (e.g. apartment building or single family home, mode of transportation to work, and number of

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

[4]The larger proportional increase in excess mortality for non-Hispanic Black people compared to White people once we exclude the oldest individuals is consistent with other work that stratifies by age group, such as Ford et al. (2020) and Alsan et al. (2021).

people per room), and the nature of work (specifically industry and occupation, ability to work from home, and whether the individual would be classified as an "essential worker"). The living arrangement variables capture the differential ability of individuals to isolate from others who are potentially contagious, which directly impacts infection probabilities and subsequent labor market effects from illness. The nature of work variables affect the amount of on-the-job exposure to the virus as well as exposure to changes in labor demand, either due to a decline in consumer demand or due to shelter-in-place restrictions on business operations.

We find that even these relatively limited measures of how people live and work can account for a meaningful share of the disparate impacts of the pandemic that we document. Specifically, we estimate that these exposure measures can account for about 15 percent of the Hispanic-White age-adjusted gap in excess mortality, 23 percent of the non-Hispanic Black-White age-adjusted gap, and 45 percent of the age-adjusted gap in excess mortality for those without a BA relative to those with a BA. We also find that these same covariates can account for about 35-40 percent of the age-adjusted gaps in employment declines for these demographic groups.

Our paper contributes to several related literatures. Most narrowly, it adds to the large – and still rapidly growing – 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). While almost all groups suffered lost years of life due to the pandemic, it has been well-documented that racial and ethnic minorities and individuals without a BA were disproportionately affected.[5] The economic consequences of the pandemic were similarly

[5]For example, during the initial months of the pandemic, minorities had higher recorded COVID-19

dramatic, with substantial decreases in consumer spending and business revenues (Chetty, Friedman, et al. 2020), 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. 2020; 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; Evans et al. 2021; Cutler 2022; Goda and Soltas 2022; Ziauddeen et al. 2022). The economic consequences too have disproportionately been felt by racial and ethnic minorities and by those without a BA.[6] Our findings, which are consistent with this existing literature, provide a set of estimates of the pandemic impacts in the first year that are directly comparable across demographic groups and across health and economic outcomes; they also leverage the rich descriptors in our data to look at the role of exposure to the pandemic in accounting for these disparate impacts.

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), and, conversely, how shocks to population health may impact the economy (Adda 2016; Barro et al. 2020;

mortality rates (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). Minorities also experienced greater all-cause mortality during the pandemic's initial months (Alsan et al. 2021; Miller et al. 2021; Polyakova et al. 2021), and these gaps persisted through the pandemic's first year (Cronin and Evans 2021; Ruhm 2022; Foster et al. 2022). The literature has also 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). Researchers have also documented differences in the pandemic's mortality impacts by income, occupation, and industry (Miller et al. 2021; Chen, Riley, et al. 2022; Schwandt et al. 2022).

[6]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. 2020; Lee et al. 2021; Cortes and Forsythe 2022; Polyakova et al. 2020). Even a full year into the pandemic, data suggest that non-White workers were more likely than White workers to experience employment declines (Cortes and Forsythe 2022). 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) 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).

Correia et al. 2020). 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, while Hoynes et al. (2012) and Charles et al. (2016) show that recessions have disproportionately impacted racial and ethnic minorities, as well as those with less education.

Naturally, our measure of how much differences in the risk of exposure to the virus and to the economic ramifications of the pandemic can explain the substantial heterogeneity in the pandemic's impact has several important limitations. Since we only observe the exposure measures recorded in our data, it is possible that richer measures of exposure could account for larger shares of disparities. Our decomposition of variation is also statistical rather than causal – it is possible that the "explanatory" power of covariates may in fact derive from their correlation with other factors that are causally related to the pandemic's impacts. Our findings are also 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 and measurement in Section 2. We present estimates of the variation in damages across groups in Section 3, and estimates of what share of these gaps in damages can be accounted for by differences in exposure in Section 4. Section 5 briefly concludes.

2 Data

2.1 All-Cause Mortality

We measure the health impact of the pandemic by its impact on all-cause mortality. This has two important advantages relative to using COVID-specific death counts. First, it is not contaminated by measurement error in the choice of what to label a "COVID" death, which could systematically vary across groups. Second, it allows us to capture not only direct effects of the pandemic on mortality but also potential indirect effects that might occur, for example, due to the declines in economic activity (Ruhm 2000; 2005; 2015; Stevens et al. 2015), 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).[7]

We use mortality records from January 2011 through February 2021 from the Census Bureau's version of the Social Security Administration's Numerical Identification (Census Numident) database.[8] The Census Numident includes individual-level data with the date of birth and date of death (if deceased) for all people with a U.S. Social Security number (SSN).[9] 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 the numerator and denominator, as they record not only deceased but also living people at any given moment.

We link the Census Numident to other Census Bureau data to obtain information about the state of residence for everyone alive in a given year, as well as records of race and ethnicity.[10] We can distinguish between Hispanic origin and non-Hispanic origin. Within

[7]Previous research looking at excess mortality by cause of death has found that the pandemic increased several non-COVID causes of death, including deaths from heart disease, Alzheimer's disease, diabetes, and strokes, as well as deaths during childbirth (Ahmad and Anderson 2021; Woolf et al. 2021; Hoyert 2022).

[8]Existing research on the COVID-19 pandemic that has used the Census Numident to measure mortality includes Miller et al. (2021), Polyakova et al. (2021), and Foster et al. (2022).

[9]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 November 18, 2021 and has been deemed to be a complete record of deaths through March 2021 (Foster et al. 2022). More information about the measurement of mortality in the Census Numident file is available in Finlay and Genadek (2021) and Appendix A.1.

[10]This merge uses a unique individual-level anonymous identifier common across all Census data sources,

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.

For a subset of the Census Numident population, we also obtain additional demographic and socio-economic information by merging in responses from the American Community Survey (ACS).[11] 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. Specifically, we observe level of completed education, disability status, industry, occupation, mode of transportation to work, insurance coverage, housing type (e.g. one-family, apartment building, or other), group quarters (such as a nursing home, prison, or dormitory), the family income relative to the poverty index, and the people per room in the household. Appendix A.2 provides more information about how these variables are defined and coded.

The ACS surveys a different random sample of U.S. households each year. For each (January - December) 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 lagged ACS waves lets us increase the number of observations by pooling multiple ACS samples and avoids capturing responses that are

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). We obtain information about the state of residence by merging in the 2010-2020 Master Address File-Auxiliary Reference File (MAF-ARF). The MAF-ARF includes address information obtained from a variety of administrative and Census survey sources (Dillon 2021). For 2021, we use the 2020 address recorded in the MAF-ARF. As in Polyakova et al. (2021), we obtain the record of race and ethnicity by merging in self-reported race and ethnicity from the 2010 Decennial Census. When race/ethnicity is not available in this file, we use the race/ethnicity variable recorded in the Census Bureau's 2010 Modeled Race File.

[11]The PIK identifier is again used to merge in responses.

endogenous to the effects of the pandemic in years 2020-2021. For any analyses using the merged ACS-Numident dataset, we use the ACS person sampling weights.

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. 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 we do not have race/ethnicity information for individuals born after 2010 (and hence in 2021, we only observe race/ethnicity for individuals who were 11 years old, or older). The upper age restriction aims to restrict the measurement error from historic death undercounts in Census Numident. Appendix A.1 and Appendix Table C.1 provide more detail on these and several other restrictions we make to the data to ensure that we have a subset of data where we can reliably observe mortality.

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 the publicly available Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) from 2011 to 2021, 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 2011 (i.e. March 2011 - February 2012) through 2020 (i.e. March 2020 - February 2021).[12]

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

[12]Existing research on the COVID-19 pandemic that has used the CPS to measure economic outcomes includes Cowan (2020), Montenovo et al. (2020), Lee et al. (2021), Cortes and Forsythe (2022), Forsythe et al. (2022), and Goldin (2022).

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 and education, as well as some measures of exposure similar to those in ACS – state, 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.3 provides the full list of the covariates used and their definitions. A drawback to our analyses using the CPS is that the covariates are measured contemporaneously with employment, and may be affected by the pandemic. This is not an issue for the mortality analysis, since covariates are all measured several years prior to mortality (and always pre-pandemic).

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 for five datasets that we use in our analysis. We report these statistics for the last "year" in our data – year 2020 (March 2020 to February 2021) – which we also define as the first year of the pandemic. Appendix Table C.2 is an analogous table that pools all years (2011 to 2020) of our data. In 2020, we observe 241.5 million 11-

to 99-year-old individuals in the full Census Numident dataset (Column 1 of Table 1). The ACS-Numident linked subset (Column 2) captures 21.7 million (9.0%) of these individuals. The distribution of demographics between the two datasets is comparable. In the linked ACS-Numident subset, the average person is 46 years old; 48% of individuals are male. 14% of observations are 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 people, and 0.4% have a record of "other or two or more races." In these same data, 24% have less than a high school degree, 50% have a high school degree but less than a BA, and about 26% have a BA or higher.

Columns (3) to (5) of Table 1 report summary statistics for the subsets of data restricted to working-age adults, age 25 to 64 (inclusive). This is the age range for which it is meaningful to compute economic damages; it is also the age range we will focus on in our decomposition analyses, since work-related risk of exposure variables are well-defined for this group. We observe a total of 143 million individuals in this age range in the full Census Numident (Column 3) and 12 million (8.5%) of them are captured in the ACS-Numident linked dataset (Column 4). The demographics of this subset are similar to the age 11 to 99 ACS-Numident dataset. The main difference is in the observed levels of education: we are restricting the data to younger cohorts, who are more likely to have completed high school or received a college degree, and we are excluding individuals too young to have completed their education. In these data, 8% of individuals have less than a high school degree, 58% have completed high school but less than a BA degree, and 34% have a BA degree or higher.

The last column of Table 1 records the summary statistics for the CPS sample used in the analyses of economic damages. We have around 216,000 individuals in year 2020 sample. The composition of the sample is fairly similar in age, sex, and education to 2020 ACS-Numident data for ages 25 to 64, but differs in race and ethnicity. The CPS sample is less likely to consist of non-Hispanic White people (59% in the CPS sample compared to 66% in the ACS-Numident data for ages 25 to 64) and more likely to have Hispanic people (19% in the CPS sample relative to 14% in the ACS-Numident data).

Table 2 and Table 3 show the distribution of the work and living arrangement covariates in the working age (25-64) ACS-Numident and CPS datasets, respectively, overall and separately by race/ethnicity and education. Compared to non-Hispanic White people, Hispanic and non-Hispanic Black people are much less likely to have an occupation classified as a "work-from-home" occupation (47% among non-Hispanic White, 36% among non-Hispanic Black, and 34% among Hispanic people in ACS-Numident; 40% among non-Hispanic White, 28% among non-Hispanic Black, and 24% among Hispanic people in CPS). They are also more likely to take public transit to work, more than twice as likely to live in an apartment building versus a single-family home, and tend to have move people per room in their households. Across education groups, individuals with at least a BA are much more likely to have an occupation that would allow them to work from home, relative to those with less than a BA (66% versus 32% in ACS-Numident and 56% versus 22% in CPS). They are somewhat more likely than those without a BA to take public transportation to work, but are less likely to live in apartment buildings and have fewer people per room in their households. These patterns are consistent with Hispanic and non-Hispanic Black people as well as individuals without a BA having more interactions with other people at work and at home and thus facing a higher risk of exposure to the virus. Similarly, differences in the ability to work from home also suggest that exposure to economic contractions may systematically differ across these groups.

3 Measuring Health and Economic Damages

3.1 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 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 is thus the 12 months between March 2020 and February 2021; we refer to this below as $t = 2020$.

We measure the impact of the pandemic by estimating the following linear probability model on data from January 2011 through February 2021:

$$y_{imt} = \gamma_m + \delta \times t + \sum_{\mu=1}^{14} \phi_\mu \mathbb{1}_{\{mt-Dec2019=\mu\}} + \epsilon_{imt} \tag{1}$$

Here, γ_m are month fixed effects that allow for separate intercepts for each calendar month, and δ measures the common annual linear time trend across all months. We include separate indicator variables for fourteen months from January 2020 through February 2021. The set of ϕ_μ 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 2021 to the predicted level of mortality or employment based on the historical trend, $\hat{y}_{mt} = \hat{\gamma}_m + \hat{\delta} \times t$. We use heteroskedastcity-robust standard errors, as well as relevant survey weights when appropriate.[13]

[13] 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 regression 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-

Our main analyses summarize damages over the 12-month period from March 2020 through February 2021. To compute this, we estimate a linear probability model at the annual level using data from 2011 - 2020:[14]

$$y_{it} = \alpha + \beta \times t + \theta \times \mathbb{1}_{\{t=2020\}} + \epsilon_{it} \tag{2}$$

Here, α is a common intercept and β measures the common annual linear time trend. θ is the coefficient of interest and measures how much the outcome in 2020 deviated from the historical time trend. Based on the estimates in equation 2, for any year t we can compute the predicted outcome as $\hat{y}_t = \hat{\alpha} + \hat{\beta} \times t$. We again use heteroskedastcity-robust standard errors, as well as relevant survey weights where appropriate.[15] 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 employment estimates, we thus define y_{it} to be the average of y_{imt} indicators across all months m in year t in which i was surveyed.

To estimate gaps in economic and health damages across different groups (such as by race/ethnicity or by education), we re-visit the annual specification in equation 2, but now allow for all slopes and intercepts to be group-specific:

$$y_{i(\rho)t} = \alpha_\rho + \beta_\rho * t + \theta_\rho \times \mathbb{1}_{\{t=2020\}} + \epsilon_{it} \tag{3}$$

where we let ρ index different categories of each group (e.g. different education levels, different racial/ethnic groups, different states, etc.). Analogous to the estimates in the full

level regression clustered at the year-month-race-sex-county level.

[14]Recall year t includes data from March through December of that calendar year, and January and February of the subsequent calendar year

[15]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.

sample, our primary coefficients of interest are θ_ρ, which now measure the group-specific deviations from the (group-specific) historical trend in the outcome. 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.[16]

3.2 Aggregate Damages

Figures 1A and 1B show observed and predicted annual mortality for years 2011 to 2020, among all people aged 11-99 and 25-64 years, respectively. Predicted mortality is estimated following Equation 2. For both age groups, mortality had generally been increasing steadily over the past decade. For ages 11-99, the time trend in mortality is nearly perfectly linear, and is captured well by our linear specification. The 25- to 64-year-old group has much lower mortality, and there is more variation in mortality rates over time, but the linear trend fits the data very well from 2014 onward. For both age groups, we observe a sharp increase in mortality in 2020 (March 2020 - February 2021). For 11- to 99-year-olds, the observed mortality rate in 2020 is 128 deaths per 10,000, compared to the predicted rate of 106 deaths per 10,000; that is, observed mortality was 20 percent higher than expected mortality during the first year of the pandemic. We observe the same relative increase for 25- to 64-year-olds, with the observed mortality rate of 47 deaths per 10,000 and the predicted rate of 38 deaths per 10,000 (also a ratio of 1.2).

Panel 1C shows the analogous time patterns for the annual employment-to-population ratio, among 25- to 64-year-olds. The employment-to-population ratio has been steadily increasing over the last decade, on an almost perfectly linear trend. We observe a sharp drop in employment in 2020 from 76 people employed per 100 to 71 people employed; that

[16] An exception to this approach is the analysis of differences in *monthly* damages across states. To reduce the computational complexity, we estimate monthly damages state by state rather than in a pooled regression with interactions.

is, the average monthly employment-to-population ratio declined by about 6.5 percent during the first year of the pandemic.

Figures 2A, 2B, and 2C show similar time series of predicted and observed mortality and employment, by month, for the months immediately before and during the pandemic: January 2020 through February 2021. Monthly predictions are estimated using Equation 1.[17] Observed mortality lines up closely with predicted mortality in January and February 2020 for both age groups, before visibly diverging starting with March 2020. For both age groups, the differences between observed and predicted mortality peaked in December 2020 and January 2021. The largest drop in employment happened in April 2020; the employment-to-population ratio dropped by 10 percentage points, from 76 people employed per 100 to 66 per 100. It then rebounded gradually, but never fully recovered in the first year of the pandemic, stabilizing at about 72 people employed per 100 in October of 2020.

We explore differences in mortality and economic damages by age, using 10-year age bins (Appendix Table C.4); for economic damages we limit the age range to ages 20-69.[18] All 10-year age groups experienced statistically significant annual excess mortality and average monthly employment declines. Excess mortality increases monotonically with age, with the oldest age group (90-99) experiencing an excess of 307 deaths per 10,000 throughout the year, and the 20-29 age group experiencing an excess of 2 deaths per 10,000. Notably, while the levels of mortality and of excess mortality vary substantially across ages, the *ratio* of excess to predicted mortality is fairly similar across all age groups. For economic damages, the pattern is reversed, with older age groups experiencing smaller employment declines; the oldest working age group (ages 60-69) had an average monthly employment decline of 3 jobs per 100, while the youngest working age group (ages 20-29) lost about 9 per 100 jobs.

[17] Appendix Figure C.1 shows the annual predicted and observed values of each outcome within selected months, which suggest that the linear annual time trend works well for each calendar month.

[18] This extends the total age range for the economic analyses from 65 to 69, in order to have a complete 10-year age bin for 60 to 69 years.

3.3 Variation in Damages by Location, Occupation, and Income

We estimate substantial dispersion in the effects of the pandemic across states, both in terms of economic and health damages. For example, the difference in average employment displacement between the 5th and 45th most affected states was 4.7 workers per 100 (6.55 in New Jersey and 1.89 in Alabama); the difference in excess mortality between the 5th and 45th most affected states was 20.5 deaths per 10,000 (28.8 in New Mexico and 8.3 in Vermont). Nevada and Hawaii experienced the highest rate of missing jobs of any states (which could reflect the importance of their tourism industries). Mississippi, Alabama, Louisiana, and New York experienced the highest health damages.[19]

These economic and health damages were uncorrelated across states (Figure 3).[20] Nevada, for example, had considerable economic damages (an average of 11.1 per 100 lower employment rate over the first 12 months of the pandemic compared to the median state which had 4.6), but was typical in its excess mortality among ages 11-99 (21.6 per 10,000 compared to the median of 21.7 per 10,000). On the other hand, of the states with the highest overall excess mortality, Mississippi (34.2 excess deaths per 10,000), Alabama (33.6 excess deaths per 10,000), and Louisiana (32.9 excess deaths per 10,000) had below median economic damages, while New York (32.7 excess deaths per 10,000) had above median economic damages.

Figure 4 shows that economic damages were inter-temporally persistent, while mortality damages were not. Nearly all states (except New York and New Jersey that were hit at the beginning of the pandemic) experienced larger mortality shocks in an average month between May 2020 and February 2021. But there was relatively little relationship between the size of the state's excess mortality in April 2020 and its subsequent average monthly excess mortality.[21] By contrast, economic damages were persistent across states (Figure 4B),

[19] Appendix Table C.3 and Appendix Figure C.3 present the estimates separately by state.

[20] This is in contrast with the initial effects of the pandemic in April 2020, when the damages had a positive correlation and a few states were more significant outliers in excess mortality (Polyakova et al. 2020).

[21] This lack of a correlation holds even when excluding New York and New Jersey, the two states that were the largest outliers in terms of excess mortality in April 2020 (see Appendix Figure C.2).

with states such as Nevada and Hawaii that had the largest economic damage in April 2020 continuing to have large damage throughout the course of the pandemic's first year. However, in contrast with the mortality impacts, almost all states partially recovered economically throughout the first year; in every state except Connecticut, the economic shocks were larger in April 2020 than an average month from May 2020 - February 2021. This is consistent with patterns in previous research finding that different waves of the pandemic resulted in health effects that were concentrated in different regions of the country (Woolf et al. 2021); in contrast, persistent economic damage may have been driven by the fact that particular consumer-facing industries (such as tourism), and the states that were dependent on them, were continuously affected economically by the national conditions of the pandemic.

There was also substantial heterogeneity in damages from the pandemic across different sectors of the economy, with health and economic damages correlated across industries and occupations (Figure 5). Across industries, excess mortality varied between 2 per 10,000 and 10 per 10,000. The industry with the highest excess mortality was utilities, with mining/quarry/oil/gas following closely behind (both nearly 10 per 10,000). For economic damages, the industries that were the largest outliers were arts, entertainment, and recreation, as well as accommodations and food, which each had an employment-population ratio almost 20 per 100 lower than expected. By occupation, building, grounds cleaning, and maintenance were the occupations with the highest excess mortality (14 per 10,000), while food prep/service and personal care/service experienced the highest economic damage (20 per 100 and 14 per 100, respectively); full estimates for industries and occupations are shown Appendix Tables C.5 and C.6, respectively, as well as Appendix Figure C.4.[22]

[22] For comparison, Miller et al. (2021), used the same linked ACS-Numident data we use but for April-June 2020. During that quarter, they find the largest 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 (building, grounds cleaning, and maintenance; material moving; and food preparation and service), but we use estimates over a longer time period. Like Miller et al. (2021), however, we find that mortality damages by work-from-home status are much larger than mortality differences by essential worker status (Appendix Table C.7).

There was also heterogeneity in both health and economic damages by income, as shown in Figure 6. Panel (A) plots excess deaths per 10,000 among ages 25-64 based on the respondent's family income relative to poverty thresholds as observed in the ACS; there is a striking monotonic relationship in which excess deaths generally decreased at higher levels of family income. Panel (B) plots missing jobs per 100 based on the bins of annual family income reported in the CPS. The relationship is non-monotone. We observe that job losses are increasing in income at lower levels of family income (less than $35,000 per year), but are decreasing in income at higher income levels. This non-monotonicity may partially be a result of the fact that family income in the CPS is measured during the past year, and so that can be affected directly by job loss. Overall, individuals with higher incomes experienced the lowest economic and health damages of the pandemic.

3.4 Variation in Damages Across Demographic Groups

The health and economic consequences of the pandemic's first year were markedly unequal by race, by ethnicity, and by education level. Figure 7 shows that economic damages (among ages 25-64) and excess mortality (among ages 11-99) were generally positively correlated by racial and ethnic group. The groups that were hit the hardest economically were also those with the highest excess mortality. The groups with the largest excess mortality included non-Hispanic American Indian/Alaskan people (36 per 10,000), non-Hispanic Black people (32 per 10,000), and Hispanic people (27 per 10,000); in comparison, non-Hispanic White people had an excess mortality of 20 per 10,000.[23] The high excess mortality for American

[23]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 (2022) finds that between March 2020 and February 2021, the ratio of observed to predicted deaths among all individuals in the U.S. is 1.22 overall, 1.17 among non-Hispanic White individuals, 1.32 among non-Hispanic Black individuals, and 1.51 among Hispanic individuals. This is close to our estimates, where we find a ratio of observed to predicted deaths of 1.21 overall, 1.16 among non-Hispanic White individuals, 1.32 among non-Hispanic Black individuals, and 1.50 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. (2022) find that mortality was 1.15

Indian and Alaskan Native people is consistent with early reports showing disproportionate deaths among these groups during the pandemic (Hatcher et al. 2020). In terms of economic damages, non-Hispanic Black and Hispanic people experienced an average monthly decline in the employment-population ratio of 7.5; in comparison, non-Hispanic White individuals had a decline of 4.2. Table 4 shows point estimates of economic and health damages by demographic group. Columns (3) and (4) also show that among 25- to 64-year-olds, similarly pronounced non-Hispanic Black-White and Hispanic-White gaps in excess mortality were observed, despite being lower in absolute levels; we use this age range in our analysis of how much differences in exposure contributed to these gaps.

Figure 8 shows that there were also stark gradients in both excess mortality and economic damages across groups with different levels of education. In general, both types of damages were lower in the higher educated groups. For example among those whose highest level of education was a high school diploma or GED, annual economic damage was 7 per 100 and annual excess mortality was 34 per 10,000. Among those whose highest educational attainment was a Bachelor's degree, economic and mortality damages were lower, with 5 per 100 jobs lost and 13 per 10,000 excess deaths. Individuals with less than a high school degree were a stark outlier in terms of excess mortality, with nearly six times higher excess mortality relative to those with a college degree.

4 Contribution of Exposure to Damage Gaps

4.1 Econometric Framework

For individuals between the ages of 25 and 64 for whom we observe measures of work and living arrangements, we measure how much of the differences in (annual) health and economic

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.

damages across demographic groups can be accounted for by (observable) differences in the likelihood of exposure to the virus and economic restrictions. We focus our analyses on three specific demographic comparisons with the largest sample sizes: gaps in health and economic damages between non-Hispanic Black and non-Hispanic White individuals, between Hispanic and non-Hispanic White individuals, and between individuals without a BA degree and those with at least a BA degree.[24]

To do so, we estimate a variant of Equation 3 that includes various additional covariates:

$$y_{i(\rho)t} = \alpha_\rho + \beta_\rho * t + \theta_\rho \times \mathbb{1}_{\{t=2020\}} + f(a, X) + \epsilon_{it} \tag{4}$$

The function $f(a, X)$ adds adjustments for differences in the age distribution (a) based on five-year age bins as well as in other covariates (X) across different demographic groups. For all elements in f we include both the indicators for the values of the covariate(s) and their interaction with an indicator for $t = 2020$, to allow for separate effects of the pandemic by these covariates.[25]

We treat the age-adjusted specification as our baseline measure of gaps for this decomposition exercise, given the pronounced differences in the age distribution across groups and the starkly differential incidence of pandemic impact by age (Ford et al. 2020; Polyakova et al. 2020; Alsan et al. 2021; Polyakova et al. 2021). To the age-adjusted baseline, we flexibly add observables of interest $x \in X$ and measure how much adding one x at a time or all

[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 during the first three quarters of 2020 and to Cortes and Forsythe (2022) who decompose Black-White differences in year-on-year job displacement probabilities in the CPS during April 2020 and February 2021.

[25] In addition to our main decomposition results, we show a more flexible decomposition specification in Appendix Tables C.8, C.9, and C.10. There, we allow coefficients on each covariate to vary by demographic group, similar in spirit to the Oaxaca-Blinder decomposition; Appendix B describes the full setup of this estimation. These decompositions are more flexible, but less easily interpretable, as compared to our main decompositions as the share of the gap "explained" requires an arbitrary choice of which group's coefficients to use when adjusting the distribution of covariates. Nevertheless, results are qualitatively consistent with the main decomposition results, although the exact magnitudes vary and depend substantially on which group's coefficients are used as the baseline.

$x \in X$ jointly changes the point estimates of θ_ρ (which now measures age-adjusted gaps in damages across demographic groups).[26]

For the analyses of gaps in excess mortality, X includes the following measures that proxy for differences in the risk of exposure: state, 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 an essential worker (we refer to these variables as "nature of work" measures). 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 report the results from adding only a few observed 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.

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. As for mortality, we also report how our estimates are affected by the inclusion of variables that likely correlate with the determinants of 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. Our main estimates of interest are how coefficients θ_ρ change when we jointly include all variables for living arrangements and the nature of work; this captures how much our observable proxies for the risk of exposure can explain the demographic gaps in pandemic

[26] 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., forthcoming), and geographic gaps in infant mortality (Chen et al. 2016).

impact.

4.2 Results

Table 5 shows the results of estimating Equation 4 for non-Hispanic Black-White gaps in both health and economic damages among ages 25-64. The "Gap" column shows the difference in damages 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 θ_ρ for different values of X relative to the "Age Adjusted" row. The unadjusted Black-White gap among 25- to 64-year-olds in March 2020 - February 2021 is 10.7 per 10,000 for excess mortality and 3.4 per 100 for missing employment.[27] Adjusting for age results in a slight increase in the Black-White gap in excess mortality from 10.7 per 10,000 to 11.2 per 10,000, and a slight decrease (from 3.4 to 3.2 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 8 percent of the excess mortality gap. Together, the living arrangement and nature of work variables explain almost a quarter (23 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 17% and 13% of the gap in excess mortality, respectively. Jointly, they can improve the explanatory power of our exposure variables by 10 percentage points, still leaving about two-thirds of the mortality

[27] This mortality gap differs slightly from that reported in Table 4 because here we use the linked ACS-Numident dataset rather than the full Census Numident data in Table 4.

gap unaccounted for; it seems likely that unmeasured differences in health capital and other factors that affect the severity of the health shock conditional on exposure may be important in explaining some of this remaining gap.

Next, looking at the Black-White gap in economic damages, we find that industry and occupation alone can each explain 35% to 40% of the gaps (Panel C). All together, differences in exposure can account for 39% of the employment gap and even with all covariates included, more than half of the Black-White gap in employment damages remains unexplained. This suggests that variation in unmeasured "severity" factors – human capital and economic agility in response to an economic shock – may also play an important role in driving the variation in economic outcomes across demographic groups.

Table 6 shows the same results for Hispanic-White gaps in each outcome. Adjusting for age again increases the estimated mortality gap, from 9.1 per 10,000 to 9.8 per 10,000. About 15 percent of this gap can be explained by our measures of exposure in Panel B and C; we can explain approximately a third of the gap when we include all observed covariates. For economic damages, the age-adjusted gap is 3.0 per 100, and about 36 percent of that can be explained by our measures of exposure. All of the covariates can together explain almost half of this gap (45%); the covariates that individually appear to be the most important are income (reducing the gap by 27%) and occupation (reducing the gap by 24%). The important role of occupation in explaining both the economic and mortality Hispanic-White gaps is consistent with particular occupations, such as those with more in-person interactions, having both a greater risk of exposure to the virus (among those still working) and a greater drop in employment during the pandemic.

Finally, Table 7 repeats this exercise for gaps based on Bachelor's degree attainment. The age-adjusted gap in excess mortality is 7.6 per 10,000 and the age-adjusted gap in economic damage is 2.8 per 100; both of these are smaller than the Black-White and Hispanic-White gaps. In this case, however, the full set of covariates that we observe can explain a much larger share of the gap: 78.1% of the excess mortality gap and 58.6% of the gap in economic damages. The exposure variables for living arrangements and nature of work explain 45.1% and 39.5% of the gaps, respectively. For mortality, occupation can explain a third of the gap on its own. Occupation and industry on their own are also important in explaining the disparate economic impacts on their own (38.4% of the gap explained by occupation and 26.4% by industry). Income can account for a third of the mortality and half of the BA-non-BA gap on its own and for mortality retains explanatory power conditional on the exposure covariates.

5 Conclusion

We document substantial variation in the economic and health damages experienced by different groups in the first year of the pandemic, and explore how much of this heterogeneity could be accounted for by differences in exposure to the virus. Specifically, using linked administrative and survey-data, we find substantial differences in the pandemic's impact on excess all-cause mortality and on employment by race, ethnicity, and education; we also investigate the role that differences in living arrangements and the nature of work play in explaining these disparities.

We also find several patterns in the incidence of damages from the pandemic. First, we find no correlation between annual health and economic damages across states. Second, we find that along demographic and socio-economic margins, health and economic damages were concentrated in the same groups. Racial and ethnic minority groups, people without a Bachelor's degree, those with lower family incomes, and those working in service industries and jobs not suitable to working from home were impacted the most, both in terms of lower employment levels and higher excess all-cause mortality. Third, we estimate that differences in location, living arrangements and what people do for work can explain 15 percent of the age-adjusted Hispanic-White difference in excess mortality, almost one-quarter of the Black-White difference, and almost half of the non-BA-BA difference; they can also explain over one-third of the differences in age-adjusted economic damages between these groups. These findings suggest that differences in exposure to the virus and to economic contractions played an important role in the disparate impacts of the pandemic.

Of course, there are several important caveats to keep in mind. First, our decompositions are limited to the measures we have available; it is possible that with richer measures of exposure we could account for a greater portion of the disparate impacts. Second, these decompositions are descriptive, and not necessarily causal. Third, our results speak only to the first year of the pandemic. A useful direction for further work would be to estimate, for subsequent, post-vaccine years of the pandemic, the levels of health and economic damages, the differences in these damages across demographic groups, and the role of exposure in accounting for those differences.

Nonetheless, the results from the first year suggest that differences in exposure may play an important role in explaining the disparate economic and health impacts of the pandemic across different groups. These findings mirror the findings in the broader literature on social determinants of health and economic outcomes.

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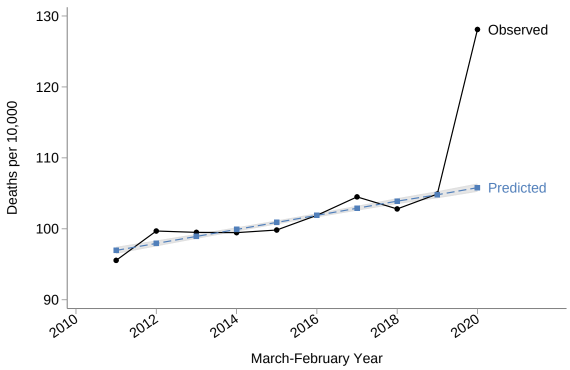
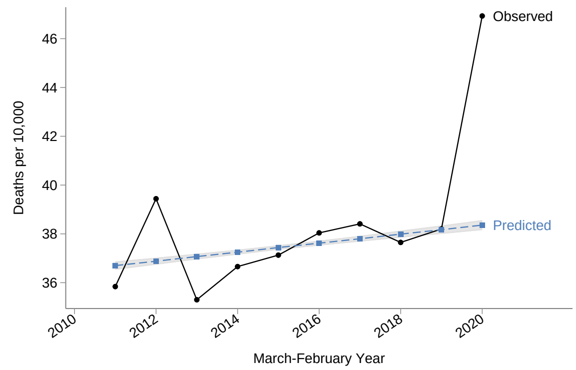
Exhibits

Figure 1: **Annual Mortality and Employment, 2011-2020**

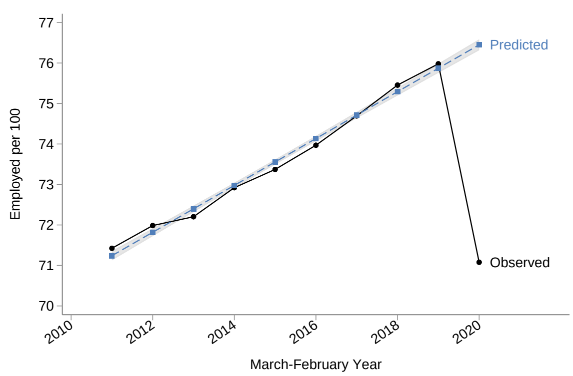
(A) Mortality, Ages 11-99



(B) Mortality, Ages 25-64



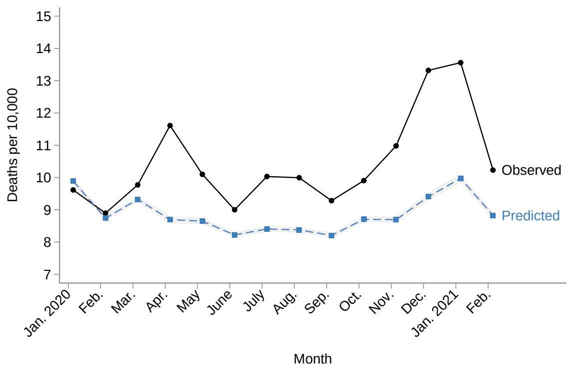
(C) Employment-Population Ratio, Ages 25-64



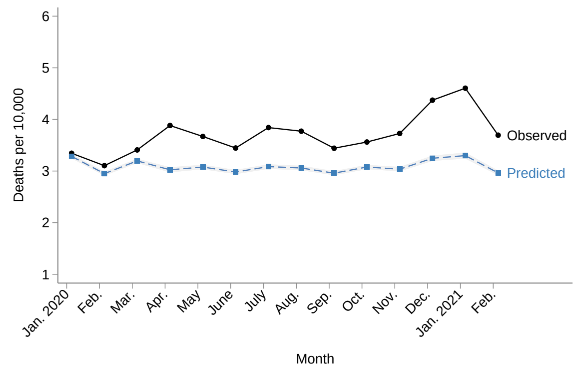
Notes: Panels (A) and (B) show annual observed and predicted mortality per 10,000 people among all individuals ages 11-99 (Panel A) and among working-age adults (ages 24-64) (Panel B) using the full Census Numident dataset. Panel (C) shows observed and predicted annual employment-to-population ratio per 100 among working-age adults over the same time period. The annual employment-to-population ratio is defined as the average across months. In all panels, a year is defined as 12 months from March to February. The data is shown for March 2011 to February 2021. The dashed trend lines for predicted mortality and employment-to-population are estimated as specified in Equation 2. The 95% confidence interval for the estimates of trend is shaded in grey and is based on heteroskedasticity-robust standard errors and CPS survey weights (in C). **Source**: Authors' calculations from Census Numident and the 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: **Monthly Mortality and Employment, 2020**

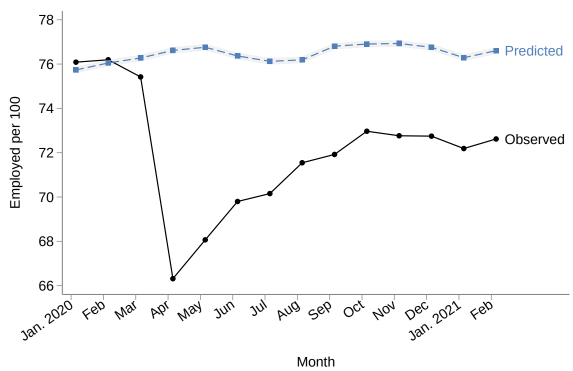
(A) Mortality, Ages 11-99



(B) Mortality, Ages 25-64

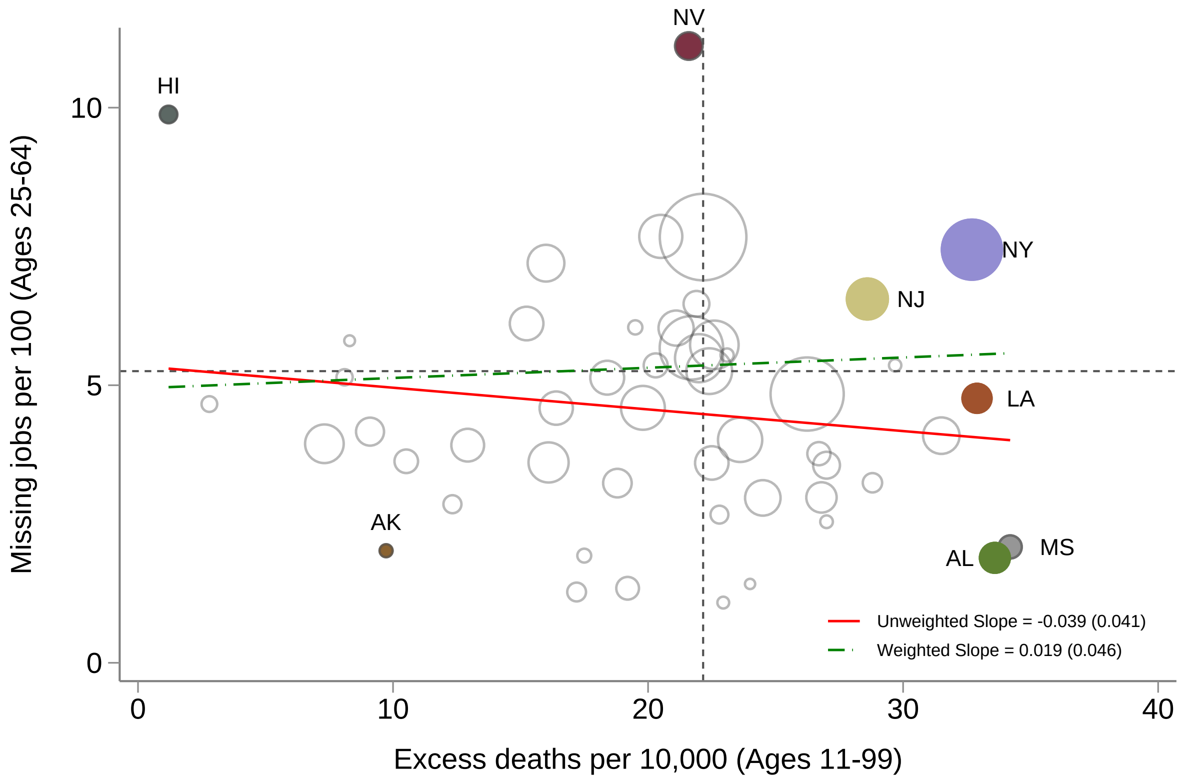


(C) Employment-Population Ratio, Ages 25-64



Notes: Panels (A) and (B) show monthly observed and predicted mortality per 10,000 people among all individuals ages 11-99 (Panel A) and among working-age adults (ages 24-64) (Panel B) using the full Census Numident dataset. Panel (C) shows observed and predicted monthly employment-to-population ratio per 100 among working-age adults over the same time period. The data is shown for January 2020 to February 2021. The dashed trend lines for predicted mortality and employment-to-population are estimated as specified in Equation 1. The 95% confidence interval for the estimates of trend is shaded in grey and is based on heteroskedasticity-robust standard errors and CPS survey weights (in C). **Source**: Authors' calculations from Census Numident and the 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.

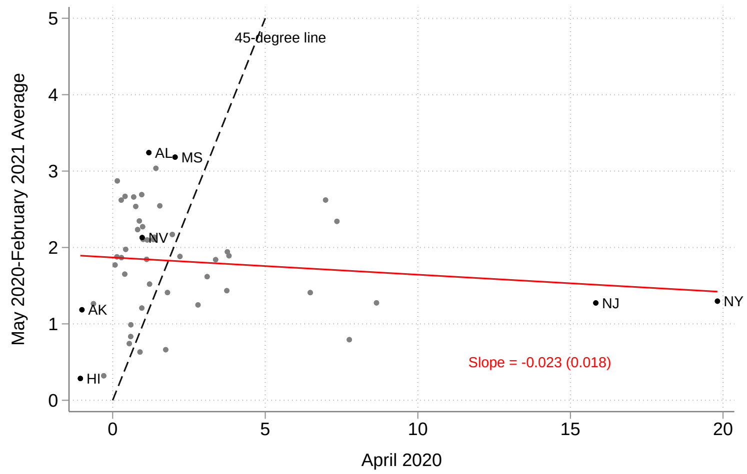
Figure 3: **Economic and Health Damages by State**



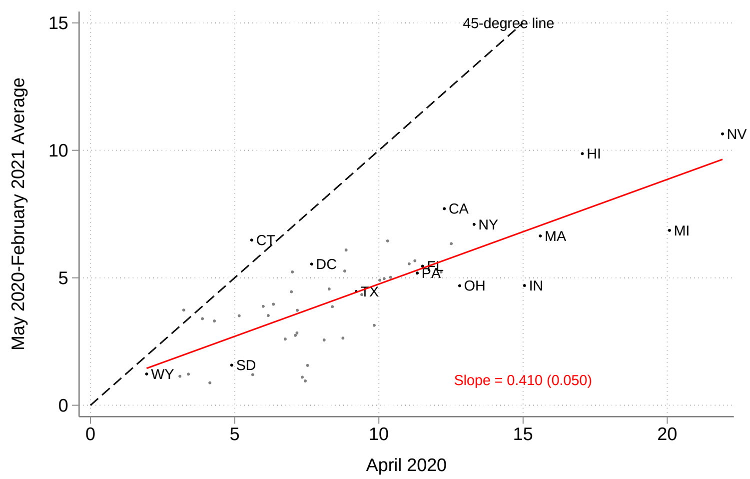
Notes: This graph plots annual excess all-cause mortality (among 11- to 99-year-olds) against annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 in each U.S. state. Damages are estimated as specified in Equation 3. Each circle on the graph represents one state, and the size of each circle is proportional to the weighted population size aged 25 to 64 in the CPS sample in 2020. The mortality results use the full Census Numident dataset. The dashed vertical and horizontal lines demarcate the level of damages in the median state. The lines of best fit and their slopes are given in solid (unweighted) and dot-dashed (weighted by state population, same as the circle size) patterns. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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: **Inter-temporal Persistence of Pandemic Damages by State**

(A) Excess Deaths per 10,000 (Ages 11-99)



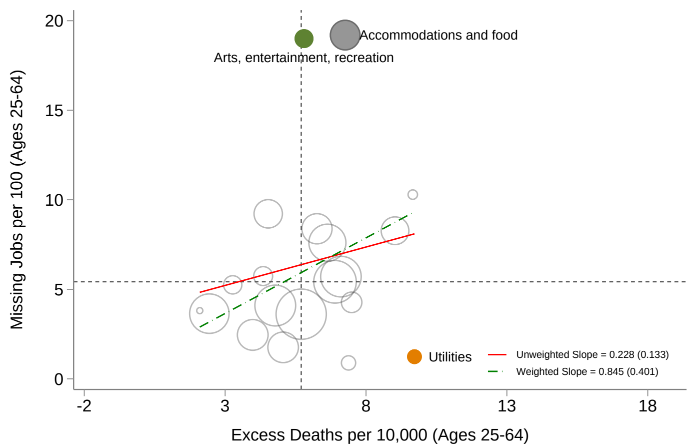
(B) Missing Jobs per 100 (Ages 25-64)



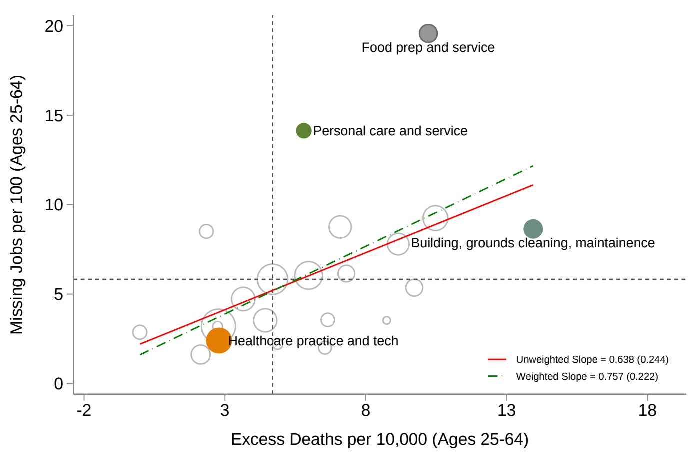
Notes: These exhibits compare average health damages (Panel A) and economic damages (Panel B) between May 2020 and February 2021 to damages during April 2020, for each state. Monthly damages are estimated separately by state as specified in Equation 1, and are averaged across months May 2020 to February 2021 on the y-axis. Excess mortality is reported for 11- to 99-year-olds; economic damages are reported for 25- to 64-year-olds. Mortality results use the full Census Numident dataset. The solid line is the line of best fit from an unweighted regression; the dashed line is the 45-degree line. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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: **Economic and Health Damages by Industry and Occupation**

(A) Industry



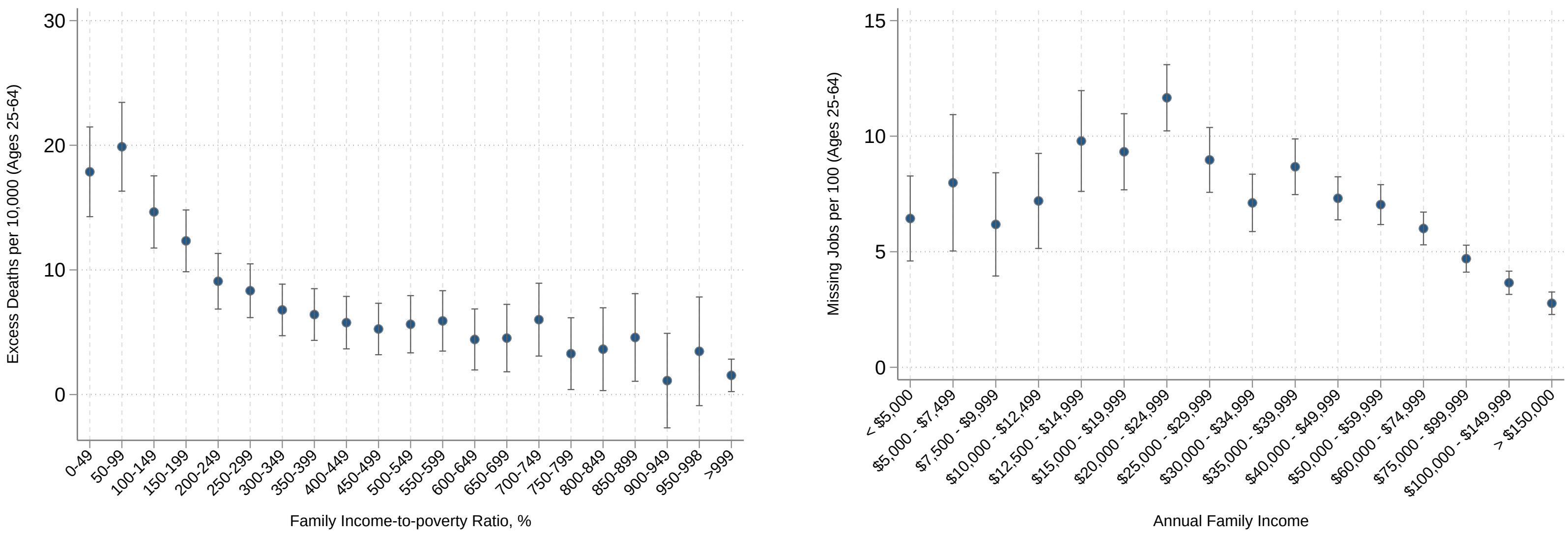
(B) Occupation



Notes: This graph plots annual excess all-cause mortality (among 25- to 64-year-olds) against annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 by industry (Panel A) and occupation (Panel B). Damages are estimated as specified in Equation 3. Each circle on the graphs represents one industry or one occupation, and the size of each circle is proportional to the weighted population size aged 25 to 64 in the CPS sample in 2020. To improve readability of the graph, one (small) industry "company management," for which we estimate close to zero economic impact, is excluded from Panel (A). The mortality results use the ACS-Numident linked dataset. The dashed vertical and horizontal lines demarcate the level of damages in the median industry or occupation. The lines of best fit and their slopes are given in solid (unweighted) and dot-dashed (weighted by group population, same as the circle size) patterns. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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.

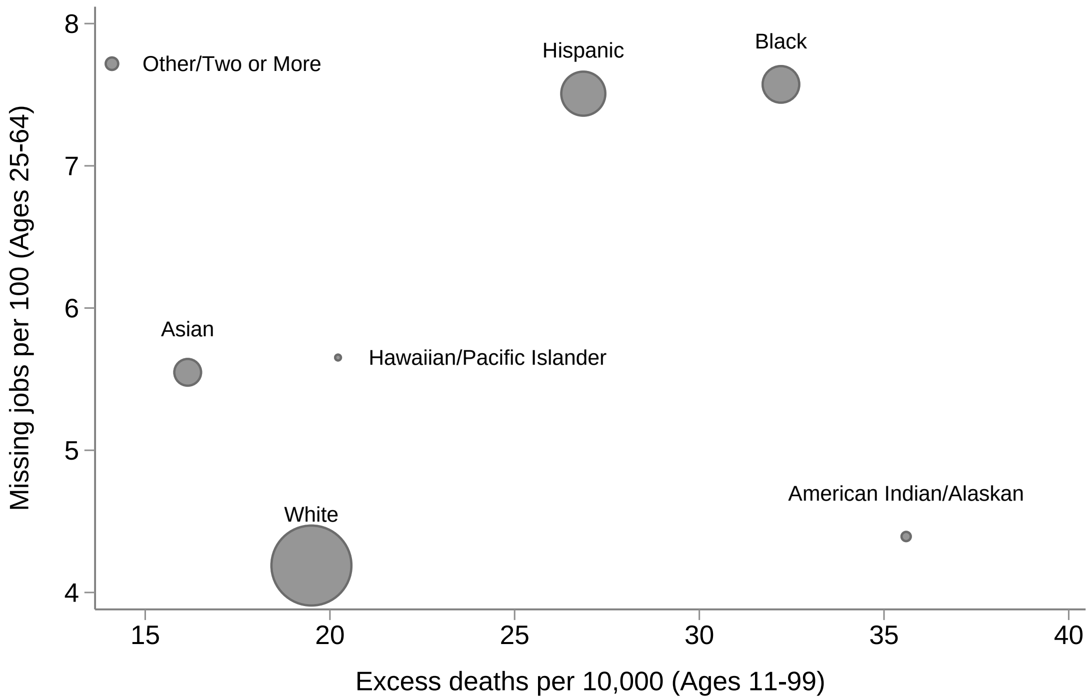
Figure 6: **Economic and Health Damages by Income**

(A) Health Damages (B) Economic Damages



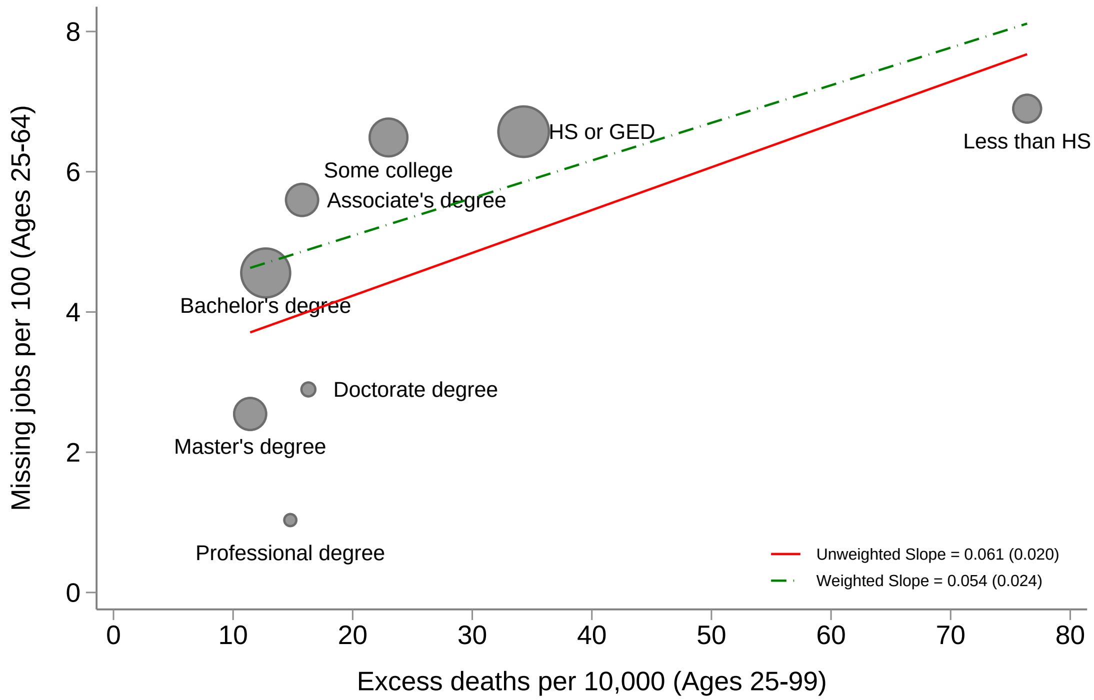
Notes: These graphs plot annual excess all-cause mortality (among 25- to 64-year-olds) and annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 by income. For mortality analyses (Panel A), our income measure is the ratio of a family's income to the poverty threshold, multiplied by 100, as reported in ACS; for economic damage analyses (Panel B), our income measure is annual family income, in contemporaneous dollars, during the 12 months prior to when the person was surveyed, as reported in CPS. Damages are estimated as specified in Equation 3. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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: **Economic and Health Damages by Race and Ethnicity**



Notes: This graph plots annual excess all-cause mortality (among 11- to 99-year-olds) against annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 by race and ethnic group. All groups other than "Hispanic" are limited to Non-Hispanic individuals. Damages are estimated as specified in Equation 3. Each circle on the graphs 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 in 2020. The mortality results use the full Census Numident dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, 2010 Census Modeled Race File, 1-Year American Community Survey, and the 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 8: **Economic and Health Damages by Education Level**



Notes: This graph plots annual excess all-cause mortality (among 25- to 99-year-olds) against annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 by the level of educational attainment. Damages are estimated as specified in Equation 3. Each circle on the graphs 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 in 2020. The mortality results use the ACS-Numident linked dataset. The lines of best fit and their slopes are given in solid (unweighted) and dot-dashed (weighted by group population, same as the circle size) patterns. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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 1: **Summary Statistics**

	(1)	(2)	(3)	(4)	(5)
	Ages 11-99		**Ages 25-64**		
	Numident	ACS-Numident	Numident	ACS-Numident	CPS
People (Unweighted)	241,500,000	21,720,000	142,900,000	12,100,000	216,356
Percent Died	1.27	1.27	0.46	0.44	.
Percent Employed	.	.	.	.	71.08
Panel A: Demographics					
Average Age	45.13	45.65	44.50	44.75	43.77
% in each category					
Male	48.84	48.00	49.38	49.00	49.13
Panel B: Race/Ethnicity					
Hispanic	14.69	14.26	14.40	14.27	18.84
Non-Hispanic White	65.98	67.19	65.25	66.25	58.62
Non-Hispanic Black	12.57	12.01	13.16	12.47	13.24
Non-Hispanic Asian	5.27	5.21	5.63	5.63	6.64
Non-Hispanic American Indian/Alaskan	0.90	0.82	0.95	0.85	0.81
Non-Hispanic Hawaiian/Pacific Islander	0.19	0.17	0.21	0.18	0.34
Non-Hispanic Other/Two or More Races	0.40	0.35	0.40	0.36	1.51
Panel C: Education					
Less than HS	.	24.10	.	8.20	8.52
High School or GED	.	22.37	.	24.72	27.37
Some College	.	19.84	.	23.59	14.98
Associates	.	7.23	.	9.55	10.68
Bachelors	.	16.58	.	22.14	24.57
Masters	.	6.97	.	8.53	10.41
Professional Degree	.	1.69	.	2.00	1.48
Doctorate	.	1.12	.	1.24	1.98
Missing Education	.	0.10	.	0.02	.

Notes: This table shows the summary statistics for the final year of our data (March 2020 through February 2021). Column (1) and (3) use the full Census Numident dataset; see Section 2 for the list of restrictions on the raw data. Columns (2) and (4) use the linked ACS-Numident dataset. ACS person-level weights and CPS sample weights are used in columns (2), (4), and (5) unless specified otherwise. GED stands for 'General Educational Development Test'. Mortality results are rounded to the second decimal place to comply with the Census disclosure requirements. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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 2: **Distribution of Covariates Observed in ACS**

	(1)	(2)	(3)	(4)	(5)	(6)
		By Race/Ethnicity			**By Education**	
	Overall	Hispanic	Non-Hispanic White	Non-Hispanic Black	No Bachelor's	Bachelor's or Higher
Mean Age	44.75	42.74	45.44	43.63	44.58	45.09
% in each category						
Race/Ethnicity						
Hispanic	14.27	100.00	0.00	0.00	17.60	7.77
Non-Hispanic White	66.25	0.00	100.00	0.00	62.41	73.74
Non-Hispanic Black	12.47	0.00	0.00	100.00	14.58	8.36
Education						
BA or higher	33.93	18.48	37.77	22.75	0.00	100.00
Work Mode						
Essential Worker	60.39	60.55	60.54	63.15	60.07	60.97
Work from Home	44.09	34.42	47.02	36.26	31.70	66.33
Poverty Index						
Below 100%	10.15	13.05	8.13	18.10	13.34	3.90
Below 250%	32.59	46.10	27.13	48.11	41.77	14.67
Mode of Transportation						
Car, Truck or Van	87.21	87.33	88.17	84.14	89.28	83.78
Public Transport	4.63	5.74	3.21	8.64	3.42	6.99
Walking, Bike, Motorcycle	2.73	2.55	2.82	2.18	2.45	3.26
Work from Home (transportation)	4.53	2.99	5.24	2.60	3.29	6.94
Other	0.91	1.05	0.80	1.26	0.95	0.82
House Type						
One-Family Home	75.29	68.88	79.36	62.62	73.26	79.26
Apartment	20.05	26.71	15.63	32.90	19.89	20.35
Mobile, RV or Other	4.66	4.47	5.12	3.75	6.55	0.99
People per Room						
0 - 0.2	4.11	1.50	4.87	4.09	3.36	5.56
0.2 - 0.4	27.36	13.53	31.76	24.42	24.27	33.40
0.4 - 0.6	30.87	23.49	33.15	28.65	29.34	33.86
0.6 - 0.8	19.00	23.00	17.56	20.50	20.31	16.44
0.8 - 1.0	7.03	11.67	5.72	7.74	8.28	4.60
At least 1.0	11.63	26.86	7.06	13.87	14.15	6.73
Group Quarters (GQ)						
Health GQ	0.02	0.01	0.02	0.04	0.02	0.00
Non-Health GQ	0.62	0.58	0.52	1.27	0.90	0.08
Other Non-Institutional GQ	0.05	0.05	0.04	0.12	0.07	0.01
Not Group Quarters	99.31	99.36	99.43	98.58	99.00	99.90
Disabled	8.96	7.93	9.02	11.65	11.47	4.08
Insured	88.63	80.31	91.05	84.72	84.98	95.73

Notes: This table shows the distribution of covariates, for people ages 25-64, observed in the American Community Survey, by demographic group, for the final year of data in the ACS-Numident dataset (March 2020 through February 2021). All statistics are weighted with ACS person-level weights. **Source:** Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 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 3: **Distribution of Covariates Observed in CPS**

	(1)	(2)	(3)	(4)	(5)	(6)
		By Race/Ethnicity			**By Education**	
	Overall	Hispanic	Non-Hispanic White	Non-Hispanic Black	No Bachelor's	Bachelor's or Higher
Mean Age	43.77	41.78	44.86	42.95	44.29	42.94
% in each category						
Race/Ethnicity						
Hispanic	18.84	100.00	0.00	0.00	24.07	10.45
Non-Hispanic White	58.62	0.00	100.00	0.00	53.95	66.10
Non-Hispanic Black	13.24	0.00	0.00	100.00	15.24	10.03
Education						
BA or higher	38.43	21.33	43.34	29.13	0.00	100.00
Work Mode						
Essential Worker	49.41	49.80	50.22	50.21	47.55	52.38
Work from Home	35.44	23.81	40.02	28.35	22.46	56.24
Family Income						
Under $15,000	6.78	7.73	5.15	13.15	9.44	2.53
Under $40,000	25.69	36.15	19.87	39.58	34.95	10.87
Under $60,000	40.85	54.69	33.70	57.27	53.02	21.35
Young Child						
No Young Child	19.39	22.82	18.50	18.48	20.62	17.43
Has Young Child	28.07	34.55	25.80	26.27	26.98	29.82
No Child	52.54	42.63	55.70	55.25	52.41	52.74
Disabled	7.78	6.15	8.25	9.78	10.37	3.64

Notes: This table shows the distribution of covariates, for people ages 25-64, observed in the Current Population Survey, by demographic group, for the final year of data in our sample (March 2020 through February 2021). Monthly CPS data were aggregated to the annual level as detailed in A.3. All statistics are weighted with CPS sample weights. **Source:** Authors' calculations from Current Population Survey.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Ages 11-99*		**Ages 25-64**			
	Excess Deaths per 10,000				**Missing Jobs per 100**	
Specification	Excess	Predicted	Excess	Predicted	Missing jobs	Predicted
Panel A: Overall						
All Races	22.30	105.80	8.57	38.36	5.37	76.45
	[21.72–22.88]		[8.36–8.78]		[5.24–5.51]	
Panel B: Race/Ethnicity						
Hispanic	26.86	53.41	14.83	25.96	7.52	76.03
	[24.32–29.40]		[13.54–16.12]		[6.89–8.14]	
Non-Hispanic White	19.50	123.10	5.35	39.65	4.19	77.66
	[18.01–20.99]		[4.88–5.82]		[3.89–4.48]	
Non-Hispanic Black	32.21	95.79	16.71	50.22	7.56	73.02
	[30.06–34.36]		[15.47–17.95]		[6.78–8.35]	
Panel C: Education						
No Bachelor's	34.80	154.40	10.26	45.06	6.41	71.66
	[33.66–35.94]		[9.45–11.07]		[6.08–6.74]	
Bachelor's or Higher	12.68	77.73	2.77	18.30	3.80	84.22
	[11.57–13.79]		[2.09–3.45]		[3.45–4.15]	

* Ages 25-99 for Panel C: Education

Notes: This reports annual excess all-cause mortality and annual losses in the employment-to-population ratio for the period from March 2020 through February 2021, overall and by demographic group. Damages are estimated as specified in Equation 2, separately for each group. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the full Numident data in Panels A and B, and the ACS-Numident linked dataset in Panel C. 95% confidence internals are reported in square brackets. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, 2010 Census Modeled Race File, 1-Year American Community Survey, and the 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 5: **Decomposition of Gaps in Economic and Health 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						
Unadjusted	10.65	(1.16)	4.8%	3.38	(0.43)	–4.7%
Age-Adjusted	11.19	(1.16)	baseline	3.22	(0.42)	baseline
Panel B: Living Arrangement Variables						
State	10.37	(1.18)	7.3%	3.35	(0.43)	–3.8%*
People per Room	10.79	(1.16)	3.6%			
Housing Type	10.63	(1.16)	5.0%			
Group Quarters	10.85	(1.16)	3.0%			
Mode of Transportation to Work	10.78	(1.16)	3.7%			
Panel C: Nature of Work Variables						
Industry	10.72	(1.16)	4.2%	2.08	(0.24)	35.4%
Occupation	10.25	(1.16)	8.4%	1.97	(0.24)	39.0%
Work from Home	10.54	(1.16)	5.8%	2.79	(0.37)	13.3%
Essential Worker	10.92	(1.16)	2.4%	3.17	(0.40)	1.8%*
Panel D: Severity Variables						
Disability	10.92	(1.16)	2.4%	3.47	(0.40)	–7.6%
Sex	11.47	(1.16)	–2.5%	3.25	(0.42)	–0.7%*
Young Child				3.27	(0.42)	–1.4%
Health Insurance	11.20	(1.16)	–0.1%			
Panel E: Income and Education						
Income	9.24	(1.17)	17.4%	2.56	(0.40)	20.6%
Education	9.69	(1.16)	13.4%	2.97	(0.41)	7.9%
Panel F: Variable Combinations						
Living Arrangements	9.17	(1.19)	18.1%	3.35	(0.43)	–3.8%*
Nature of Work	10.25	(1.17)	8.4%	1.91	(0.24)	40.7%
Living Arrangements and Nature of Work	8.64	(1.20)	22.8%	1.98	(0.24)	38.5%
All Variables	7.46	(1.21)	33.3%	1.76	(0.24)	45.5%

* 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 annual all-cause mortality and in losses in the employment-to-population ratio for the period from March 2020 through February 2021. The data is restricted to people 25-64 years old. Mortality estimates are based on the linked ACS-Numident dataset. Differences in damages are estimated as specified in Equation 4. Each row includes covariates specified in Panels B, C, D, E, and F. All rows except the first 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, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, 2010 Census Modeled Race File, 1-Year American Community Survey, and the 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 6: **Decomposition of Gaps in Economic and Health 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						
Unadjusted	9.10	(0.85)	7.52%	3.33	(0.35)	–9.8%
Age-Adjusted	9.84	(0.86)	baseline	3.03	(0.35)	baseline
Panel B: Living Arrangement Variables						
State	10.03	(0.90)	–1.92%	2.53	(0.37)	16.5%
People per Room	9.14	(0.88)	7.09%			
Housing Type	9.59	(0.86)	2.51%			
Group Quarters	9.87	(0.86)	–0.27%			
Mode of Transportation to Work	9.53	(0.86)	3.17%			
Panel C: Nature of Work Variables						
Industry	9.18	(0.86)	6.75%	2.40	(0.19)	20.9%
Occupation	8.69	(0.87)	11.75%	2.30	(0.19)	24.1%
Work from Home	9.14	(0.86)	7.16%	2.80	(0.31)	7.8%*
Essential Worker	9.54	(0.86)	3.06%	2.93	(0.34)	3.5%*
Panel D: Severity Variables						
Disability	10.02	(0.86)	–1.82%	2.78	(0.34)	8.5%
Sex	9.83	(0.86)	0.08%	3.06	(0.34)	–0.8%*
Young Child				3.11	(0.35)	–2.6%
Health Insurance	9.91	(0.87)	–0.75%			
Panel E: Income and Education						
Income	8.50	(0.87)	13.62%	2.21	(0.34)	27.3%
Education	7.07	(0.88)	28.18%	3.01	(0.36)	0.8%*
Panel F: Variable Combinations						
Living Arrangements	9.31	(0.92)	5.37%*	2.53	(0.37)	16.5%
Nature of Work	8.64	(0.87)	12.15%	2.20	(0.19)	27.5%
Living Arrangements and Nature of Work	8.35	(0.93)	15.20%	1.94	(0.20)	36.2%
All Variables	6.55	(0.94)	33.41%	1.67	(0.21)	44.9%

* 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 annual all-cause mortality and in losses in the employment-to-population ratio for the period from March 2020 through February 2021. The data is restricted to people 25-64 years old. Mortality estimates are based on the linked ACS-Numident dataset. Differences in damages are estimated as specified in Equation 4. Each row includes covariates specified in Panels B, C, D, E, and F. All rows except the first 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, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, 2010 Census Modeled Race File, 1-Year American Community Survey, and the 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 7: **Decomposition of Gaps in Economic and Health Damages between those with and without a BA**

	(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						
Unadjusted	7.49	(0.54)	1.1%*	2.61	(0.24)	7.2%
Age-Adjusted	7.57	(0.54)	baseline	2.82	(0.24)	baseline
Panel B: Living Arrangement Variables						
State	7.32	(0.54)	3.3%	3.01	(0.24)	–6.8%
People per Room	6.98	(0.56)	7.8%			
Housing Type	7.10	(0.55)	6.2%			
Group Quarters	7.30	(0.54)	3.6%			
Mode of Transportation to Work	6.88	(0.54)	9.1%			
Panel C: Nature of Work Variables						
Industry	6.35	(0.56)	16.1%	2.07	(0.14)	26.4%
Occupation	5.35	(0.60)	29.3%	1.73	(0.15)	38.4%
Work from Home	6.09	(0.55)	19.6%	2.86	(0.22)	–1.6%*
Essential Worker	6.88	(0.53)	9.2%	2.66	(0.24)	5.6%*
Panel D: Severity Variables						
Disability	6.56	(0.53)	13.4%	3.17	(0.24)	–12.4%
Sex	7.37	(0.54)	2.7%	2.88	(0.24)	–2.1%*
Young Child				2.81	(0.24)	0.1%
Health Insurance	7.26	(0.55)	4.1%			
Panel E: Income and Race/Ethnicity						
Income	5.00	(0.57)	33.9%	1.39	(0.25)	50.5%
Race/Ethnicity	6.08	(0.55)	19.7%	2.79	(0.25)	0.8%
Panel F: Variable Combinations						
Living Arrangements	5.65	(0.55)	25.4%	3.01	(0.24)	–6.8%
Nature of Work	5.18	(0.61)	31.6%	1.58	(0.15)	43.9%
Living Arrangements and Nature of Work	4.16	(0.63)	45.1%	1.70	(0.15)	39.5%
All Variables	1.66	(0.65)	78.1%	1.17	(0.15)	58.6%

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

Notes: This table shows the estimated differences—between individuals without a BA degree and those with a BA degree—in excess annual all-cause mortality and in losses in the employment-to-population ratio for the period from March 2020 through February 2021. The data is restricted to people 25-64 years old. Mortality estimates are based on the linked ACS-Numident dataset. Differences in damages are estimated as specified in Equation 4. Each row includes covariates specified in Panels B, C, D, E, and F. All rows except the first 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, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 2010 Decennial Census, 2010 Census Modeled Race File, 1-Year American Community Survey, and the 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.

A Data Appendix

A.1 Census Numident Data Construction

We use the U.S. Census Bureau's version of the Social Security Administration's Numerical Identification file (Census Numident) (2021 quarter 3 updated vintage) for our mortality analyses. 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 419 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 size of the dataset:

- **Step 1**: To be able to measure age for everyone in our data, we drop observations for 1.9 million individuals who have a missing year and month of birth; we allow the exact date of birth to be missing. After this step, the data consists of approximately 417 million individuals.

- **Step 2**: We drop observations for a small number of individuals (112,000) who have a recorded death that is missing the year and month; the exact date can be missing.

- **Step 3**: To account for historical underreporting of deaths or data entry errors, we drop observations for approximately 15 million individuals who would have been at least 100 years old prior to 2010. 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 402 million individuals.

- **Step 4**: We 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. We only keep individuals that satisfy at least one of the following conditions: (a) died during January 2011-February 2021 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 343 million individuals remaining in the dataset.

- **Step 5**: We drop observations for individuals if we do not have information on their race and ethnicity – see the description of our sources for race and ethnicity below.

- **Step 6**: We drop 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.

- **Step 7**: Finally, we restrict the age range to start with individuals who are at least 11 years old, since we do not have race/ethnicity information for individuals born after 2010 (and hence in 2021, we only observe race/ethnicity for 11-year-olds and older individuals).

The resulting "full" Census Numident dataset for years 2011-2020 consists of approximately 2.4 billion individual-years between the ages of 11 and 99 and 1.4 billion individual-years between the ages of 25 and 64. This corresponds to 242 million unique individuals aged 11-99 years and 143 million unique individuals aged 25-64 years in 2020. Out of these people, we are able to locate American Community Survey survey responses for 22 million (age 11-99) and 12 million (age 25-64). The linked ACS-Numident dataset consists of approximately 207 million individual-year observations between the ages of 11 and 99 and 119 million individual-year observations between the ages of 25 and 64.

Our information on race/ethnicity comes from two sources: the 2010 Decennial Census and the 2010 Modeled Race file produced by the Census Bureau. 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.2 ACS Data Construction

We use the following variables from the American Community Survey in our analysis. For all variables, missing values are counted as a separate category; a missing observation generally occurs if the question is not relevant given the respondent's characteristics such as their age or employment status.

- **People per room**: 6 bins 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).

- **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. Dingel and Neiman (2020) base their classification on a survey about the share of jobs that can be done from home, and consider an occupation to be "work-from-home" if at least 50% of the jobs within the occupation can be done from home.

- **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.

- **Disability status**: disabled or non-disabled. Disabled individuals are those who 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.

- **Health insurance**: indicator variable for having any type of health insurance coverage. (This variable is only available in the ACS beginning in 2008, so individuals earlier in our data have a larger share of missing values for this covariate if their linked ACS year is earlier than 2008.)

- **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.

- **Education**: When used as a covariate, the education variable includes following categories: less than high school; high school or GED; some college; associate's degree; bachelor's degree; master's degree; professional degree; and doctorate degree. When decomposing education gaps, two categories are used: BA or above, and less than a BA.

A.3 CPS Data Construction

For economic analyses using the IPUMS CPS files (Flood et al. 2022), we start with the set of 15,422,335 individual-month observations between January 2011 and February 2021, restricted to individuals who live in any of the 50 United States or the District of Columbia and are non-institutionalized. We then limit our CPS sample to the non-military population (resulting in 15,369,667 individual-months remaining), those who are at least 25 years old (resulting in 10,579,633 individual-months remaining), and those who are younger than 65 years old (resulting in 8,043,000 individual-months remaining).

For annual analyses, we collapse the data to an annual level. We define an individual's age as the average of ages reported across different response months (for most people, this is 4 months over a 12 month period). For categorical covariates (such as race/ethnicity, disability status, industry, and occupation), we use the individual's modal response to surveys over the year. 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 groups we observe them for. We observe that around 7% of the people in our data switched between an essential and a non-essential job during the year we observed them, and about 5% switched between a work-from-home and non-work-from-home job. For employment, we take the (unweighted) proportion of months that individuals were surveyed during a 12-month period in which they reported that they were employed.

We use the following variables from CPS in our analysis. For all variables, missing values are counted as a separate category.

- **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. Some unemployed individuals or those not in the labor force may be coded under 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. 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 by Dingel and Neiman (2020), based on broad occupation categories. Dingel and Neiman (2020) base their classification on a survey about the share of jobs that can be done from home, and consider an occupation to be "work-from-home" if at least 50% of the jobs within the occupation can be done from home. Similar to the occupation definition, some unemployed individuals or those not in the labor force may be coded under their most recent job's work-from-home status. Otherwise, we coded these individuals as non-work-from-home workers.

- **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, some unemployed individuals or those not in the labor force may be coded under their most recent job's essential status. Otherwise, we coded these individuals as non-essential workers.

- **Disability status**: disabled or non-disabled. Disabled individuals are defined in the CPS as "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 in hearing and eye and remembering and physical and mobility and personal care limitation)."

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

- **Income**: reports 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.

- **Education**: When used as a covariate, the education variable includes following categories: less than high school; high school or GED; some college; associate's degree;

bachelor's degree; master's degree; professional degree; and doctorate degree. When decomposing gaps in damages by education, two categories are used: BA or above, and less than a BA.

- **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.

B Oaxaca-Blinder Style Decomposition

In a robustness exercise for the analyses of variance in Section 4, we consider a more flexible decomposition that allows the coefficients on the covariates to be group-specific (i.e., vary across race/ethnicity or education groups). This is similar in spirit to the Oaxaca-Blinder decomposition, although in contrast with the standard decomposition, we implement our estimation in a single equation to adjust for age throughout.

Consider a demographic dimension of interest, within which each group is indexed by ρ and for which we are interested in computing gaps in the excess values of an outcome y in 2020 (for example, for education, ρ takes two values – the group without a BA degree and the group with a BA or above degree). Let X denote a discretized covariate (for example, occupation), for which each discrete value is indexed with x. For simplicity of the algebraic exposition, we treat X as one covariate in what follows, but it can also be a vector of discretized covariates, in which case there are analogous regression terms for each covariate in the vector added to the regression. We estimate:

$$y_{it} = \beta_\rho * t + \gamma_a + \gamma_{2020a} + \pi_{\rho x} + \pi_{2020\rho x} + \epsilon_{it} \tag{5}$$

Here, $\beta_\rho * t$ is a group-specific linear time trend. γ_a is a set of age bin fixed effects and γ_{2020a} is a set of age fixed effects interacted with an indicator for year 2020, which allows for an age-group-specific deviation from time trend in 2020. $\pi_{\rho x}$ are fixed effects for each level of the covariate X interacted with group fixed effects, thus allowing each group-specific intercepts to vary across levels of X. $\pi_{2020\rho x}$ are group-covariate fixed effects interacted with an indicator for year 2020, allowing for the group-specific deviation from trend in 2020 to vary depending on the level of the ccovariate. This equation differs from Equation 4 only through the fact that the coefficients π_x and π_{2020x} are now allowed to vary by demographic group ρ; as in Equation 4, we do not allow age fixed effects γ_a and age-specific 2020 deviations γ_{2020a} to vary by demographic group.

The age-adjusted gap in damages between a group ρ and ρ' in 2020 is then given by:

$$\sum_{x \in X} \Big(\pi_{2020\rho x} Pr(x|\rho) - \pi_{2020\rho' x} Pr(x|\rho') \Big) \tag{6}$$

Note that unlike in our main specification, the size of this gap may now vary based on the covariate(s) X that are used, in part because the age coefficients may change as additional covariates are added. The age-adjusted gap in excess outcomes can be decomposed as:

$$\sum_{x \in X} \Big(\pi_{2020\rho x} - \pi_{2020\rho' x} \Big) Pr(x|\rho') + \sum_{x \in X} \Big((Pr(x|\rho) - Pr(x|\rho'))\pi_{2020\rho x} \Big) \tag{7}$$

The first term (*unexplained portion*) is the portion of the age-adjusted gap in the outcome that is attributable to differences in the returns to X (if both groups had the same distribution of X as individuals in group ρ'). The second term (*explained portion*) is the portion of the age-adjusted gap in the outcome that is attributable to differences in the distribution of the X (if both groups had the same returns to X as individuals in group ρ).

We therefore compute the *explained share* of the gap in outcomes as:

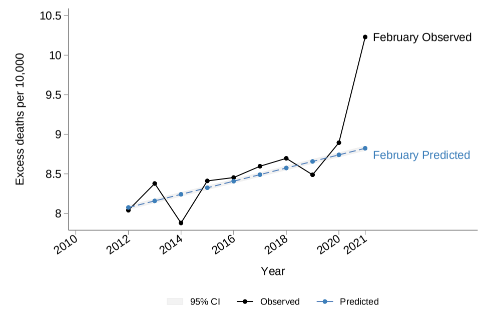
$$\frac{\sum_{x \in X} \Big((Pr(x|\rho) - Pr(x|\rho'))\pi_{2020\rho x} \Big)}{\sum_{x \in X} \Big(\pi_{2020\rho x} Pr(x|\rho) - \pi_{2020\rho' x} Pr(x|\rho') \Big)} \tag{8}$$

The choice of which group to use as the reference group for the coefficients π_{2020} in the numerator is arbitrary, so for each decomposition we show results that use the estimated coefficient for each group in computing the share explained. For example, columns with "Black Coefficients" in Appendix Table C.8 use $\pi_{2020,Black,x}$ in the numerator and columns with "White Coefficients" use $\pi_{2020,White,x}$.

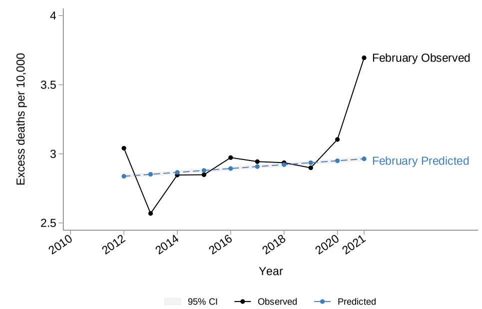
C Appendix Exhibits

Figure C.1: **Monthly Mortality and Employment, 2011-2020, for selected months (continues on next page)**

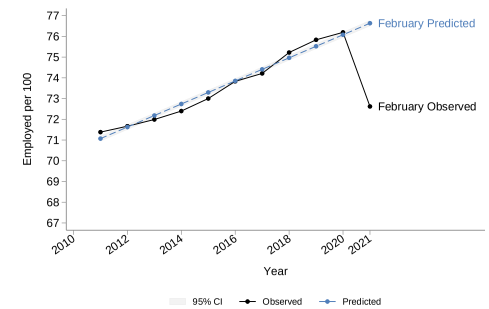
(A) Mortality per 10,000 (Ages 11-99) February



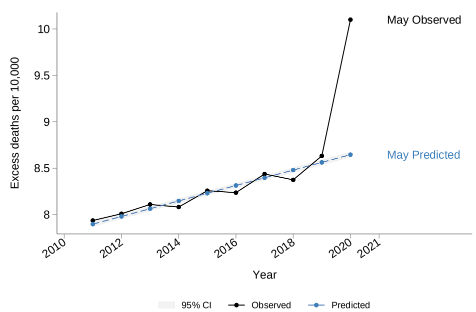
(B) Mortality per 10,000 (Ages 25-64) February



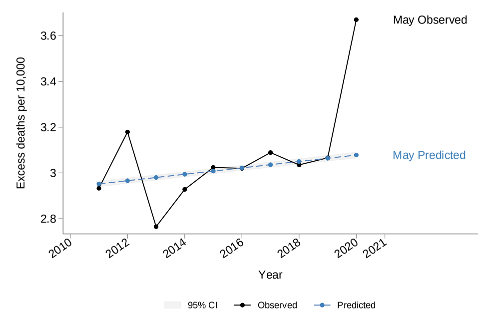
(C) Employment per 100 (Ages 25-64) February



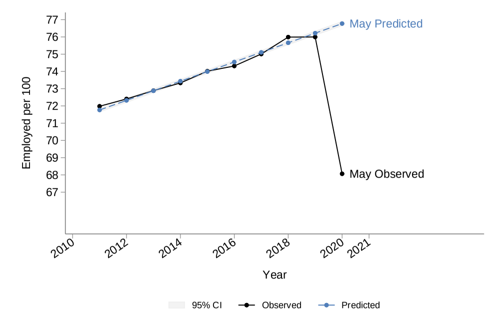
(D) Mortality per 10,000 (Ages 11-99) May



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



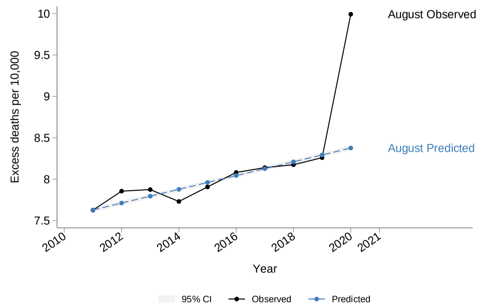
(F) Employment per 100 (Ages 25-64) May



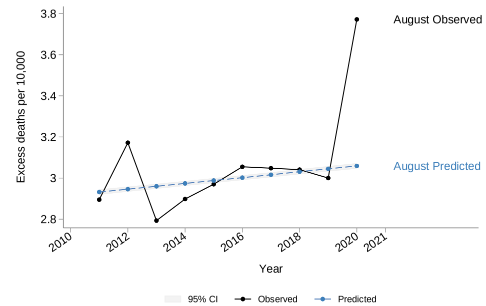
Notes: Panels show monthly observed and predicted mortality per 10,000 people among all individuals ages 11-99 (Panel A,D,G,J) and among working-age adults (ages 24-64) (Panels B, E, H, K) using the full Census Numident dataset. Panels (C, F, I, L) show observed and predicted monthly employment-to-population ratio per 100 among 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 trend lines for predicted mortality and employment-to-population are estimated as specified in Equation 1. The 95% confidence interval for the estimates of trend is shaded in grey 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 the 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.1: **Monthly Mortality and Employment, 2011-2020, for selected months (continued)**

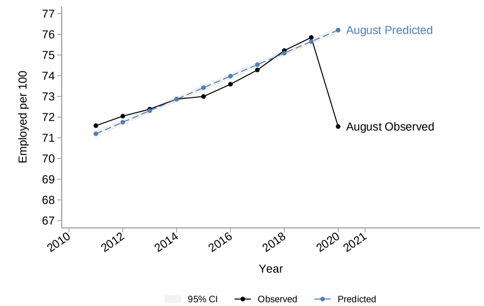
(G) Mortality per 10,000 (Ages 11-99) August



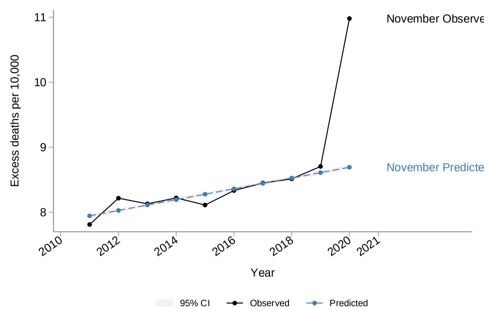
(H) Mortality per 10,000 (Ages 25-64) August



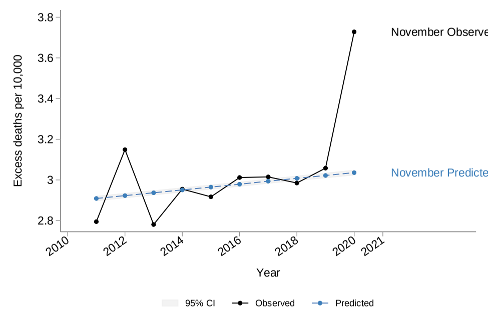
(I) Employment per 100 (Ages 25-64) August



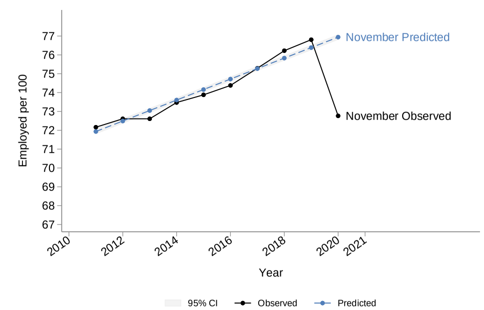
(J) Mortality per 10,000 (Ages 11-99) November



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

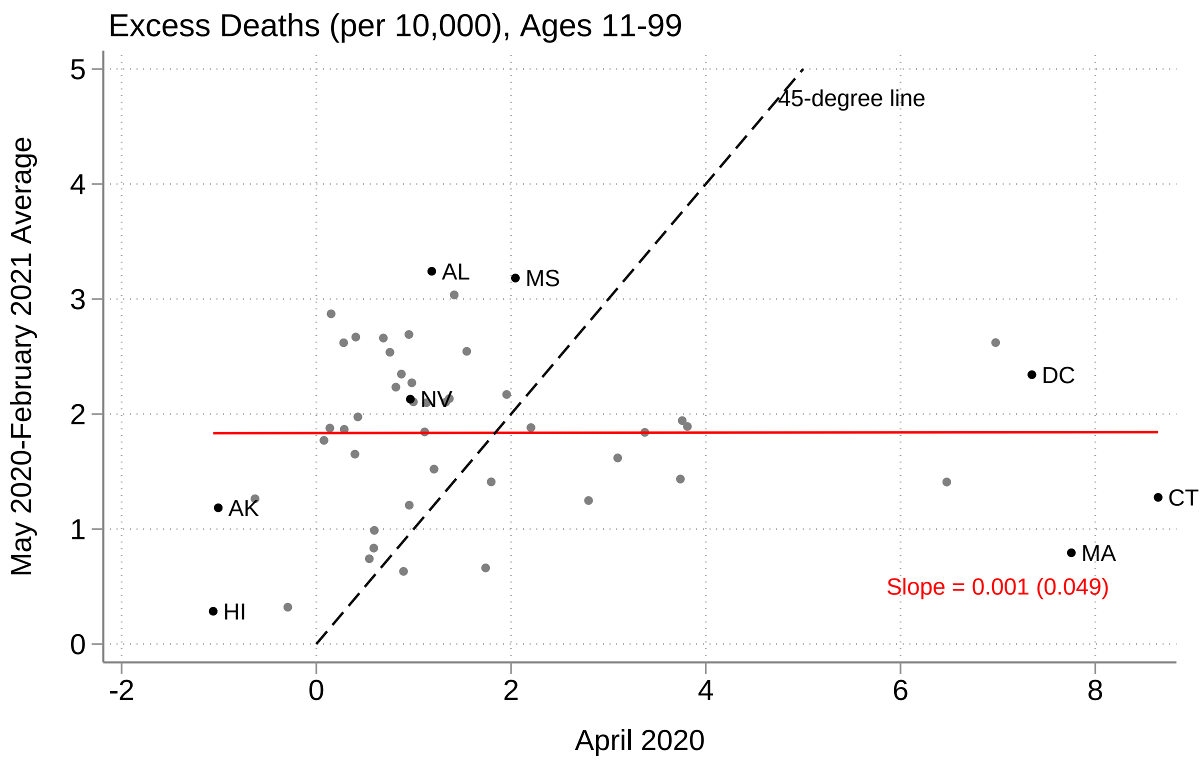


(L) Employment per 100 (Ages 25-64) November



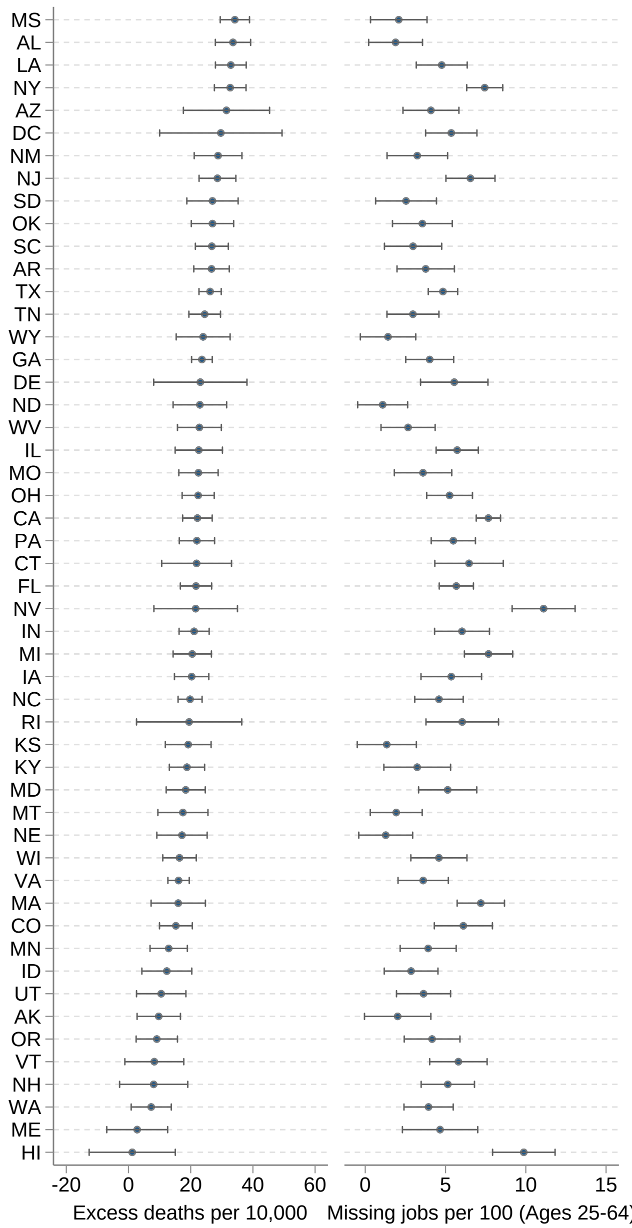
Notes: Panels show monthly observed and predicted mortality per 10,000 people among all individuals ages 11-99 (Panel A,D,G,J) and among working-age adults (ages 24-64) (Panels B, E, H, K) using the full Census Numident dataset. Panels (C, F, I, L) show observed and predicted monthly employment-to-population ratio per 100 among 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 trend lines for predicted mortality and employment-to-population are estimated as specified in Equation 1. The 95% confidence interval for the estimates of trend is shaded in grey 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 the 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: **Inter-temporal Persistence of Excess Mortality by State (Excluding NY and NJ)**



Notes: This exhibit compares average excess deaths (per 10,000) between May 2020 and February 2021 to excess deaths (per 10,000) during April 2020, for each state, excluding New York and New Jersey (the two states that were the largest outliers in terms of the highest mortality impacts in April 2020). Excess mortality is reported for 11- to 99-year-olds. Monthly damages are estimated separately by state as specified in Equation 1, and are averaged across months May 2020 to February 2021 on the y-axis. Mortality results use the full Census Numident dataset. The solid line is the line of best fit from an unweighted regression; the dashed line is the 45-degree line. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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.

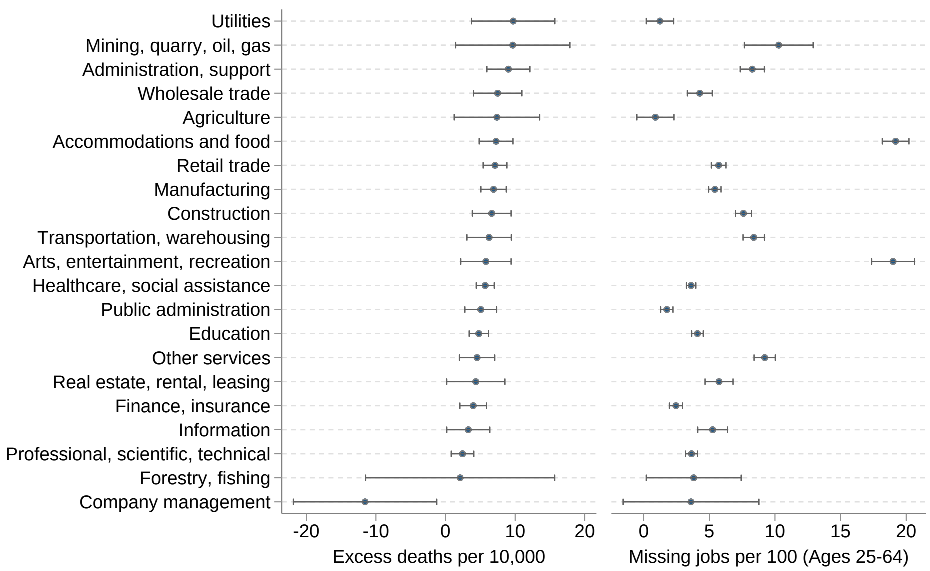
Figure C.3: **Economic and Health Damages by State**



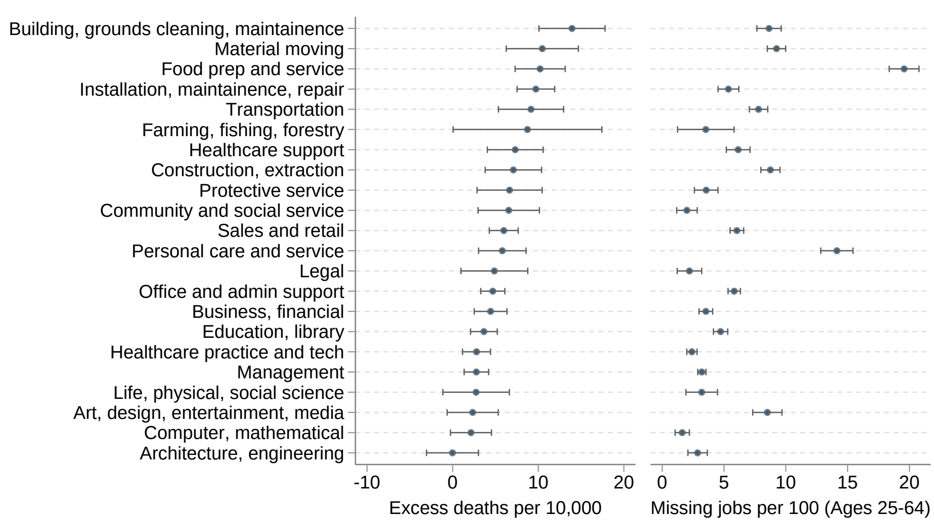
Notes: This graph plots estimates and 95% confidence intervals of annual excess all-cause mortality (among 11- to 99-year-olds) and annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 in each U.S. state. Damages are estimated as specified in Equation 3. The mortality results use the full Census Numident dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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.4: **Economic and Health Damages by Industry and Occupation**

(A) Industry



(B) Occupation



Notes: This graph plots annual excess all-cause mortality (among 25- to 64-year-olds) and annual economic damages (among 25- to 64-year-olds) from March 2020 through February 2021 by industry (Panel A) and occupation (Panel B). Damages are estimated as specified in Equation 3. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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.1: **Census Numident and ACS-Numident Sample Size**

	(1)	(2)	(3)	(4)	(5)	(6)
Restriction	**Individuals Remaining**	**Individuals Dropped at step**	**Individual-Years Remaining (Numident)**	**Individuals Remaining in 2020 (Numident)**	**Individual-Years Remaining (ACS-Numident)**	**Individuals Remaining in 2020 (ACS-Numident)**
Numident File without Death before 2010	418,800,000					
Require Birth Month and Year	416,900,000	1,894,000				
Require Death Month and Year if Died	416,800,000	112,000				
Drop Individuals at Least 100 Before 2010	402,200,000	14,630,000				
Require Can Verify Alive Start of 2010	343,200,000	59,000,000				
Initial Person-Year Sample			3,032,000,000	308,700,000	241,700,000	25,330,000
Drop if Missing Race			2,847,000,000	272,200,000	235,600,000	23,700,000
Drop if not in the US			2,572,000,000	245,000,000	218,600,000	21,990,000
Ages 11–99 Sample			2,382,000,000	241,500,000	206,700,000	21,710,000
Ages 25–64 Sample			1,439,000,000	142,900,000	118,700,000	12,100,000

Notes: This table shows the size of the datasets and the number of individuals dropped for each restriction described in A.1. Years refer to March of the indicated year through February of the following calendar year. All reported numbers were rounded following the Census Bureau guidelines. **Source**: Authors' calculations from Census Numident and 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.2: **Summary Statistics, Years 2011-2020**

	(1)	(2)	(3)	(4)	(5)
	Ages 11-99		**Ages 25-64**		
	Numident	ACS-Numident	Numident	ACS-Numident	CPS
People (Unweighted)	2,382,000,000	206,700,000	1,439,000,000	118,700,000	2,500,994
Percent Died	1.03	1.04	0.38	0.37	.
Percent Employed	.	.	.	.	73.32
Panel A: Demographics					
Average Age	44.29	44.77	44.49	44.77	43.93
% in each category					
Male	48.77	48.00	49.17	49.00	49.03
Panel B: Race/Ethnicity	.	.	.	.	.
Hispanic	13.69	13.20	13.23	12.99	17.06
Non-Hispanic White	67.34	68.74	67.10	68.35	61.75
Non-Hispanic Black	12.33	11.79	12.56	11.93	12.67
Non-Hispanic Asian	5.18	4.95	5.61	5.40	6.14
Non-Hispanic American Indian/Alaskan	0.90	0.83	0.93	0.85	0.76
Non-Hispanic Hawaiian/Pacific Islander	0.19	0.17	0.20	0.18	0.32
Non-Hispanic Other/Two or More Races	0.38	0.33	0.36	0.32	1.29
Panel C: Education					
Less than HS	.	25.69	.	9.19	9.92
High School or GED	.	23.10	.	25.74	28.14
Some College	.	20.06	.	24.03	16.39
Associates	.	6.72	.	9.13	10.54
Bachelors	.	15.46	.	20.95	22.59
Masters	.	6.26	.	7.84	9.24
Professional Degree	.	1.60	.	1.97	1.46
Doctorate	.	1.00	.	1.13	1.71
Missing Education	.	0.11	.	0.03	.

Notes: This table shows the summary statistics for all years of data in our data (March 2011 through February 2021). Column (1) and (3) use the full Census Numident dataset; see Section 2 for the list of restrictions on the raw data. Columns (2) and (4) use the linked dataset between Census Numident and ACS. ACS person-level weights and CPS sample weights are used in columns (2), (4), and (5) unless specified otherwise. GED stands for 'General Educational Development Test'. Mortality results are rounded to the second decimal place to comply with the Census disclosure requirements. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), 1-Year American Community Survey, and the 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 Health and Economic Damages by State**

	(1)	(2)	(3)	(4)	(5)	(6)
State	**Annual Excess Mortality (per 10,000)**	**Annual Predicted Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**Predicted Employment (per 100)**	**(SE)**
AL	33.60	129.60	(2.89)	1.89	69.84	(0.86)
AK	9.73	79.57	(3.56)	2.02	71.04	(1.05)
AZ	31.50	107.20	(7.07)	4.09	75.35	(0.89)
AR	26.70	127.60	(2.91)	3.77	71.98	(0.91)
CA	22.16	87.64	(2.42)	7.67	75.32	(0.39)
CO	15.24	84.62	(2.69)	6.11	81.35	(0.92)
CT	21.90	106.90	(5.73)	6.47	79.72	(1.09)
DE	23.10	117.00	(7.65)	5.54	78.82	(1.07)
DC	29.69	89.71	(10.04)	5.36	81.15	(0.82)
FL	21.70	120.20	(2.57)	5.67	75.04	(0.54)
GA	23.61	99.39	(1.69)	4.02	75.37	(0.76)
HI	1.20	108.60	(7.06)	9.88	77.36	(0.99)
ID	12.33	96.17	(4.09)	2.86	77.57	(0.85)
IL	22.60	104.10	(3.88)	5.73	77.79	(0.67)
IN	21.10	116.50	(2.47)	6.03	78.86	(0.87)
IA	20.30	112.80	(2.82)	5.36	83.41	(0.96)
KS	19.20	110.10	(3.75)	1.34	78.84	(0.94)
KY	18.80	127.90	(2.89)	3.24	71.23	(1.06)
LA	32.90	114.00	(2.52)	4.76	71.79	(0.81)
ME	2.80	125.20	(5.00)	4.66	78.97	(1.20)
MD	18.40	102.50	(3.21)	5.14	80.75	(0.92)
MA	16.00	103.40	(4.46)	7.20	79.53	(0.75)
MI	20.50	116.30	(3.14)	7.68	75.54	(0.77)
MN	12.93	94.67	(3.06)	3.92	82.48	(0.89)
MS	34.20	126.80	(2.40)	2.09	68.03	(0.90)
MO	22.50	119.40	(3.22)	3.60	77.94	(0.91)
MT	17.50	109.20	(4.11)	1.93	77.56	(0.83)
NE	17.20	102.60	(4.13)	1.28	82.88	(0.86)
NV	21.60	103.60	(6.86)	11.11	76.20	(1.00)
NH	8.10	106.80	(5.59)	5.14	83.08	(0.85)
NJ	28.60	103.30	(3.02)	6.55	78.66	(0.78)
NM	28.80	112.70	(3.92)	3.24	69.66	(0.96)
NY	32.70	100.60	(2.60)	7.44	75.11	(0.57)
NC	19.80	111.30	(1.97)	4.59	75.05	(0.77)
ND	22.95	97.75	(4.39)	1.09	81.33	(0.79)
OH	22.40	121.80	(2.63)	5.25	76.79	(0.73)
OK	27.00	121.10	(3.48)	3.56	73.81	(0.95)
OR	9.10	102.20	(3.39)	4.16	76.66	(0.89)
PA	22.00	122.30	(2.90)	5.49	77.00	(0.70)
RI	19.50	116.00	(8.63)	6.04	78.88	(1.15)
SC	26.80	118.20	(2.70)	2.98	74.05	(0.91)
SD	27.00	106.20	(4.20)	2.54	82.28	(0.97)
TN	24.50	124.80	(2.59)	2.97	74.40	(0.83)
TX	26.24	89.66	(1.83)	4.84	76.26	(0.47)
UT	10.52	72.47	(4.05)	3.63	79.41	(0.86)
VT	8.30	107.60	(4.83)	5.80	80.55	(0.91)
VA	16.10	99.40	(1.75)	3.61	78.18	(0.80)
WA	7.31	92.79	(3.29)	3.95	76.83	(0.78)
WV	22.80	150.20	(3.60)	2.67	68.78	(0.86)
WI	16.40	107.60	(2.75)	4.59	81.30	(0.89)
WY	24.00	101.40	(4.42)	1.42	77.54	(0.88)

Notes: This table reports annual excess all-cause mortality (age 11-99) and annual losses in the employment-to-population ratio (age 25-64) for the period from March 2020 through February 2021, by state. Damages are estimated as specified in Equation 3. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the full Numident dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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 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	0.60	3.61	(0.06)	.	.	.
20-29	2.08	11.23	(0.10)	8.80	74.18	(0.26)
30-39	3.46	15.68	(0.13)	5.87	81.08	(0.24)
40-49	7.13	24.42	(0.18)	5.46	81.14	(0.24)
50-59	12.58	54.42	(0.34)	4.28	74.03	(0.25)
60-69	26.40	125.20	(0.69)	3.17	45.74	(0.29)
70-79	62.20	282.20	(1.42)	.	.	.
80-89	143.40	776.20	(3.77)	.	.	.
90-99	307.00	1875.00	(8.62)	.	.	.

Notes: This table reports annual excess all-cause mortality (age 11-99) and annual losses in the employment-to-population ratio (age 25-64) for the period from March 2020 through February 2021, by age group. Damages are estimated as specified in Equation 3. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the full Numident dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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: **Full Results by Industry**

	(1)	(2)	(3)	(4)	(5)	(6)
Industry	**Annual Excess Mortality (per 10,000)**	**Annual Predicted Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**Predicted Employment (per 100)**	**(SE)**
Forestry, fishing	2.10	41.51	(6.93)	3.81	92.04	(1.84)
Professional, scientific, technical	2.44	19.80	(0.83)	3.64	97.32	(0.23)
Information	3.27	23.14	(1.58)	5.25	96.56	(0.58)
Finance, insurance	3.98	19.83	(0.98)	2.45	98.15	(0.26)
Real estate, rental, leasing	4.35	30.70	(2.13)	5.74	97.12	(0.54)
Other services	4.53	30.96	(1.30)	9.22	96.16	(0.41)
Education	4.78	18.80	(0.71)	4.10	96.39	(0.22)
Public administration	5.06	27.43	(1.16)	1.76	97.73	(0.24)
Healthcare, social assistance	5.70	23.35	(0.66)	3.61	96.74	(0.18)
Arts, entertainment, recreation	5.80	26.62	(1.84)	19.00	95.36	(0.83)
Transportation, warehousing	6.26	43.21	(1.63)	8.38	96.06	(0.42)
Construction	6.63	43.63	(1.42)	7.60	96.56	(0.31)
Manufacturing	6.90	36.17	(0.93)	5.42	97.16	(0.24)
Retail trade	7.11	30.33	(0.87)	5.71	95.21	(0.28)
Accommodations and food	7.26	31.19	(1.24)	19.20	94.28	(0.52)
Agriculture	7.38	35.81	(3.13)	0.89	92.80	(0.72)
Wholesale trade	7.49	31.23	(1.78)	4.27	96.92	(0.49)
Administration, support	9.03	37.84	(1.58)	8.27	94.15	(0.47)
Mining, quarry, oil, gas	9.66	34.75	(4.19)	10.29	95.45	(1.34)
Utilities	9.72	30.09	(3.05)	1.24	97.80	(0.53)

Notes: This table reports annual excess all-cause mortality (ages 25-64) and annual losses in the employment-to-population ratio (ages 25-64) for the period from March 2020 through February 2021, by industry. Damages are estimated as specified in Equation 3. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. Results are presented in ascending order by annual excess mortality. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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: **Full Results by Occupation**

	(1)	(2)	(3)	(4)	(5)	(6)
Occupation	**Annual Excess Mortality (per 10,000)**	**Annual Predicted Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**Predicted Employment (per 100)**	**(SE)**
Architecture, engineering	–0.02	22.91	(1.55)	2.87	98.36	(0.40)
Computer, mathematical	2.14	20.22	(1.22)	1.62	97.50	(0.29)
Art, design, entertainment, media	2.34	19.80	(1.52)	8.51	96.12	(0.60)
Life, physical, social science	2.74	15.84	(1.98)	3.20	97.43	(0.65)
Management	2.77	23.83	(0.73)	3.21	97.95	(0.17)
Healthcare practice and tech	2.79	18.20	(0.83)	2.40	97.89	(0.21)
Education, library	3.65	16.34	(0.79)	4.72	96.05	(0.29)
Business, financial	4.43	19.73	(0.98)	3.53	97.47	(0.28)
Office and admin support	4.69	27.31	(0.72)	5.83	96.35	(0.26)
Legal	4.87	16.86	(1.99)	2.21	97.89	(0.51)
Personal care and service	5.80	25.56	(1.42)	14.13	94.62	(0.67)
Sales and retail	5.97	27.29	(0.86)	6.04	96.00	(0.28)
Community and social service	6.55	21.28	(1.83)	2.00	97.49	(0.42)
Protective service	6.65	29.95	(1.94)	3.56	97.42	(0.49)
Construction, extraction	7.09	48.04	(1.68)	8.76	95.65	(0.39)
Healthcare support	7.31	24.87	(1.67)	6.15	95.72	(0.49)
Farming, fishing, forestry	8.74	39.39	(4.43)	3.53	89.71	(1.17)
Transportation	9.15	48.75	(1.94)	7.80	96.06	(0.38)
Installation, maintainence, repair	9.72	42.66	(1.12)	5.36	97.08	(0.43)
Food prep and service	10.22	32.62	(1.49)	19.57	93.58	(0.61)
Material moving	10.47	45.33	(2.15)	9.25	94.86	(0.38)
Building, grounds cleaning, maintainence	13.94	45.04	(1.97)	8.64	94.01	(0.50)

Notes: This table reports annual excess all-cause mortality (ages 25-64) and annual losses in the employment-to-population ratio (ages 25-64) for the period from March 2020 through February 2021, by occupation. Damages are estimated as specified in Equation 3. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. Results are presented in ascending order by annual excess mortality. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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 Health and Economic Damages by Disability, Essential Worker Status, and Ability to Work from Home**

	(1)	(2)	(3)	(4)	(5)	(6)
Specification	**Annual Excess Mortality (per 10,000)**	**Annual Predicted Mortality (per 10,000)**	**(SE)**	**Annual Economic Damage (per 100)**	**Predicted Employment (per 100)**	**(SE)**
Panel A: Disability						
Disabled	20.20	133.20	(1.85)	2.00	31.43	(0.45)
Not Disabled	5.49	27.41	(0.27)	5.80	80.40	(0.13)
Panel B: Essential Worker						
Non-essential	5.50	28.09	(0.44)	7.14	57.72	(0.20)
Essential	6.13	29.70	(0.36)	4.51	96.55	(0.09)
Panel C: Work from Home						
Non-work from home	7.86	34.13	(0.41)	6.01	65.02	(0.17)
Work from home	3.49	22.52	(0.35)	4.18	97.19	(0.10)

Notes: This table reports annual excess all-cause mortality (ages 25-64) and annual losses in the employment-to-population ratio (ages 25-64) for the period from March 2020 through February 2021, by several groups as specified in panel titles. Damages are estimated as specified in Equation 3. We also report predicted levels of all-cause mortality and employment-to-population ratio based on the historical trend. The damages measure the deviation of observed outcomes relative to the trend-based prediction. The mortality results use the ACS-Numident linked dataset. **Source**: Authors' calculations from Census Numident, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and the 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: **Oaxaca-Blinder Style Decomposition of Gaps in Economic and Health Damages between Black and White Individuals**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Excess Deaths per 10,000					**Missing Jobs per 100**				
Specification	Baseline Gap	Explained Gap (Black Coeffs.)	% Gap Explained (Black Coeffs.)	Explained Gap (White Coeffs.)	% Gap Explained (White Coeffs.)	Baseline Gap	Explained Gap (Black Coeffs.)	% Gap Explained (Black Coeffs.)	Explained Gap (White Coeffs.)	% Gap Explained (White Coeffs.)
Age-Adjusted	11.19	.	.	.	.	3.22	.	.	.	.
Living Arrangements	11.81	3.39	28.7%	2.40	20.4%	3.26	–0.17	–5.2%	–0.09	–2.8%
Work Variables	11.42	1.18	10.3%	1.00	8.8%	2.33	0.46	19.8%	0.31	13.2%
Living and Work	11.52	3.02	26.2%	2.84	24.7%	2.34	0.38	16.1%	0.22	9.2%
Severity	10.79	0.61	5.6%	0.41	3.8%	3.37	–0.09	–2.7%	–0.07	–2.1%
Education and Income	11.03	2.60	23.6%	2.42	22.0%	3.47	1.24	35.7%	1.07	30.7%
All Variables	10.83	3.75	34.6%	3.98	36.8%	2.61	0.84	32.0%	0.44	16.9%

Notes: This table shows the estimated Black-White gaps in annual excess mortality per 10,000 and decline in the employment to population ratio from March 2020-February 2021 for people 25-64 years old using the decomposition specification described in Appendix B, and the share of each gap explained by differences in the distribution of groups of covariates indicated in the "Specification" column. See Table 5 for the sets of covariates included in each specification. Baseline gaps are calculated following Equation 6 and the explained gaps are calculated as the second term of Equation 7, with the explained share calculated following Equation 8. The "explained gap" refers to the portion of the estimated gap that are explained by differences in the covariate distributions across groups; columns for the explained gap with respect to Black coefficients use the estimated coefficients on each covariate for Black individuals and columns for the explained gap with respect to White coefficients use the estimated coefficients on each covariate for White individuals. All rows control for 5-year age bins. Mortality estimates are based on the linked Numident-ACS dataset; employment estimates use the CPS sample. Regressions are weighted with ACS or CPS survey weights. Heteroskedasticity-robust standard errors are shown in parentheses. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and 2005-2018 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: **Oaxaca-Blinder Style Decomposition of Gaps in Economic and Health Damages between Hispanic and White Individuals**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Excess Deaths per 10,000					**Missing Jobs per 100**				
Specification	Baseline Gap	Explained Gap (Hispanic Coeffs.)	% Gap Explained (Hispanic Coeffs.)	Explained Gap (White Coeffs.)	% Gap Explained (White Coeffs.)	Baseline Gap	Explained Gap (Hispanic Coeffs.)	% Gap Explained (Hispanic Coeffs.)	Explained Gap (White Coeffs.)	% Gap Explained (White Coeffs.)
Age-Adjusted	9.84	.	.	.	.	3.03	.	.	.	.
Living Arrangements	9.72	4.17	43.0%	–0.53	–5.5%	3.03	0.54	17.7%	0.54	17.8%
Work Variables	9.76	2.02	20.7%	1.13	11.6%	2.79	0.71	25.6%	0.45	16.1%
Living and Work	9.72	5.45	56.1%	0.28	2.9%	2.78	1.08	38.8%	0.76	27.4%
Severity	9.46	0.15	1.5%	0.82	8.7%	2.92	0.10	3.6%	0.08	2.8%
Education and Income	9.41	4.95	52.6%	3.20	34.0%	3.11	1.38	44.3%	1.08	34.8%
All Variables	9.46	7.08	74.8%	2.39	25.3%	3.25	1.56	48.1%	0.92	28.3%

Notes: This table shows the estimated Hispanic-White gaps in annual excess mortality per 10,000 and decline in the employment to population ratio from March 2020-February 2021 for people 25-64 years old using the decomposition specification described in Appendix B, and the share of each gap explained by differences in the distribution of groups of covariates indicated in the "Specification" column. See Table 6 for the sets of covariates included in each specification. Baseline gaps are calculated following Equation 6 and the explained gaps are calculated as the second term of Equation 7, with the explained share calculated following Equation 8. The "explained gap" refers to the portion of the estimated gap that are explained by differences in the covariate distributions across groups; columns for the explained gap with respect to Hispanic coefficients use the estimated coefficients on each covariate for Hispanic individuals and columns for the explained gap with respect to White coefficients use the estimated coefficients on each covariate for White individuals. All rows control for 5-year age bins. Mortality estimates are based on the linked Numident-ACS dataset; employment estimates use the CPS sample. Regressions are weighted with ACS or CPS survey weights. Heteroskedasticity-robust standard errors are shown in parentheses. **Source**: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and 2005-2018 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.10: **Oaxaca-Blinder Style Decomposition of Gaps in Economic and Health Damages between those with and without a BA**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Excess Deaths per 10,000					**Missing Jobs per 100**				
Specification	Baseline Gap	Explained Gap (BA Coeffs.)	% Gap Explained (BA Coeffs.)	Explained Gap (Non-BA Coeffs.)	% Gap Explained (Non-BA Coeffs.)	Baseline Gap	Explained Gap (BA Coeffs.)	% Gap Explained (BA Coeffs.)	Explained Gap (Non-BA Coeffs.)	% Gap Explained (Non-BA Coeffs.)
Age-Adjusted	7.57	.	.	.	.	2.82	.	.	.	.
Living Arrangements	8.22	2.49	30.3%	1.37	16.7%	2.82	–0.27	–9.6%	–0.09	–3.1%
Work Variables	7.87	3.29	41.8%	1.89	24.0%	2.43	0.01	0.4%	1.44	59.4%
Living and Work	8.04	4.33	53.8%	2.70	33.6%	2.44	–0.14	–5.9%	1.36	55.9%
Severity	7.17	1.79	25.0%	1.14	15.9%	2.72	–0.30	–10.9%	–0.19	–7.1%
Race and Income	8.21	4.46	54.3%	2.61	31.7%	3.07	1.53	50.0%	2.12	69.0%
All Variables	7.37	6.79	92.2%	4.38	59.3%	2.65	0.44	16.4%	1.95	73.5%

Notes: This table shows the estimated gaps in annual excess mortality per 10,000 between individuals with and without a Bachelor's degree and decline in the employment to population ratio from March 2020-February 2021 for people 25-64 years old using the decomposition specification described in Appendix B, and the share of each gap explained by differences in the distribution of groups of covariates indicated in the "Specification" column. See Table 7 for the sets of covariates included in each specification. Baseline gaps are calculated following Equation 6 and the explained gaps are calculated as the second term of Equation 7, with the explained share calculated following Equation 8. The "explained gap" refers to the portion of the estimated gap that are explained by differences in the covariate distributions across groups; columns for the explained gap with respect to non-B.A. coefficients use the estimated coefficients on each covariate for individuals without a B.A. and columns for the explained gap with respect to B.A. coefficients use the estimated coefficients on each covariate for individuals with a B.A.. All rows control for 5-year age bins. Mortality estimates are based on the linked Numident-ACS dataset; employment estimates use the CPS sample. Regressions are weighted with ACS or CPS survey weights. Heteroskedasticity-robust standard errors are shown in parentheses.
Source: Authors' calculations from Census Numident, 2010 Decennial Census, 2010 Census Modeled Race File, 2010-2019 Master Address File - Auxiliary Reference File (MAF-ARF), and 2005-2018 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.